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Does the Adoption of Complex Software Impact Employment Composition and the Skill Content of Occupations? Evidence from Chilean Firms *

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A major concern with the rapid spread of technology is that it replaces some jobs, displacing workers. However, technology may raise firm productivity, generating more jobs. The paper contributes to this debate by exploiting a novel panel data set for Chilean firms in all sectors between 2007 and 2013. While previous studies examine the impacts of automation on the use of routine tasks by middle-educated workers. This study focuses on a measure of complex software that is typically used by more educated workers in cognitive and nonroutine tasks for client, production, and business management. The instrumental variables estimates show that in the medium run, firms' adoption of complex software affects firms' employment decisions and the skill content of occupations. The adoption of complex software reallocates employment from skilled workers to administrative and unskilled production workers. This reallocation leads to an increase in the use of routine and manual tasks and a reduction in the use of abstract tasks within firms. Interestingly, the impacts tend to be concentrated in sectors with a less educated workforce, suggesting that technology can constrain job creation for the more skilled workers there. The paper concludes that the type of technology matters for understanding the impacts of technology adoption on the labor market.

JEL codes: J23, J24, O33.
Keywords: complex software, tasks, skills, employment structure, Chile.

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1. Introduction

Technology adoption, and especially information and communication technology (ICT) adoption, has expanded dramatically during the last decade throughout the world (World Bank, 2016). Its impact on jobs and the skills that are demanded by employers is a topic of great interest as it is an important driver of future labor demand. The main concern is that the growing use of ICT at the workplace is leading to a polarization of labor markets in developed countries, whereby employment and earnings are shifting away from middle-skilled jobs into both high-skilled and low-skilled jobs (Autor and Dorn, 2013; Frey and Osborne, 2013; Autor, 2014). 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 automatized and explicit rules and procedures (Autor et al., 2003). More recently, however, technologies are advancing even faster (e.g., robots and artificial intelligence), automating tasks that are typically performed by higher-educated workers (Brynjolfsson and McAfee, 2014; Autor, 2015). These tasks performed by technology are increasingly non-routine analytical and cognitive tasks. Examples include deep-learning systems applied to medicine, or machines being able to compose music. A crucial research and policy question is thus how these more advanced types of software and technologies are affecting the firm's employment composition and the skill content of occupations.

To our knowledge, we are the first paper assessing the impacts of the firm's use of more advanced technologies on the demand for skills and jobs, in the medium run. We exploit a novel firm-level survey for Chile across a six-year interval, between 2007 and 2013, when the adoption of a complex technology, such as client management, business or production software packages, is observed. We inquire whether the adoption of complex software has led to significant labor reallocation within firms on tasks with different skills contents. To date, the literature has mainly looked at the impacts of the automation process associated with computers. We argue that complex software is more likely to be already replacing the use of routine-cognitive and analytical tasks, which are typically performed by more skilled workers.

Our firm-level findings show several interesting patterns for Chile. First, the level of the managerial human capital is an important driver of the adoption of advanced technologies. In particular, younger, more experienced and more formally educated managers working in younger and larger firms are more likely to perceive benefits in implementing advanced technological changes. Second, in the *medium run*, this advanced technology adoption, which is arguably replacing already more non-routine and abstract tasks, is leading to a significant expansion of jobs among administrative and unskilled production workers. Furthermore, it also reallocates employment within firms away from skilled production workers. Third, consistent with these employment shifts, the adoption of complex software is associated with an increase in firms' use of routine and manual tasks, and with a reduction in firms' use of abstract tasks which are now arguably being performed by technology. Finally, our findings are mainly driven by advanced technology adoption in sectors with a relatively low-educated workforce and low-productivity, where most of the unskilled workers are employed (e.g., wholesale and retail trade and manufacturing sectors). In sum, taken together these findings suggest that the adoption of more advanced technologies, such as complex software, has the potential to be inclusive among the lower skilled workers. These results shed new light on an important policy debate and contribute to a better understanding of the medium-term impacts of advanced technological adoption on firm-level employment decisions and the task content of occupations.

We exploit three micro data sets. First, we use a novel firm-level survey of formal private firms in the Chilean economy across all sectors of activity, *Encuesta Longitudinal de Empresas* (henceforth ELE) for the period 2007-2013. This data set is rich in capturing *direct* measures of technology adoption and the human capital of the workforce. Second, we use Chilean data on the task content of each occupation from the Programme for the International Assessment of Adult Competencies (PIAAC) survey (henceforth PIAAC survey) as of 2014. Third, we explore the Chilean national household survey (CASEN), for 2006 and 2013, to obtain information on ICT use at the sub-national level which is used in our instrumental variable approach. This combination of data sources is unique. First, it allows us to assess and differentiate impacts of complex software adoption across different employment/occupation categories (managers, administrative workers, skilled and unskilled production workers) as well as across the task content of occupations, and thus identify which groups disproportionately benefit and which ones bear the cost of this 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. Despite strong poverty reduction and economic growth supported by the commodity boom and several market-oriented structural reforms over the past decades, Chile's degree of income inequality has remained persistently high, and is still today among the highest in the world. The Chilean economy is currently looking for sources of diversification and for a model of growth that is more based on knowledge and technology intensity and that can also be more inclusive (World Bank, 2017).

