Software Adoption, Employment Composition, and the Skill Content of Occupations in Chilean Firms

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ABSTRACT We contribute to the technology, skills, and jobs debate by exploiting a novel dataset for Chilean firms between 2007 and 2013, with information on the firms’ adoption of complex software used in client management, production, or administration and business software packages. Instrumental variables estimates show that, in the medium-run, adoption of this complex software reallocates employment away from professional and technical workers, toward administrative and unskilled workers (production and services). Adoption also increases the use of routine and manual tasks and reduces that of abstract tasks within firms. The contrast between ours and previous findings shows that labour market impacts of technology adoption hinge on the type of technology and its complementarity with the skills content of occupations.

1. Introduction

Technology adoption, and especially information and communication technology (ICT) adoption, has expanded dramatically during the last decade (World Bank, 2016). The impact of ICT on the jobs and skills demanded by employers is a topic of great interest and an important driver of future labour demand. However, a concern is that the growing use of ICT is leading to a polarisation of labour markets in developed countries, whereby employment and earnings are shifting away from middle-skilled jobs into both high-skilled and low-skilled jobs (Autor, 2014; Autor & Dorn, 2013; Frey & Osborne, 2013). Some authors argue that this change is explained by changes in the task composition of jobs following digital technology adoption, as computers carry out activities that follow automated and explicit rules and procedures (Autor, Levy, & Murnane, 2003). More recently technologies are advancing even faster (for example, robots and artificial intelligence), automating tasks typically performed by more educated workers (Autor, 2015; Brynjolfsson & McAfee, 2014). These are increasingly non-routine analytical and cognitive tasks, such as deep-learning systems applied to medicine, or machines composing music. A crucial research and policy question is how these more advanced types of software and technologies are affecting firms’ employment composition and the skill content of occupations.

To our knowledge, we are the first paper assessing the medium-run impacts of firms’ adoption of advanced technologies on their demand for skills and jobs. We exploit a novel firm-level longitudinal survey for Chile across a six-year interval, 2007–2013, when the adoption of complex technology used
in client management, production, or administration and business software packages, is observed. We inquire as to whether the adoption of complex software is associated with labour reallocation within firms, across tasks using different skills. To date, the literature has mainly looked at the impacts of the automation process due to the use of computers (for example, Autor et al., 2003; Autor and Dorn, 2013). We argue that complex software, an advanced but intermediate technology between plain computers and full artificial intelligence, is more likely to already be replacing the use of routine-cognitive and analytical tasks, typically performed by more skilled workers.

Our findings show interesting patterns for Chile. First, in the medium run, complex software adoption is associated with a significant expansion of jobs among administrative and unskilled production and services workers and a reallocation of employment away from professionals and technical workers within firms. Second, consistent with these employment shifts, the adoption of complex software is linked to an increase in firms’ use of routine and manual tasks, and a reduction in firms’ use of abstract tasks, which are arguably performed by technology. Finally, our findings are driven by patterns of advanced technology adoption in sectors with relatively low-educated workforce and low-productivity, where most unskilled workers are employed. Altogether these findings suggest that the adoption of advanced technologies, such as complex software, have the potential to be inclusive for lower-skilled workers. Although our analysis is specific to Chile and to a particular type of technology, we believe it sheds new light on an important policy debate and begins to improve our understanding of the medium-term impacts of advanced technological adoption on changing patterns in the demand for skills.

We estimate a reduced-form specification relating the firm’s adoption of complex software with the shares of different occupations in the firm’s total employment and with an index capturing the skills content of different tasks across occupations, between 2007 and 2013. We face two empirical challenges. First, the firm’s complex software adoption decision is likely jointly made with employment and skills choices based on unobserved firm characteristics (for example, managers’ ability). Second, complex software adoption depends on the firm’s actual mix of occupations and skills. We mitigate these concerns in two ways: (i) exploiting the panel nature of the dataset to account for time-invariant firm unobservable characteristics via firm fixed effects and (ii) instrumenting firm-level adoption of complex software with a proxy for the sub-national degree of technological progress – the regional share of households with access to a computer – allowing that regional rollout to impact differentially firms depending on their sector’s pre-determined ICT intensity. We argue that firms located in regions with stronger computer demand and operating in ICT-intensive sectors are more likely to adopt complex software.

We exploit three micro datasets. First, we use a novel firm-level survey of formal private firms across all sizes and sectors in the Chilean economy, Encuesta Longitudinal de Empresas (henceforth ELE) for 2007 and 2013, that captures direct measures of technology adoption and the workforce’s human capital. Second, we use Chilean data on the task content of each occupation from the 2014 Programme for the International Assessment of Adult Competencies survey (henceforth PIAAC). Third, we explore the Chilean national household survey (henceforth CASEN), for 2006 and 2013, to obtain information on sub-national ICT use.

This combination of data sources is unique. First, it allows us to assess impacts of complex software adoption across different occupations (managers, administrative workers, professionals, and technical workers, and unskilled production and services workers) and across the task content of occupations, thus identifying which groups disproportionately benefit and which bear the cost of technology adoption. Second, Chile is a particularly interesting setting to study the impacts of ICT adoption on the demand for skills and jobs due to its high and persistent degree of income inequality. The Chilean economy is currently looking for sources of diversification and a more knowledge- and technologically-intensive growth model that can also be more inclusive (Dutz, Almeida, & Packard, 2018).