Our empirical methodology is straightforward. We consider a reduced-form specification relating the adoption of complex software with different occupation shares and measures of the task content of occupations at the firm-level, between 2007 and 2013.[1] In this setting, there are two concerns. First, the firm's decision to adopt complex software is likely to be made jointly with employment and skills choices and be based on firm characteristics, such as managerial quality, that are to a large extent unobservable in our data set. Second, the decision to adopt complex software may depend on the firm's actual mix of occupations and skills used. We mitigate these concerns in two ways. First, the panel nature of our firm-level data set allows us to account for all time-invariant firm unobservable characteristics through the inclusion of firm fixed effects in our reduced form. Hence, for each firm, we relate *changes* in the adoption of complex software with *changes* in shares of different occupations in total employment and changes in the task content of occupations. Second, we instrument the adoption of complex software at the firm level with a proxy for the degree of technological progress at the sub-national level, which is the regional share of households with access to a computer; furthermore, we allow this technological rollout to impact differentially firms depending on their sector's ICT intensity. ICT intensity is measured as of 2003, prior to our sample period, for exogeneity reasons.

Our paper makes several contributions to the literature. First, to our knowledge, this paper is the first assessment of the impact of advanced technology adoption on the task content of occupations at the firm-level. In order to assess that impact, we construct several firm-level task indexes, weighting the task content of each occupation category by its share in the firm's total employment. We divide the task content of occupations into four categories: abstract, routine-cognitive, routine-manual, and non-routine-manual following the task-based literature (see Autor and Handel (2013) for the United States (U.S.) and Messina et al. (2016) for Latin America). Second, we provide evidence on the labor market impacts of ICT adoption at the firm level for a high-income Latin American country with very high inequality levels where there are important

[1] The sample period - 2007-2013 - encompasses the global financial crisis of 2007-2008, when aggregate gross domestic product (GDP) fell and labor market outcomes worsened in Chile. However, the impacts of the crisis were short-lived (Cruces et al., 2017; SEDLAC, 2017).

policy concerns on how to make the economy more productive and diversified while inclusive. Third, in contrast with most of the literature we exploit data on the task content of occupations that is specific to the country of study (in our case the Chilean PIAAC survey).[2] This is an important contribution as most of the previous literature exploited information on the task content of occupations for the U.S. assuming this content was similar in other countries.

The remainder of the paper proceeds as follows. Section 2 reviews the literature while Section 3 describes the data and summary statistics. Section 4 discusses the conceptual approach and our testable hypotheses. Section 5 presents the econometric strategy and Section 6 discusses the main results. Section 7 focuses on robustness checks and heterogeneity in the effects while Section 8 discusses additional results and section 9 concludes.

2. Literature Review

Our paper relates to two important literatures. First, we relate to the literature studying the impact of ICT adoption on the composition of employment and the demand for skills, focusing heavily on developed countries. A first group of studies introduces an intermediate nexus between technology and labor market outcomes given by tasks and how skills are allocated to tasks to produce output. Using this framework, they analyze the impacts of ICT adoption on tasks performed by workers and on the demand for skills (Acemoglu, 1999; Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013 and Autor, 2014 for the U.S.; Goos and Manning, 2007 for the United Kingdom; and Goos et al., 2014 and Michaels et al., 2014 for European countries more broadly). These studies measure technological development with the adoption and use of computers in the workplace. Using industry, occupation or industry-occupation data obtained from census, or household and labor force surveys, the studies attempt to provide causal evidence. Evidence is supportive of the idea that computers substitute middle-skilled workers by carrying out activities following explicit rules (i.e., routine tasks), while they complement high-skilled workers as the latter perform activities difficult to automate, such as problem-solving and creative activities (i.e., non-routine cognitive tasks). A pattern of employment polarization emerges as a consequence, where low- and high-skilled occupations

[2] In a related study Almeida et al. (2017) assess the impacts of internet access on the skill content of occupations exploring a unique concordance between Brazilian firm-level data and measures of the task content of occupations, but in contrast to our study they use task content measures as defined in the U.S. Department of Labor's Occupational Information Network (O*NET).

gain share in total employment at the expense of middle-skilled occupations as a result of computerization.

A second group of studies relies on the estimation of partial correlations based on firm-level data from developed countries to analyze the adjustment in employment, skills, and wages due to ICT adoption. They use a wide variety of firm-level ICT adoption measures such as IT capital stock, computer adoption, the number of computers, IT investment, and the number of IT workers. Their results indicate that ICT adoption is associated with a higher relative demand for skilled workers and higher wages (Caroli and Van Reenen, 2001; Greenan and Topiol-Bensaid, 2001; Bresnahan et al., 2002). A handful of more recent studies establish a causal relationship between ICT adoption - measured by IT investment and access to broadband internet - and labor outcomes at the firm-level. The results generally show that the adoption of ICT by firms does not lead to changes in overall employment but tends to be linked to increased wages and better labor outcomes for skilled workers - argued to carry out non-routine abstract and cognitive tasks - and worse outcomes for unskilled workers - argued to perform more routine tasks which are automated with the use of ICT (Bartel et al., 2007; De Stefano et al., 2014; Akerman et al., 2015; Gaggl and Wright, 2016).

The evidence for emerging economies is much scarcer and our paper fills in this important gap in the literature. Studies using occupational data obtained from household or labor force surveys are generally aligned with the idea that ICT impacts more negatively occupations engaged in routine tasks and non-routine manual tasks. In particular, they show that occupations using ICT more intensively have a high demand for cognitive skills and a low demand for routine and non-routine manual skills in developing countries (Santos et al., 2015). However, there is very weak evidence of labor market polarization in Latin America, perhaps suggesting that any impacts of ICT adoption during the 2000s were overcome by the strong commodity boom experienced by most economies which benefited primarily low-skilled workers (Cruces et al., 2017; Maloney and Molina, 2016). The evidence for Chile is, however, different. In spite of the commodity boom, there is evidence based on Chile’s household survey (the CASEN which we also use in our analysis) of some labor market polarization as the employment share of occupations with a high content of routine skills and a low content of abstract skills fell, while the employment share of occupations with a moderately high content of abstract and routine skills increased (Messina et al., 2016).[3] In addition, there is evidence based also on Chile's CASEN survey of a wage premium associated with the use of computers at the workplace between 2000 and 2006 (Benavente et al., 2011).

For emerging economies, there is still a dearth of studies on the labor market impacts of ICT adoption at the firm level. Among the few, Dutz et al. (2012) show that ICT-intensive firms in Brazil exhibit higher wage growth across all skill groups, but not faster employment growth. Wage growth is especially high for workers changing firms but not so high for workers remaining within the same firm. Their evidence suggests that, during a time of technological change, firms in Brazil were able to absorb jobs and generate wage increases across all skills. Brambilla and Tortarolo (2017) study the impact of ICT investment on productivity, employment and wages for Argentinean firms in the manufacturing sector using survey-based retrospective information for 2010-2012. They find that in the short run ICT adoption leads to increases in firm productivity and wages with the effects being larger for initially high-productivity and high-skill firms, and to decreases in the share of unskilled labor, supporting the view that ICT is complementary with skilled labor.

Second, this paper relates to the emerging literature stressing the fact that technological innovation is an ongoing process, with more sophisticated technologies being developed constantly and producing substantive impacts in the labor market. Examples include advances in automation, robotics, and artificial intelligence, with potentially worrying consequences for labor markets (Frey and Osborne, 2013; Brynjolfsson and McAfee, 2011; Brynjolfsson and McAfee, 2014; Graetz and Michaels, 2015; Acemoglu and Restrepo; 2016). In particular, Brynjolfsson and McAfee (2014) argue that more sophisticated technological innovations are no longer confined simply to routine tasks but rather they are spreading to domains usually defined as non-routine, and they are performing tasks that are typically led by more high-skilled workers. An example of this trend is the number of tasks usually performed by lawyers and accountants that are being undertaken by sophisticated algorithms. Machine learning techniques are advancing in the direction of being able to program a machine to master a non-routine task autonomously (Autor, 2015). The ensuing concern is therefore that such technological innovations may in the future replace many types of jobs previously insulated from more routine-biased technological

[3] The study also shows indirect evidence for Brazil, Mexico, and Peru in the 2000s suggesting an increase in the share of high-wage occupations in total employment.

developments, such as those imbedded in the use of computers. World Bank (2016) follows Frey and Osbourne (2013) in investigating the feasibility of automating existing jobs given current and potential technological advances, based on the occupations of workers and show for OECD countries that over the next couple of decades half of the jobs could be automated. Arntz et al. (2016) follow a task-based approach and allow for heterogeneity of workers' tasks within occupations and demonstrate that the threat from technological advances is less pronounced, with a much smaller percentage of jobs in OECD countries being automatable in the future.

In our paper, we measure ICT adoption at the firm level with the use of complex software including client management, production, and business software. To our knowledge only one study, Bloom et al. (2014), examines the impacts of complex software on firm organizational decisions, although it does not consider the impact on the demand for different types of skills. Their conjecture is that the use of business software reduces the costs for workers to access information, and this allows workers to solve more problems and rely less on the training of specialists. Their evidence for firms in the U.S. and Europe confirms that indeed the use of business software increases decentralization within the firm, leading to more autonomy and a wider span of control for local plant managers. Iacovone and Pereira-Lopez (2017) adopt an indirect approach whereby they consider the use of business software as a possible mechanism to explain the positive impact of ICT adoption on the demand for skilled workers estimated for Mexican firms. They show that ICT adoption leads to organization adjustments in the form of the use of business software.

3. Data and Summary Statistics

3.1 Data Sets and Definitions

In the paper, we exploit several data sets. First, we exploit a nationwide longitudinal firm-level survey, ELE, which is representative of all economic activities in Chile except for public administration, health, education, domestic service, and extraterritorial organizations.[4] We use the 2007 and 2013 waves of the survey. Appendix A provides technical details on the ELE survey.

[4] A small number of recent studies rely on ELE survey data (2007 and 2009 rounds) to study links between ICT and innovation (Santoleri, 2015; Alvarez, 2016) and innovation and wages (Cirillo, 2016).