We contribute to the literature in different ways. First, this paper is the first assessment of the link between advanced technology adoption and firm-level task content of occupations. Previous firm-level studies examine the impact of ICT measures such as IT capital stock/investment, computer adoption, broadband internet access, and number of IT workers on firms’ employment, skills, and wages (Doms,
Dunne, & Troske, 1997; Entorf, Gollac, & Kramarz, 1999; Caroli & Van Reenen, 2001; Greenan, Meiresse, & Topiol-Bensaid, 2001; Bresnahan, Brynjolfsson, & Hitt, 2002; Bartel, Ichniowski, & Shaw, 2007; De Stefano, Kneller, & Timmis, 2014; Akerman, Gaarder, & Mogstad, 2015; Gaggl & Wright, 2017). To our knowledge only Bloom, Garicano, Sadun, and Van Reenen (2014) examine the impacts of complex software but focus on firms’ organisational decisions rather than skill demand. We construct firm-level task indexes, weighing the task content of each occupation by its share in firm total employment. We divide the task content of occupations into abstract, routine, and manual categories following the task-based literature (see Autor and Handel, 2013 for the United States; Messina, Oviedo, and Pica, 2016 for Latin America). Second, while previous literature focused on developed economies, we offer evidence for an emerging economy with high income inequality and some labour market polarisation (Messina et al., 2016). Third, we exploit data on the task content of occupations specific to the country of study (Chile’s PIAAC survey) whereas most previous studies exploit the United States task content of occupations assuming rankings are similar across countries.

The remainder of the paper proceeds as follows. Section 2 describes the data and summary statistics while Section 3 discusses the conceptual approach and testable hypotheses. Section 4 presents the econometric strategy. Section 5 discusses the main results. Section 6 focuses on heterogeneity and additional results and Section 7 concludes.

2. Data and summary statistics

2.1. Datasets and definitions

In the paper we exploit several datasets. First, we exploit a longitudinal firm-level survey representative of most economic activities in Chile, ELE, between 2007 and 2013. Technical details are provided in the Supplementary Materials and all variables used are defined in Appendix Table A1.

ELE is a unique dataset to answer our research questions as it collects rich information on firm technology adoption, including use of computers and complex software. Complex software use captures the use of client management, production, or administration and business software packages. This software can perform complex tasks within firms such as the planning of production levels (based on expected demand and stocks), inventory and order management, product pricing, management of marketing and clients, estimating production costs along the production process, controlling optimisation of processes, and billing, accounting, finance, and human resources. Specific examples are Customer Relationship Management (CRM) software to manage business-customer relationships or Enterprise Resource Planning (ERP) software that integrates many functions, including inventory and order management, accounting, human resources, client management, onto a system to streamline processes and information across the entire firm. This variable markedly differs from more standard ICT measures in the literature (for example, computer use, internet access, or IT capital/investment) and we argue it likely impacts the firm’s production process differently. Complex software adoption is largely managed by highly skilled workers and can lead complex routine but also non-routine analytical tasks. For instance, currently production software can perform the planning of production levels which was in the past carried out by professionals such as engineers.

ELE also collects rich information about the firm’s labour force including firm’s total employment across four occupation categories – managers, administrative workers, professionals and technical workers, and unskilled production and services workers. Unfortunately, there is no additional information to generate occupational groupings more aligned with international occupations’ classifications (such as ISCO). As control variables we use firm size, age, exporter status, foreign ownership, access to credit, degree of education, number of years of experience, and age of the manager. In some empirical exercises, we consider as firm outcomes: whether the firm is engaged in subcontracting activities and different types of training provided.

Second, we exploit the 2014 Chilean PIAAC survey on adult skills collected by the OECD which measures cognitive and workplace skills (for example, literacy, numeracy, and problem-solving) across occupations. We use these to compute an index of the task content of occupations. Drawing on
Acemoglu and Autor (2011) and Autor and Handel (2013), we define the task content of occupations using abstract, routine, and manual tasks categories. Abstract comprises abstract problem-solving and creative, organisational, and managerial tasks, while routine involve codifiable tasks that follow explicit procedures, and manual comprises tasks that require physical adaptability. To define the task content of a specific occupation we identify in the PIAAC the set of questions closer to those used by other adult skills surveys (for example, DOT, PDII, O*NET, or STEP surveys used by Autor et al. (2003), Autor and Handel (2013), Di Carlo et al. (2016), and Messina et al. (2016)). The methodology used to construct the task content measures and the PIAAC questions used are detailed in the Supplementary Materials.

We define the firm-level task indexes as a weighted average of the task content measures across all occupations, with weights given by the share of each occupation in the firm’s total employment:

\[
K^k_{jt} = \sum_{c=1}^{4} shr_{jtc} \cdot task^k_c
\]

where \(j\) designates a firm, \(t\) a year, \(c\) is one of the four occupations in ELE (managers, administrative workers, professionals and technical workers, and unskilled production and services workers), \(k\) is a type of task (abstract, routine, and manual), \(task^k_c\) is the average of task content \(k\) in occupation \(c\), and \(shr_{jtc}\) is the share of occupation \(c\) in firm total employment.

Panel A of Table 1 provides for each occupation, the average task content across firms in the sample (\(task^k_c\)). Occupations with higher values are more intense in the indicated task. Panel B provides a schematic summary of the intensity of each task content measure for each occupation, showing whether the use of each task is above (+) or below (−) the average use of that task across all occupations. The shaded fields indicate the most important tasks for each occupation. The results show that the intensity of use of abstract and manual tasks is correlated with the skill intensity of occupations. Managerial, professionals, and technical occupations are more intensive in abstract tasks. Unskilled production and services occupations are more intensive in manual tasks. Routine tasks are more important for administrative and unskilled production and services occupations.