The ELE survey is unique to answer our research questions as it collects rich information on firm technology adoption, ranging from the use of computers, to the use of complex software, and to access to the internet.[5] The use of complex software captures the use of client management, production or business software packages. This type of software can perform complex tasks within firms such as the planning of production levels (based on expected demand and stocks), product pricing, estimating production costs along the production process, forecasting of agricultural production, and controlling optimization of processes. This variable markedly differs from other ICT measures used in the literature (e.g., computer use, internet access, or IT capital/investment) and we argue it likely impacts the firm's production process in different ways. Complex software adoption is largely managed by highly skilled workers and can lead quite complex routine-cognitive but also non-routine analytical tasks. For instance, today production software can already perform the planning of the level of production, which had in the past been carried out by professional workers (such as engineers).[6]

The ELE survey also collects rich information about the firm's labor force, including the firm's total employment across four occupation categories - managers, administrative workers, skilled production workers, and unskilled production workers. Table B1 (Appendix B) defines these categories. In some of the empirical exercises, we will also consider as outcomes indicator variables for whether the firm is engaged in subcontracting activities, as well as for different types of training provided by the firm. Finally, we also use firm size, age, exporter status, foreign ownership, access to credit, as well as the degree of education, the number of years of experience, and the age of the manager as control variables.

Second, we exploit the Chilean PIAAC survey for 2014, which is a survey of adult skills collected by OECD. It measures several cognitive and workplace skills (e.g., literacy, numeracy and problem-solving) across occupations which are used to compute the task content of occupations.[7] Drawing on Acemoglu and Autor (2011) and Autor and Handel (2013), we define the task content of occupations using the following categories: abstract, routine-cognitive, routine-manual, and non-routine-manual tasks. Abstract comprises abstract problem-solving and creative, organizational and managerial tasks while routine-cognitive and routine-manual involve

[5] All variables from the ELE survey are defined in Table B1 (Appendix B).

[6] Some authors even argue that the increased automation and streamlining of processes that accompanies the use of business and production software might significantly constrain workers in their creativity (Engelstätter and Sarbu, 2013).

[7] For more details see http://www.oecd.org/skills/piaac/.

codifiable tasks that follow explicit procedures, and non-routine-manual comprises tasks that require physical adaptability. To define the task content of a specific occupation we identify in the PIAAC survey the set of questions closer to those used by other adult skills surveys (e.g., DOT, PDII, O*NET or STEP surveys used by e.g., Autor et al. (2003), Autor and Handel (2013), Di Carlo et al. (2016), and Messina et al. (2016)). Appendix A discusses the methodology used to construct the task content measures for each of the four occupation categories included in the ELE survey. Appendix B reports details on the exact PIAAC survey questions used to compute each task content measure (Table B2).

Table 1 provides a schematic summary of the intensity of each task content measure for each of the occupation categories in the ELE survey.[8] Table 1 shows, for a given occupation, whether the use of each task is above (+) or below (-) the average use of that same 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 has a clear correlation with the skill level of the occupations. Managerial and skilled production occupations are more intensive in abstract tasks as the task value is above the average across all occupations. Unskilled production occupations are more intensive in non-routine-manual tasks. Routine tasks, both cognitive and manual, are more important for administrative and unskilled production occupations. When analyzing which are the most important tasks for each occupation category separately, we find that abstract and non-routine-manual tasks are the most important for managers.[9] For administrative workers, the most important tasks are routine-cognitive and routine-manual. For skilled production workers, the most important tasks are abstract and routine-cognitive tasks – these are the set of tasks we expect to be potentially replaced by the complex software. Finally, for unskilled production workers the most important tasks are non-routine-manual and routine-manual. We define *firm-level task indexes* as a weighted average of the task content measures across occupations, where the weights are given by the share of each occupation in the firm's total employment:

[8] The actual values of the task content measures for each occupation category are shown in Panel A of Table B3 (Appendix B).

[9] The relative importance of non-routine-manual tasks for managers is in line with the finding by Messina et al. (2016) based on the STEP survey that occupations with a high content of non-routine-manual tasks include high-level occupations like database and network professionals, managing directors, and chief executives.

$$K_{jt}^{k} = \sum_{c=1}^{4} shr_{jtc} * task_{c}^{k} \tag{1}$$

where *j* designates a firm, *t* a year, *c* is one of the four occupation categories in the ELE survey (managers, administrative workers, skilled production workers, and unskilled production workers), k is a type of task (abstract, routine-cognitive, routine-manual, and non-routine-manual), $task_{c}^{k}$ is the task content measure reported in Panel A of Table B3 (Appendix B) and shr_{jtc} is the firm share in total employment of a given occupation category.

Third, we exploit the CASEN survey, a nationwide household survey for Chile collected by the Ministry of Social Development which is representative at the regional level. We use the 2006 and 2013 rounds of the CASEN survey which cover all fifteen regions in Chile. We construct regional measures of technological development that are used as instrumental variables: the share of households in the region with a computer in use and the share of households in the region with at least one cell phone. We also construct measures that capture the degree of regional development that we use as control variables: the share of urban households in the region, the average number of years of education of members of the households in the region, and the average per capita income of households in the region.

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

3.2 Sample and Summary Statistics

Our main firm-level sample, based on the ELE survey, is a balanced panel of 1,852 firms observed both in 2007 and 2013. We start by selecting firms that are present in 2007 and 2013 (a total of 1,992 firms) and that report non-missing information on firm employment and software variables as well as firm control variables that will be included in our main specification. By focusing on a balanced panel of firms we are able to exploit changes over a six-year period in the outcomes of interest. We conjecture that this is a sufficiently long period to allow us to observe any potential expansion impacts following the adoption of complex software that could be hindered in the short run when firms have more fixed factors of production. We then exclude a set of outliers, defined as firms reporting very large changes in employment composition during the period (total of 140).[10] This group has likely misreported information and their inclusion could bias our estimates. We show that our main findings are not driven by this step in the definition of our estimating sample.

Table B4 (Appendix B) shows the sector and the size composition of our final sample covering all sectors of the Chilean economy. Close to 40% of firms operate either in the wholesale and retail trade sector or in real estate and business activities, and less than a fifth operate in manufacturing. On average, close to 80% of firms in the sample are micro or small whereas only 8% of firms are large.

Table 2 reports summary statistics for our final sample of 1,852 firms. Panel A covers the summary statistics for our main dependent variables of interest. During the period, there was a slight downsizing of firms in our sample. On average firms in the sample have 54 workers in 2007 and 44 workers in 2013. In this sample, predominantly of micro firms, unskilled production workers are the major occupation, accounting on average for about half of firm total employment. Skilled production workers are the next most important occupation accounting, on average, for a fifth of firm employment. Between 2007 and 2013 the share of managers fell, from 14% to 7% of total employment and so did the share of skilled production workers (from 23% to 19% of total employment). There was also an important increase in the share of unskilled production workers (from 46% to 58% of total employment), while the share of administrative workers barely changed. On average firms in the sample tend to make a rather large use of non-routine-manual and routine tasks and a lower use of abstract tasks. Note that, by construction, the observed changes in the indexes capturing the task content of occupations at the firm level follow closely the changes in the shares of each occupation in firm total employment. Between 2007 and 2013, the index capturing the abstract content of occupations declined whereas the opposite was verified for the routine-cognitive, routine-manual, and non-routine-manual indexes. The large standard deviations shown for all these measures indicate a substantial degree of heterogeneity across firms in our main outcomes of interest.

Panel B of Table 2 reports summary statistics for our main explanatory variable of interest: a dummy variable for whether the firm uses complex software. In our sample, 47% of firms in

[10] For example, a large manufacturing firm located in the Metropolitan region reports having managers, administrative workers, skilled production workers and no unskilled production workers in 2007 but having only unskilled production workers in 2013. Such radical changes in the structure of employment lead to extreme changes in occupation shares over time, from 0 to 1 or the other way around.

Chile use complex software in 2007 and this percentage declines to 39% in 2013. This reduction is in line with the aforementioned evidence on the downsizing of firms over the period, perhaps as a result of the global financial crisis, as small firms are less likely to adopt complex software (a finding which will be shown below). Figure 1 shows an important degree of variability in the use of complex software across sectors and regions in Chile. In some of the regions and sectors, the average use of complex software increases, while in other regions and sectors the average use declines between 2007 and 2013. The *increase* in the use of complex software was driven mainly by firms in services sectors. Geographically, regions spread throughout the country exhibit an increase in the use of complex software over time.

One of the first important research questions we address is to identify which firms in our sample actually have incentives to adopt new complex software during this period. Table 3 reports several reduced-form Probit regressions documenting interesting patterns. Larger firms, exporting and foreign-owned firms, firms not experiencing credit constraints are all more likely to adopt advanced technology over this period, even after controlling for sector of activity and region. In addition, the quality of the managerial human capital is also a critical determinant of technological adoption. In particular, firms with younger managers and those with higher levels of formal education and past labor market experience are more likely to adopt complex software.

Since our main reduced-form equation will exploit *changes* in the adoption of complex software for a balanced panel, we examine the prevalence of firms switching adoption status and the distribution of switchers across size categories and sectors. Between 2007 and 2013, 25% of firms in Chile switch their complex software adoption status.[11]

Finally, Table B6 (Appendix B) provides the descriptive statistics for all the variables with variation at the local level, which are used as instruments in the instrumental variable specification. The regional percentage of households with a computer in use increased from 31% in 2006 (on average across all regions) to close to 57% in 2013. All regions experienced an increase in the share of households with a computer in use between 2006 and 2013 with improvements ranging between 19 percentage points in the Araucania region to a 32 percentage

[11] From the 25% of firms switching their complex software adoption status, 12% move from not using to using the software, while 13% move from using to not using the software. Table B5 (Appendix B) shows that most switchers are micro and small firms (86% of the total number of switchers) and firms operating in wholesale and retail trade (30% of the total), manufacturing (16% of the total), and real estate and business activities sectors (12% of the total).

points in the Aysen region. The regional share of households with cell phones also increased substantially over time in Chile, from an average of 60% in 2006 to 90% in 2013.

4. Conceptual Framework and Testable Hypotheses

Our testable hypotheses are as follows.