Third, we exploit CASEN, a nationwide household survey for Chile, collected by the Ministry of Social Development which is representative across the 15 regions. We use data for 2006 and 2013 and construct regional measures of technological development/sophistication: the share of households with a computer in use and the share of households with at least one cell phone. This information is used to construct instrumental variables. We also construct measures of regional development: the share of

### Table 1. Task content measures based on the PIAAC survey by occupation in the ELE survey

|                  | Abstract | Routine | Manual |
|------------------|----------|---------|--------|
| Managers         | 1.081    | −1.320  | −1.137 |
| Administrative workers | −0.127  | 0.556   | 0.274  |
| Professionals and technical workers | 0.347    | −0.191  | −0.362 |
| Unskilled production and services workers | −1.302   | 0.955   | 1.225  |

Panel B shows whether each task content measure of a given occupation in ELE is above (+) or below (−) the average of that task content across all occupations. Shaded fields indicate the most important tasks content for each occupation.
urban households, the average number of years of education of members of the households, and the average household per capita income. These measures are used as control variables.

Finally, we exploit 2003 Chilean input-output matrix, published by Chile’s Central Bank. For each 1-digit sector among 11, we calculate the share of ICT inputs – defined as telecommunication services – in the total value of inputs used by the sector.

2.2. Sample and summary statistics

Using ELE, we construct our firm-level estimating sample: a balanced panel of 1,852 firms observed in 2007 and 2013. The balanced panel allows us to exploit changes in outcomes of interest over a six-year period. We conjecture this is a sufficiently long period to observe potential impacts following complex software adoption that could be hindered in the short-run when firms have more fixed factors of production. To obtain our firm-level estimating sample we consider firms with non-missing information on employment, software, and control variables included in our main specification (a total of 1,992 firms). We exclude outliers, defined as firms reporting very large changes in employment composition during the period (total of 140). The outliers likely have misreported information and their inclusion could bias our estimates. However, we will show our findings are not driven by this.

The sector and size composition of our final sample are shown in Table 2. Close to 40 per cent of firms operate in the wholesale and retail trade sector or in real estate and business activities, and less than a fifth operate in manufacturing. On average, 75 per cent of firms are micro or small whereas only 12 per cent of firms are large.

Table 3 reports summary statistics for our estimating sample. Panel A covers the main outcome variables. During the period, there was some firm downsizing from an average of 54 workers in 2007 to 44 workers in 2013. In this sample of predominantly micro and small firms, unskilled production and services workers are the major occupation, accounting on average for half of firm total employment and followed by professionals and technical workers accounting on average for a fifth of firm total employment. Between 2007 and 2013 the share of managers fell (from 14% to 7% of total employment) and so did that of professionals and technical workers (from 23% to 19% of total employment). The share of unskilled production and services workers increased (from 46% to 58% of total employment), while that of administrative workers barely changed. On average firms in the sample make large use of manual and routine tasks and less use of abstract tasks. By construction, the

| Table 2. Sectoral and size composition of the ELE panel sample |
|---------------------------------------------------------------|
| Size category by value of annual sales                        |
| Micro                                                        | 41.74 |
| Small                                                       | 33.86 |
| Medium                                                      | 12.09 |
| Large                                                       | 12.30 |
| Sector                                                      |       |
| Agriculture, hunting, fishing, and forestry                  | 11.3  |
| Mining and quarrying                                         | 0.9   |
| Manufacturing                                               | 16.2  |
| Electricity, gas and water supply                            | 0.2   |
| Construction                                                | 10.2  |
| Wholesale and retail trade                                   | 25.4  |
| Hotels and restaurants                                       | 5.8   |
| Transport, storage and communications                        | 7.8   |
| Financial intermediation                                     | 0.9   |
| Real estate and business activities                           | 14.5  |
| Other service activities                                     | 6.8   |

Source: Authors’ calculations based on ELE’s 2007 and 2013 waves.
Notes: Size categories are defined in Table A1.
observed changes in the firm-level task content of occupations indexes follow closely the changes in the shares of each occupation in firm total employment. Between 2007 and 2013, the abstract index declined whereas the routine and manual indexes increased. The large standard deviations of all these measures indicate a substantial degree of heterogeneity across firms in our main outcomes.

Panel B of Table 3 covers the main independent variable: a (dummy) variable for whether the firm uses complex software. In our sample, 47 per cent of firms in Chile use complex software in 2007 and this percentage declines to 39 per cent in 2013. But for a different ICT variable – the use of computers – the percentage of users increases from 81 per cent of firms in 2007 to 89 per cent in 2013. This evidence is in accordance with the increase in computer use by households across regions over the sample period (shown in the Supplementary Materials). The reduction in the share of firms using complex software is consistent with firm downsizing over the period. This is perhaps the result of the global financial crisis, as small firms are less likely to use complex software (a finding shown in the Supplementary Materials). Despite the crisis, firms continue to increase their use of computers likely for access to basic software, whose benefits exceed costs even in times of lower demand (whereas that may not be the case for complex software).

Figure 1 shows an important degree of variability in complex software use across sectors and regions in Chile and varying patterns between 2007 and 2013. The increase in complex software use over time is driven mainly by firms in services sectors but is widespread across several regions.

Table 3. Summary statistics on employment-related outcome variables, ICT use variables, and firm characteristics

| Panel A: Employment-Related and Task-Related Variables at Firm Level |
|---------------------------------------------------------------|
| Total employment | 53.66 | 280.39 | 43.59 | 443.33 |

| Shares in total employment of: |
|-------------------------------|
| Managers | 0.14 | 0.26 | 0.07 | 0.16 |
| Administ. workers | 0.17 | 0.25 | 0.16 | 0.23 |
| Professionals & technical workers | 0.23 | 0.32 | 0.19 | 0.33 |
| Unskilled prod. & services workers | 0.46 | 0.42 | 0.58 | 0.39 |

| Task indexes |
|---------------|
| Abstract task index | −0.38 | 0.76 | −0.64 | 0.65 |
| Routine task index | 0.30 | 0.64 | 0.52 | 0.50 |
| Manual task index | 0.36 | 0.73 | 0.61 | 0.62 |