Skilled production workers: The impact of complex software adoption on firm skilled production employment is ambiguous. On the one hand, we expect complex software to perform more abstract tasks and routine-cognitive tasks carried out by skilled production workers (although with different intensities, see Table B2). This impact stands in contrast with the argument posed in the literature studying the automation of routine tasks performed by middle-educated workers through the adoption of a type of technology (computer or internet) that complements skilled employment. For this reason, all else constant, we expect the use of complex software to potentially *substitute* for skilled (production) employment. Indeed, Brambilla (2017) proposes a theoretical model with heterogeneous firms on digital technology adoption and jobs 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 skilled production workers to be bounded by this consideration. Importantly, the use of complex software 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 effect or output expansion effect) there may be a reduction or an increase in the share of skilled production workers in firm total employment.

Unskilled production workers: If the adoption of complex software has an output expansion effect, then we should observe an increase in the demand for unskilled production 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, we believe that an increase in the use of services workers related to software support and IT services is possible. As the ELE survey includes workers providing software support and IT services in the unskilled production workers category, we therefore would also expect an increase in the demand for unskilled production workers even if the output level is kept fixed.

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 in that 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 the domain of administrative workers, especially those covered by client management software. At the same time, an expansion in firm output resulting from complex software adoption may increase the demand for administrative workers.

Task content of occupations: When a firm adopts complex software, the task indexes at the firm level change mainly due to changes in the shares of the different occupations. By construction, the firm-level task indexes depend on the shares of employment of each occupation and on the task content measures specific to each occupation. Considering our previous hypotheses on shares of employment, the change in the different task indexes due to complex software adoption is mostly ambiguous.

Sectoral heterogeneity in impacts: Our empirical 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 the use of complex software and skilled production workers to be potentially different across sectors due to these differences. For instance, in low-productivity sectors where both the set of tasks carried out by skilled production workers and the share of skilled production workers in total employment are small, skilled workers could be substituted by complex software. On the contrary, in high-productivity sectors where both the set of skilled workers' tasks and the share of skilled workers in total employment are large, complex software may complement skilled workers. Hence, it is possible that the impact of complex software on different occupation shares and task indexes will differ across sectors.

5. Econometric Strategy

To test the hypotheses discussed in Section 4, we consider the following reduced-form specification relating the use of complex software at the firm level to a given labor market outcome:

$$Y_{jsrt} = \beta_0 + \beta_1 software_{jsrt} + \delta X_{jsrt} + I_j + I_t + \varepsilon_{jsrt} \quad (2)$$

where j is a firm, r is a region, s is a sector, t is a year, Y is the main outcome of interest (share of each occupation in firm total employment or firm task indexes), and $software_{jsrt}$ is a dummy variable for whether the firm uses complex software in its production process. The vector X_{jsrt} includes time-varying firm observable characteristics, such as size, age, indicators for exporter status, foreign-ownership and credit constraints, and manager characteristics, while I_j and I_t are firm and year fixed effects, respectively, and ε_{jsrt} is an error term. Our main parameter of interest is β_1 which captures the impact of the adoption of complex software on our main labor market outcomes of interest.

The panel structure of the ELE survey allows us to include firm fixed effects in Equation (2). This improves upon OLS estimates of β_1, which would be biased as firms are likely to make their software adoption and employment decisions jointly based on unobserved characteristics (e.g., managerial quality). However, there are two additional problems with Equation (2). First, it is plausible that time-varying unobserved firm characteristics or shocks (e.g., a positive boost to performance) affect both a firm's choice to adopt complex software and particular types of occupations and tasks. Second, the decision to adopt complex software may itself depend on the firm's mix of occupations and tasks.

To address these problems, in addition to the inclusion of firm fixed effects, we adopt an instrumental variables strategy 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 (across Chile's 15 regions) to be positively correlated with the adoption of complex software by firms. This may happen as both firms and households benefit from reductions in the 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, i.e., an individual 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 ($reg\_computer_{rt}$) and the initial Chilean sectoral ICT intensity (ICT_intens_s) measured as of 2003.[12] The rationale for the interaction term is that

[12] A similar type of instrument was used by Iacovone et al. (2016) in a study on the impact on productivity of the use of computers by firms in Mexico. The 2003 Chilean input-output table is considered to be pre-determined from the point of view of firms' ICT adoption and employment decisions in 2007 and 2013.

the degree of technological progress at the sub-national level can impact differentially firms depending on their sector's ICT intensity.

Our reduced-form specification may be criticized for two reasons. First, the prevalence of computer use by households in a region may simply reflect the level of development or the performance of the region, itself correlated with firm employment choices. To mitigate this concern, our main specification includes in X_{jsrt} time-varying regional variables capturing the level of development of the region: the average per capita income of households, the share of urban households, and the average number of years of education of the households in the region. Second, there may be time-varying *unobserved* regional shocks affecting both use of computers by households and complex software adoption by firms located in the same region. To mitigate this concern, our main specification controls for region-specific time trends.

Our first-stage specification is thus given by the following equation:

$$software_{jsrt} = \delta_0 + \delta_1(reg\_computer_{rt} * ICT\_intens_s) + \pi X_{jsrt} + I_j + I_t + I_r * T_t + u_{jsrt} \quad (3)$$

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

The second-stage specification is given by:

$$Y_{jsrt} = \beta_0 + \beta_1 \widehat{software}_{jsrt} + \delta X_{jsrt} + I_j + I_t + I_r * T_t + \epsilon_{jsrt} \quad (4)$$

where $\widehat{software}_{jsrt}$ is estimated from the first-stage (in a two-stage least squares framework) and the error ϵ_{jsrt} is an independent and identically distributed error term. Equation (4) produces a causal impact of the adoption of complex software on firm labor outcomes, β_1, exploiting the variation within firms over time, rather than the cross-sectional variation across very different firms. Inference is based on standard errors robust to heteroscedasticity with the Huber-White approach, clustered in all our specifications at the region-sector level to account for the more aggregate degree of variability of the instrument (Moulton, 1990).

6. Impact of Firms' Use of Complex Software on Employment Composition and Task Content of Occupations

Panel A of Table 4 reports the OLS estimates of Equation (3), which is the first-stage equation. Panels B and C report the two-stage least squares estimates of Equation (4), our second-stage equation. All specifications include as controls time-varying firm characteristics - firm size categories, firm age (in logs), exporter, foreign-owned, and credit constrained indicators, age of the main manager (in logs), number of years of experience of the main manager (in logs) and indicators for the degree of education of the main manager - and time-varying region characteristics - average per capita household income in the region (in logs), share of urban households in the region, average number of years of education of the households in the region (in logs) - as well as year fixed effects and region-specific time trends. The latter account for time-varying regional unobserved shocks.

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 fact that the use of complex software decreased over time in some regions and sectors in Chile (Figure 1), the correlation between the complex software adoption variable and our proposed instrument is positive and strong. This allows us to claim that, when the use of technology increases at the region-sector level (captured by the use of computers by households interacted with the measure of sectoral ICT intensity), the firm's use of complex software also increases significantly for firms located in that same region and sector. The magnitude of this correlation is such that for each percentage point increase in the regional share of households with a computer in use and with a fixed sectoral ICT intensity, the share of firms adopting complex software increases approximately 4 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.

Panels B and C report the second-stage estimates relating the firm's adoption of complex software with the skill composition of firm employment (Panel B) and with firm task indexes (Panel C).[13] The results show that the adoption of complex software has a significant negative impact on the share of skilled production workers and a significant positive impact on the share of unskilled production workers in total employment for firms in Chile. Specifically, the adoption of complex software by a firm reduces the share of skilled production workers by 58 percentage points and increases the share of unskilled production workers by 61 percentage points on average. Panel B also shows that complex software use decreases the share of

[13] The corresponding OLS estimates are provided in Table B7 (Appendix B).

managers and increases the share of administrative workers but those effects are not statistically significant.

Panel C shows that the adoption of complex software decreases significantly the abstract task index and increases significantly the routine-cognitive, the routine-manual, and the non-routine-manual task indexes. These impacts follow strongly the effects on the shares of the different occupations, which are the weights used to construct the task indexes. For instance, the strong positive impact of complex software on the routine-cognitive task index is driven mainly by (i) the decline in the share of skilled production workers combined with the negative value of the routine-cognitive task score for them shown in Panel A of Table B3 (Appendix B), and (ii) the increase in the share of unskilled production workers combined with the positive value of the routine-cognitive task score for them shown in Panel A of Table B3 (Appendix B).

Our findings indicate that the adoption of complex software by Chilean firms, which we hypothesized is a technology that automates complex routine-cognitive and abstract tasks performed by high-educated workers, leads firms to change their occupational structure in the medium term in a way that decreases the share of some of the workers performing abstract and routine-cognitive tasks mainly (skilled production workers) and increases the share of some of the workers performing routine and non-routine-manual tasks primarily (unskilled production workers). Our interpretation for these findings is that more sophisticated software technologies are affecting labor markets differently than previous computerization 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 analyze and interpret the information coming out from the software (complementarity effect). Our results indicate that for Chile on average the substitution effect is offsetting any complementarity effect for skilled production workers. The increase in the share of unskilled production workers in total employment can be potentially explained by an expansion in firms' output and employment, with the demand for unskilled production workers increasing at a significantly higher pace than the demand for skilled production 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.[14] Table 5 shows that the adoption of complex software increases significantly the level of employment of unskilled production workers and administrative workers (the latter at a 10% confidence level), with no significant change in the level of employment of managers and skilled production workers. These findings reveal that firms adopting complex software are expanding their total employment but each occupation adjusts at a different rate.[15] The rationale for the insignificant changes in the demand for skilled production workers that accompany the significant increase in the demand for unskilled production workers and administrative workers is the adoption of the complex software which can perform some high-skilled tasks. However, it is interesting to highlight that there is no statistically significant reduction in the demand for skilled production workers, indicating this employment category still has a role in the production process.

7. Robustness Checks and Heterogeneity of Impacts

7.1 Robustness Checks

We test the robustness of our main findings on firm-level occupation shares and task indexes to different concerns. First, we test the robustness of our findings to an alternative methodology to compute the firm-level task indexes, following Autor and Handel (2013).[16] We are interested in assessing whether changing the methodology used to define the task measures results in different task content of occupations and different impacts of the adoption of complex software. Second, we test the robustness of our findings to the use of an alternative measure of the regional adoption of new technologies in the first-stage of the instrumental variable methodology. Our objective is to test whether regional household computer use is capturing the regional adoption of new technologies or is capturing other regional trends. The alternative measure is the share of households in the region with at least one cell phone.[17] Third, we explore two alternative weighting schemes to the ELE survey's cross-sectional sampling weights (exploited in our main

[14] Each specification includes the logarithm of the level of employment of an occupation to which we add 1 so as to keep in the estimating sample observations from firms with no employment in that occupation.