| Training and outsourcing variables |
|------------------------------------|
| Worker training | 0.30 | 0.46 | 0.12 | 0.32 |
| Manager training | 0.25 | 0.43 | 0.06 | 0.24 |
| Manager training on ICT | 0.02 | 0.14 | 0.00 | 0.06 |
| Outsourcing | 0.10 | 0.30 | 0.05 | 0.22 |

| Panel B: ICT Use at Firm Level |
|--------------------------------|
| Computer use | 0.81 | 0.40 | 0.89 | 0.31 |
| Complex software use | 0.47 | 0.50 | 0.39 | 0.49 |

| Panel C: Firm Characteristics |
|------------------------------|
| Firm age | 11.80 | 10.21 | 17.79 | 9.87 |
| Exporter | 0.06 | 0.24 | 0.04 | 0.19 |
| Foreign-owned | 0.02 | 0.14 | 0.01 | 0.09 |
| Credit-constrained | 0.05 | 0.21 | 0.03 | 0.16 |
| Manager age | 50.85 | 11.22 | 56.55 | 12.30 |
| Manager years of experience | 21.32 | 12.15 | 24.78 | 13.09 |
| Manager with second. education | 0.33 | 0.47 | 0.37 | 0.48 |
| Manager with college education | 0.63 | 0.48 | 0.58 | 0.49 |

Number of firms: 1,852

Source: Authors’ calculations based on ELE’s 2007 and 2013 waves and 2014 Chile PIAAC.

Notes: Statistics were obtained using ELE sampling weights.
Since our main reduced-form equation will exploit changes in complex software use, we examine the prevalence of firms switching ‘adoption’ status and find it covers 25 per cent of firms in Chile between 2007 and 2013.8

Regarding variables with regional-level variation used as instruments in the instrumental variables specification, we show in the Supplementary Materials that the regional percentage of households with a computer in use increased on average from 31 per cent in 2006 to close to 57 per cent in 2013 and all regions experienced an increase. The regional share of households with cell phones also increased substantially over time.

3. Conceptual framework and testable hypotheses

Our testable hypotheses are as follows.

3.1. Professionals and technical workers

The impact of complex software adoption on firm employment of professionals and technical workers is ambiguous. On the one hand, we expect complex software to perform more abstract and routine tasks carried out by professionals and technical workers. This impact stands in contrast with the argument in the literature on automation of routine tasks performed by middle-educated workers through the adoption of technology (computer or internet) that complements skilled employment. For this reason, all else constant, we expect complex software use to potentially substitute for employment of professionals and technical workers. Brambilla (2018) proposes a theoretical model on digital

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**Figure 1.** Complex software use across regions and sectors.
*Source:* ELE’s 2007 and 2013 waves.
*Note:* The shares were obtained using ELE sampling weights.
technology adoption and jobs with heterogeneous firms that is flexible enough to allow for substitution between skilled employment and technology. On the other hand, skilled workers have the ability to interpret/draw upon the results produced by the complex software. Hence, we expect the degree of substitution of professionals and technical workers to be bounded by this consideration. Importantly, complex software use may have positive impacts on firm efficiency and output, which would increase the demand for any type of worker. Depending on which effect dominates (substitution or output expansion) there may be a reduction or an increase in the share of professionals and technical workers in firm total employment.

3.2. Unskilled production and services workers

If the adoption of complex software has an output expansion effect, then we should observe an increase in the demand for unskilled production and services workers and a possible increase in their share in total employment (depending on the relative increase for other occupations). Keeping the firm's output level fixed, an increase in the use of services workers related to software support and IT services is possible. In ELE, these types of occupations are included in the unskilled production and services workers category.

3.3. Managers and administrative workers

The impact of complex software adoption on firm employment of managers is likely to be negligible, while the impact on firm employment administrative workers is ambiguous. We do not expect the adoption of complex software to directly affect the demand for managers; furthermore, any output expansion effect may not translate into growth because managers are not directly involved in the production process. A negative impact on employment of administrative workers is possible as some tasks covered by complex software may enter in their domain, especially those covered by client management software. Concurrently, an expansion in firm output resulting from complex software adoption may increase the demand for administrative workers.

3.4. Task content of occupations

When a firm adopts complex software, the firm-level task indexes change mainly due to changes in the shares of the different occupations. Considering our previous hypotheses on employment shares, the change in the different task indexes due to complex software adoption is mostly ambiguous.

3.5. Sectoral heterogeneity in impacts

Our analysis covers different sectors, where the set of tasks performed by each occupation and the share of each occupation in total employment are different. We expect the elasticity of substitution between complex software and professionals and technical workers to vary across sectors due to these differences. In low-productivity sectors where the set of tasks carried out by professionals and technical workers and their share in total employment are small, skilled workers could be replaced by complex software. On the contrary, in high-productivity sectors where the set of professionals and technical workers’ tasks and their share in total employment are large, complex software may complement skilled workers. Hence, the impact of complex software on different occupation shares and task indexes can differ across sectors.

4. Econometric strategy

To test the hypotheses discussed in Section 4, we consider the following reduced-form specification relating complex software use to firm-level labour-related outcomes:
Complex software employment skill content of occupations

\[ Y_{jsrt} = \beta_0 + \beta_1 \text{software}_{jsrt} + \delta X_{jsrt} + I_j + I_t + \varepsilon_{jsrt} \]  

(2)

where \( j \) is a firm, \( s \) a sector, \( r \) a region, \( t \) a year, \( Y \) is the main outcome (share of each occupation in firm total employment or firm-level task indexes), and \( \text{software}_{jsrt} \) is a dummy variable for whether the firm uses complex software. The vector \( X_{jsrt} \) includes time-varying firm characteristics – size categories, age (in logs), exporter status, foreign ownership and credit constraints, age (in logs), years of experience (in logs) and indicators for the degree of education of the main manager, time-varying regional characteristics – average per capita household income (in logs), share of urban households, average number of years of education of the households (in logs), and time-varying province-sector number of computers used by firms, and region-specific time trends. In Equation (2), \( I_j \) and \( I_t \) are firm and year fixed effects, respectively, and \( \varepsilon_{jsrt} \) is an error term.

Our parameter of interest is \( \beta_1 \), which captures the impact of complex software adoption on firm’s occupational structure or task indexes. The OLS estimates of \( \beta_1 \) can be biased as firms likely make their software adoption and employment decisions jointly based on unobserved characteristics (for example, managerial quality). Controlling for firm fixed effects improves upon OLS estimates but there are still concerns to interpret \( \beta_1 \) as a causal impact of technology adoption on firm demand for skills. First, time-varying unobserved firm characteristics or shocks (for example, a performance boost) may affect the firm’s choice to adopt complex software and drive the use of particular types of occupations and/or tasks. Second, the decision to adopt complex software may itself depend on the firm’s mix of occupations and tasks.

We hope that the instrumental variables (IV) strategy we exploit mitigates these concerns. It is based on the sub-national adoption of a more aggregated measure of ICT: the regional share of households with a computer in use. We expect the use of computers by households at the sub-national level to be positively correlated with the firm’s adoption of complex software. This may happen as both firms and households benefit from reductions in prices of technology products and from exposure to newer technologies. Nevertheless, from the perspective of an individual firm, access to computers by households in its region is exogenous, that is, the firm does not influence the computer adoption decision of households. Our instrument exploits the interaction between the regional share of households with a computer in use (\( \text{reg.computer}_r \)) and the Chilean sectoral ICT intensity (\( \text{ICT.intens}_s \)) measured as of 2003. The rationale for the interaction term is that the degree of technological progress at the sub-national level can impact differentially firms depending on their sector’s ICT intensity.

Additionally, we are concerned with three other identification challenges. First, the use of computers by households in a region may reflect the region’s level of development which is likely correlated with firms’ skills and employment choices. To mitigate this concern, our specification controls for time-varying unobserved regional shocks affecting both the use of computers by households and complex software adoption by firms such as variation in technology prices. To mitigate this concern, our specification includes region-specific time trends. Third, if firms invest in computers and other ICT technologies while investing in complex software there could be a concern with the exclusion restriction for our instrument as its impact on firm employment decisions would not operate just via the complex software adoption. To account for this possibility, our specification controls for other ICT usage at the region-sector level: the average number of computers used by firms in the region-sector each year.

Our first-stage specification is thus given by:

\[ \text{software}_{jsrt} = \delta_0 + \delta_1 (\text{reg.computer}_r * \text{ICT.intens}_s) + \pi X_{jsrt} + I_j + I_t + I_r * T_t + u_{jsrt} \]  

(3)

where \( I_r \) are region indicators and \( T_t \) a linear time trend, \( u_{jsrt} \) an independent and identically distributed (i.i.d.) error term, and all other variables are defined above.

The second-stage specification is given by:

\[ Y_{jsrt} = \beta_0 + \beta_1 \text{software}_{jsrt} + \delta X_{jsrt} + I_j + I_t + I_r * T_t + \varepsilon_{jsrt} \]  

(4)
where software_{first} is estimated from the first-stage (in a two-stage least squares framework) and the error \( e_{first} \) is an i.i.d. error term. Equation (4) estimates robust correlations between complex software adoption and firm labour outcomes exploiting variation within firms over time, rather than cross-sectional variation across very different firms. Inference is based on Huber-White standard errors robust to heteroscedasticity, clustered at the region-sector level to account for the more aggregate degree of variability of the instrument (Moulton, 1990).

5. Impact of complex software adoption on employment composition and task content of occupations

Panel A of Table 4 reports OLS estimates of Equation (3), Panels B and C report second-stage estimates of Equation (4) relating instrumented firm adoption of complex software with skill composition of firm employment (Panel B) and firm task indexes (Panel C).

Panel A shows a positive and statistically significant correlation between a firm’s adoption of complex software and the share of households with a computer in use interacted with the firm’s sector ICT intensity. Despite the decrease in software use over time in some regions and sectors in Chile (Figure 1), the correlation between complex software adoption and our proposed instrument is positive and strong. When the use of technology increases at the region-sector level, the firm’s adoption of complex software also increases significantly for firms in that region-sector. With a fixed sectoral ICT intensity, for each percentage point increase in the regional share of households with a computer in use, the share of managers increases by 0.270 units. The share of unskilled production & services workers decreases by 0.571 units, and the share of professional & technical workers decreases by 0.583 units.

Table 4. Firm complex software adoption, employment composition, and task indexes

| Dependent variable:                      | Panel A: First-stage – Firm complex software use |
|------------------------------------------|-------------------------------------------------|
|                                         | (1)                                             |
| Share of hhlds with computer* sector ICT intensity | 4.541 \[1.409]*** |
| P-value of underid. test F stat          | 0.0012                                           |
|                                         | 10.39                                           |

| Dependent variable:                      | Panel B: Second-stage – Firm employment shares |
|------------------------------------------|------------------------------------------------|
|                                         | Managers                        Professionals & technical workers Administ. workers Unskilled production & services workers |
| Firm complex software use                | (1)                              | (2)                          | (3)                               | (4)                              |
|                                         | −0.270                           | −0.583                        | 0.282                            | 0.571                            |
|                                         | [0.228]**                        | [0.258]**                     | [0.209]**                        | [0.256]**                        |

| Dependent variable:                      | Panel C: Second-Stage – Firm task indexes |
|------------------------------------------|------------------------------------------|
|                                         | Abstract Routine Manual                  |
| Firm complex software use                | (1)                                      | (2)                          | (3)                                |
|                                         | −1.273                                   | 1.170                        | 1.294                              |
|                                         | [0.506]**                               | [0.473]**                   | [0.499]**                          |
| Observations                             | 3,704                                   | 3,704                        | 3,704                              |

Source: Authors’ calculations based on ELE’s 2007 and 2013 waves and 2014 Chile PIAAC.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1, 5, and 10 per cent confidence levels, respectively. Panel A reports the estimates of the first-stage given by Equation (3). Panels B and C report the 2SLS estimates of the second-stage given by Equation (4). All regressions control for firm and year fixed effects and include time-varying firm characteristics (size categories, age [in logs], exporter, foreign-owned, and credit constrained indicators, age [in logs], number of years of experience [in logs], and indicators for the degree of education of the main manager), time-varying region characteristics (average per capita household income [in logs], share of urban households, and average number of years of education of households [in logs]), number of computers used by firms in the region-sector, as well as region-specific time trends. In Panel A, the under-identification test is based on Sanderson and Windmeijer (2016).
use, the share of firms adopting complex software increases by approximately four percentage points. The reported p-value for the Sanderson and Windmeijer (2016) under-identification test suggests that the proposed instrument is valid. The F-statistic is close to 10, the Staiger and Stock (1997) rule for rejection of the hypothesis of weak instruments with one endogenous variable.

The results in Panels B and C show that complex software adoption is negatively and significantly associated with the share of professionals and technical workers and positively and significantly associated with the share of unskilled production and services workers in firms’ total employment in Chile. Specifically, complex software adoption by a firm reduces the share of professionals and technical workers by 58 percentage points and increases the share of unskilled production workers by 57 percentage points. Panel B also shows that complex software adoption decreases the share of managers and increases the share of administrative workers, but those effects are statistically insignificant.

Panel C shows that complex software adoption is significantly negatively linked to the abstract task index and significantly positively linked to the routine and manual task indexes. These correlations follow strongly the correlations with the different occupations’ shares, which are the weights used to construct the task indexes.

The findings in Table 4 are robust to: the use of an alternative methodology to compute firm-level task indexes following Autor and Handel (2013), measuring the task content of occupations separately across sectors, the use of an alternative instrument for firm complex software use (the share of households in the region with at least one cell phone), the use of no cross-sectional sampling weights, the inclusion of 140 “outlier firms” (exhibiting very large changes in employment composition between 2007 and 2013), the use of region and sector fixed effects (ignoring the panel structure of the data), and the control for sector-specific time trends related for instance to the commodity price boom experienced by Chile over the period, as shown in the Supplementary Materials.

One could think of three additional threats to our identification strategy. First, the growing use of computers by households in a region may change the quality of the available workforce because workers become more proficient at using computers. This change could influence firms’ labour demand. Our prior is that the growing use of computers in a region does not necessarily improve workers’ aptitudes to handle complex software. Nevertheless, the region-specific time trends included in the reduced-form account for changes in the quality of a region’s workforce over time. Second, firms in ICT-intensive industries could relocate to take advantage of differential reductions in technology prices or differential quality of the workforce (via the first threat) across regions. However, in our panel there is no sub-national relocation of firms over time. Third, the growing demand for computers by households in a region could directly impact output and employment of firms involved in the production or sale of computers. Hence, we exclude from our sample two sectors – IT producers (manufacturing) and IT sellers (wholesale and retail trade) – but results are maintained (see the Supplementary Materials).

Our findings indicate that complex software adoption by Chilean firms, which we hypothesised is a technology that automates complex routine and abstract tasks performed by high-educated workers, is associated with firm changes in their occupational structure in the medium term in a way that decreases the share of some of the workers performing abstract and routine tasks mainly (professionals and technical workers) and increases the share of some of the workers performing manual tasks primarily (unskilled production and services workers). Our interpretation for these findings is that more sophisticated software technologies are affecting labour markets differently than previous computerisation and automation of routine tasks carried out by middle-educated workers. Complex software has a skill component and is thus performing some tasks previously carried out by high-educated workers (substitution effect). However, high-educated workers have the cognitive abilities to analyse and interpret the information coming out from the software (complementarity effect). Our results suggest that, in Chile, the substitution effect is on average offsetting any complementarity effect for professionals and technical workers. The increase in the share of unskilled production and services workers in total employment can be potentially explained by an expansion in firms’ output and employment, with the demand for unskilled production and services workers increasing at a significantly higher pace than the demand for professionals and technical workers due to complex software adoption. We provide evidence for this potential explanation in Table 5 where we examine whether firms change the actual levels of employment of different occupations as a result of
Complex software adoption increases significantly the level of employment of unskilled production and services workers and administrative workers (the latter at a 10% confidence level), with no significant change in the level of employment of managers and professionals and technical workers. These findings suggest that firms adopting complex software are expanding their total employment, but each occupation adjusts at a different rate. The insignificant changes in the demand for professionals and technical workers that accompany the significant increase in the demand for unskilled production and services workers and administrative workers can be explained by the adoption of the complex software allowing the automation of some high-skilled tasks. However, it is interesting to highlight that there is no statistically significant reduction in the demand for professionals and technical workers, suggesting that this employment category still has a role in the production process.

6. Heterogeneity of impact of complex software adoption

This section examines whether complex software adoption has differential impacts on firm task indexes and employment shares of different occupations depending on firm size and sector educational composition. We estimate a specification similar to Equation (4) where the complex software variable is interacted with two separate indicator variables for firms with and without a given characteristic. Table 6 reports the second-stage estimates allowing the impacts to differ by firm size (as of 2007) and sector education (as of 2007), respectively.

The estimates show that our main findings (Table 4) are explained by the behaviour of small, medium, and large firms (all included in the ‘not-micro’ firms category). The impacts on micro firms are insignificant. For non-micro firms there is also a significant increase in the share of administrative workers in total employment. It is not surprising that complex software adoption does not impact labour demand by micro firms as such a type of software is unlikely to be important for them (outside of high-tech sectors). Micro firms typically do not have intensive computation or large database management needs, they employ relatively simple management and production techniques. Complex software would not be cost-effective for them nor have large employment effects.

Table 6 also shows that the reduction in the share of professionals and technical workers with complex software adoption happens mainly in sectors with a low-educated workforce. The impact for firms in sectors with a high-educated workforce goes in the opposite direction but is statistically insignificant. For the share of unskilled production and services workers and the task indexes, we cannot identify a significant differential impact across sectors, but our findings in Section 5 are verified for sectors with a low-educated workforce. If the workforce education level is, at least
Table 6. Heterogeneity of impact of firm complex software adoption on employment composition and task indexes across firm size and sector’s workforce education level

| Dependent variable: | Panel A: Second-stage – Firm employment shares | Panel B: Second-Stage – Firm task indexes |
|---------------------|-----------------------------------------------|-----------------------------------------|
|                     | Managers & technical workers | Administr. workers | Unskilled prod. & services workers | Abstract | Routine | Manual |
| By firm size        |                                |                          |                             |          |         |         |
| Firm complex software use | −0.202 | −0.0548 | −0.0843 | 0.341 | −0.671 | 0.557 | 0.645 |
| *Micro firm         | [0.375] | [0.540] | [0.316] | [0.422] | [0.828] | [0.735] | [0.809] |
| Firm complex software use | −0.320 | −0.971 | 0.551 | 0.739 | −1.715 | 1.620 | 1.771 |
| *Non-micro firm     | [0.200] | [0.385]** | [0.257]** | [0.369]** | [0.672]** | [0.564]*** | [0.658]*** |
| P-value for test of equality of coefficients | 0.753 | 0.095 | 0.120 | 0.452 | 0.284 | 0.198 | 0.232 |
| By educational level of the workforce |                    |                          |                             |          |         |         |
| Firm complex software use | −2.430 | 1.594 | 0.665 | 0.170 | −2.380 | 3.435 | 2.577 |
| *High-educated workforce | [1.422]* | [1.112] | [0.479] | [0.425] | [1.557] | [2.019]* | [1.624] |
| Firm complex software use | −0.258 | −0.595 | 0.280 | 0.573 | −1.267 | 1.157 | 1.288 |
| *Low-educated workforce | [0.222] | [0.256]** | [0.210] | [0.258]** | [0.506]** | [0.469]** | [0.498]*** |
| P-value for test of equality of coefficients | 0.134 | 0.041 | 0.443 | 0.428 | 0.511 | 0.284 | 0.463 |
| Observations        | 3,704 | 3,704 | 3,704 | 3,704 | 3,704 | 3,704 | 3,704 |

Source: Authors’ calculations based on ELE’s 2007 and 2013 waves and 2014 Chile PIAAC.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1, 5, and 10 per cent confidence levels, respectively. All regressions control for firm and year fixed effects and include time-varying firm characteristics (size categories, age [in logs], exporter, foreign-owned, and credit constrained indicators, age [in logs], number of years of experience [in logs], and indicators for the degree of education of the main manager), time-varying region characteristics (average per capita household income [in logs], share of urban households, and average number of years of education of households [in logs]), number of computers used by firms in the region-sector, as well as region-specific time trends. Micro firms are defined in Table A1 in the Appendix and non-micro firms include small, medium and large firms. High-educated sectors are those having at least 50 per cent of their workforce with college education in 2007.
partially, a proxy for the productivity of the sector, then these results confirm our hypothesis of substitutability between professionals and technical production workers and complex software in low-productivity sectors and possible complementarity in high-productivity sectors.

We also analyse whether complex software adoption changes firms’ investment in training. The Supplementary Materials show that firms adopting complex software do not significantly change the training provided to workers, but they increase the likelihood of the manager receiving ICT-specific training.

7. Conclusion

A large body of evidence documents that labour markets are becoming more polarised in developed countries, with employment and earnings shifting from middle-skilled jobs to both high-skilled and low-skilled jobs. This has raised concerns on the extent to which technology adoption could automate routine tasks and potentially displace middle-skilled occupations. Additional concerns arise as more advanced technologies, used by more educated workers, are also increasingly replacing cognitive and analytical tasks. At the same time, many economists argue that technology adoption will, at least in the medium-run, significantly increase firm productivity and, under certain policy conditions, lead to job expansion. The overall impacts of technology adoption on employment and on the skill composition of occupations remain, therefore, an empirical question.

We are the first paper estimating, in the medium-term, the impact of the adoption of more sophisticated technologies on employment and skills composition of jobs within firms. We estimate a reduced-form specification relating complex software adoption with firm-level measures of skills composition. We mitigate potential endogeneity concerns by exploiting changes in the firm’s technology adoption between 2007 and 2013 and instrumenting that adoption with a measure of regional propensity for technological progress, whose impact is allowed to differ across sectors. Our prior is that firms are more likely to adopt complex technologies in sectors with an initially higher ICT intensity and when the household use of computers is higher in the region where they are located.

Our main findings show interesting patterns. First, in the medium-run, complex software adoption is leading to a significant expansion of jobs among administrative workers and unskilled production and services workers. Furthermore, the adoption of complex software reallocates employment within firms away from professionals and technical workers. Second, consistent with these employment shifts, the adoption of complex software is linked to an increase in firms’ use of routine and manual tasks, and a reduction in firms’ use of abstract tasks, which are now arguably being performed by technology. Finally, we show that our findings are mainly driven by the adoption of advanced technology in sectors with relatively low-education and low-productivity, where most of the unskilled workers are employed. These findings have important policy implications. First, they are consistent with the view that the adoption of advanced software can in the medium-term lead to ‘inclusive’ employment expansions as firms overcome any short-term rigidities. Second, education and training systems can substantively promote the adoption of more advanced technology, if policies support the development of digital skills, especially among employers.

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Notes

1. The sample period encompasses the 2007–2008 global financial crisis, when gross domestic product fell and labour market outcomes worsened in Chile. However, the crisis impacts were short-lived (Cruces, Fields, Jaume, & Violaz, 2017; SEDLAC, 2017).
2. For exogeneity reasons, pre-sample period ICT intensity in 2003 is used.
3. Three recent studies use ELE (2007 and 2009 rounds) to analyse links between ICT and innovation (Alvarez, 2016; Santoleri, 2015) and innovation and wages (Cirillo, 2016).
4. Some authors argue the increased automation and streamlining of processes accompanying the use of business and production software might even constrain workers in their creativity (Engelstätter & Sarbu, 2013).
5. For more details see http://www.oecd.org/skills/piaac/.
6. For example, a large manufacturing firm located in the Metropolitan region reports having managers, administrative workers, professionals and technical workers, and no unskilled production and services workers in 2007 but having only unskilled production and services workers in 2013.
7. While it would be valuable to compare the complex software adoption impacts on firm labour-related variables to those of more traditional ICT adoption we do not pursue that exercise because our sample exhibits insufficient variation in firm computer use over time to be able to estimate such impacts.
8. From the 25 per cent of firms switching complex software adoption status, 12 per cent start using the software, while 13 per cent stop using the software. In Table I of the Supplementary Materials we show that 84 per cent of switchers are micro and small firms and 30 per cent are firms operating in wholesale and retail trade, 16 per cent in manufacturing, and 12 per cent in real estate and business activities sectors.
9. A similar type of instrument was used by Iacovone, Pereira-Lopez, and Schiffbauer (2016) studying the impact on productivity of the use of computers by firms in Mexico. The 2003 Chilean input-output table is pre-determined from the point of view of firms’ ICT adoption and employment decisions in 2007 and 2013.
10. The corresponding OLS estimates are provided in Table V in the Supplementary Materials.
11. Each specification includes the logarithm of the level of employment of an occupation to which we add one so as to keep in the estimating sample observations from firms with no employment in that occupation.
12. Our conclusion of output and employment expansion due to complex software adoption draws on the positive and significant impacts on two occupation types combined with the insignificant impact on the other two occupation types. In unreported regressions we estimate the direct impact of complex software adoption on firm gross income from main activity and firm total employment and find those to be positive (though statistically insignificant at conventional confidence levels).
13. The first-stage equation (not reported) includes a similar specification.

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Table A1. Definition of variables taken from ELE

| Variables                        | Definition                                                                                                                                 |
|----------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Managers                         | Owners and partners (working in the firm without fixed remuneration 15 hours or more per week), managers, sub-managers, and other salaried workers whose functions are to administer, plan, organise, control, and direct the activities of the firm. |
| Administrative workers           | Administrative workers are defined as office and administrative workers, employees that deal directly with the public (except sales personnel), as well as any personnel in charge of accounting, statistical data entry and processing, secretariat, clerk service, and customer support. |
| Professionals and technical      | Professionals and technicians working directly with the firm’s main activity and with a high degree of competency inside the firm. Their activities cover analysis and research, application of concepts, methods, and techniques in the production or extraction of products, supervision of other workers, provision of legal services, social services, and economic and commercial services. |
| workers                          |                                                                                                                                              |
| Unskilled production and         | Non-technical personnel in charge of executing simple and routine tasks directly related to the firm’s main activity which require mainly the use of manual tools and some physical effort. Services and sales workers are also included in this category. |
| services workers                 |                                                                                                                                              |
| Abstract task index              | Weighted average of an abstract task measure for each employment category obtained from the PIAAC survey. Weights are defined as the share of each employment category in firm total employment. |
| Routine task index               | Weighted average of a routine task measure for each employment category obtained from PIAAC survey. Weights are defined as the share of each employment category in firm total employment. |
| Manual task index                | Weighted average of a manual task measure for each employment category obtained from PIAAC survey. Weights are defined as the share of each employment category in firm total employment. |
| Worker training                  | Indicator variable for whether workers (other than the manager) participated in training courses during the survey year.                       |
| Manager training                 | Indicator variable for whether the surveyed manager participated in training courses during the survey year.                                   |
| Manager training on ICT          | Indicator variable for whether the surveyed manager participated in training courses about information technology during the survey year.       |
| Outsourcing                      | Indicator variable for whether the firm outsourced any activity during the survey year.                                                    |
| Complex software use indicator   | Indicator variable for whether the firm uses client management, production, or administration and business software packages. The indicator variable is equal to 0 when the firm does not use any of these types of software or does not have a computer. |
| Computer use indicator           | Indicator variable for whether the firm has at least one computer.                                                                          |
| Average number of computers per firm | Average taken across all firms in province-sector-year of the number of computers per firm.                                    |
| Firm size                        | Firm size is captured by the firms’ total number of employees. Micro firms are those with five employees or less, small firms are those with six to 20 employees; medium firms are those with 20 to 50 employees, and large firms are those with 51 employees or more. |
| Firm age                         | Years since the firm began its activities.                                                                                                 |
| Exporter                         | Indicator variable for whether the firm exported goods or services during the survey year.                                                   |
| Foreign-owned                    | Indicator variable for whether the firm has owners that are not Chilean.                                                                     |
| Credit constrained               | Indicator variable for whether firm was rejected when asking for credit or did not accept credit conditions. The indicator is equal to 0 if the firm obtained credit or did not ask for credit. |
| Manager age                      | Age of the firm main manager.                                                                                                               |
| Manager years of experience      | Number of years of work experience of firm main manager                                                                                     |
| Manager with second. education   | Indicator variable for whether the firm main manager has secondary education, complete or incomplete.                                           |
| Manager with college education   | Indicator variable for whether the firm main manager has college (or higher) education, complete or incomplete.                              |