[15] Our conclusion of 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 total employment and find it to be positive (though statistically insignificant at conventional confidence levels).

[16] Panel B of Table B3 (Appendix B) reports the average of each task measure for each occupation using Autor and Handel's (2013) methodology.

[17] Again, this variable is interacted with the sector ICT intensity in 2003 obtained from the Chilean Input-Output matrix.

results). In particular, we use either no sampling weights or a new set of adjusted weights accounting for the fact that only some firms in the ELE survey are part of the panel. To do that, we estimate a model for the probability of a firm belonging to the panel using firm characteristics in 2007 as control variables. Then, we adjust the sampling weights multiplying them by the inverse of the probability of being selected into the panel sub-sample. Fourth, we test the robustness of our results to the inclusion of the group of 140 firms exhibiting very large changes in employment composition between 2007 and 2013 (which are excluded from the estimating sample used in Section 6). Fifth, we explore whether our results are driven by the fact that only a small share of firms in our sample (25%) actually changes their status in the adoption of complex software over time. We re-estimate our main models ignoring the panel structure of the data thus including region and sector fixed effects instead of firm fixed effects. Sixth, we explore the possibility that our main results are driven by sector-specific trends related for instance to the commodity boom experienced by Chile over the same period. Finally, we expand the measurement of task content of occupations to allow variation also across sectors.[18]

Table 6 reports all the results, with each panel reporting the results for one particular robustness check.[19] For brevity we report only the impacts on firm-level task indexes in Table 6 but we also include in our discussion of results those for the impacts on firm-level occupation shares.[20] Most estimations show a decrease in the abstract task index along with increases in the routine indexes, both cognitive and manual, and in the non-routine manual index.[21] All in all, our main findings reported in Section 6 are robust to changes in the sample size, in the instrumental variable definition, the measurement of task indexes, weighting schemes, and inclusion of sector time trends as control variables. The estimated reduction in the abstract task index and increases in routine-cognitive, routine-manual and non-routine manual indexes reflect adjustments in the occupational composition, where the skilled categories - intensive in abstract and routine-cognitive tasks performed by the complex software - lose share and the unskilled categories gain

[18] We identify in the PIAAC survey three aggregate sectors (primary, manufacturing and services) and we measure the abstract, routine-cognitive, routine-manual, and non-routine- manual task content for the four occupations separately in each of these sectors. Table B8 (Appendix B) reports the average of each task measure for each occupation in each aggregate sector.

[19] The first-stage coefficients corresponding to the various robustness checks are all positive and significant at standard confidence levels.

[20] These robustness checks are available from the authors upon request.

[21] The impacts are significant in most robustness checks with the exceptions being the specification that is estimated ignoring the panel structure of the data where there is no statistically significant change for the abstract and non-routine-manual indexes.

share in firm total employment. Finally, one could think of two additional threats to our identification strategy. First, the growing use of computers by households in a region may change the quality of the available labor force because workers become more proficient at using computers. Such change in the supply of skilled labor could thus influence the firms' labor demand. Our assumption is that the growing use of computers by workers in their household does not improve their aptitudes to handle the types of complex software that their firm may adopt. In any case, our region-specific time trends control for potential changes in the quality of a region's workforce over time. Second, firms could relocate to take advantage of differential reductions in technology prices or even the differential quality of the labor force (via the first threat) across regions. However, in our panel data there is no regional relocation of firms over time.

7.2 Heterogeneity of Impact of Complex Software Adoption

This sub-section examines whether the adoption of complex software has differential impacts on firm task indexes and employment shares of different occupations depending on firm size and sector of activity. We estimate a reduced-form second-stage equation similar to Equation (4) but where the complex software variable $software_{jsrt}$ enters once interacted with an indicator variable for firms with a given characteristic and a second time interacted with an indicator variable for firms without that characteristic. The corresponding first-stage equation (unreported) includes a similar specification. Tables 7 and 8 report the results for the second-stage equation.

Table 7 shows the estimates allowing the impact of complex software to differ according to firm size in 2007. The results indicate that our main findings in Section 6 are explained by the behavior of small, medium and large firms (covered by the not-micro firms category), while the impacts on micro firms are insignificant. For the group of not-micro firms there is also a significant reduction in the share of managers in total employment.

Table 8 presents the results when interacting the use of complex software variable with an indicator for whether the sector's workforce was high-educated in 2007 (equal to one when at least 50% of the sector's workforce has college education). The reduction in the share of skilled production workers as a result of complex software adoption is verified for firms in sectors with a low-educated workforce, while the impact for firms in sectors with a high-educated workforce goes in the opposite direction but is not statistically significant. For the share of unskilled production workers and the task indexes, we cannot identify a significant differential impact across sectors, but our findings in Section 6 are present for sectors with a low-educated workforce. If the level of education of the workforce is at least partially a proxy for the productivity of the sector, then these results confirm our hypothesis of substitutability between skilled production workers and complex software in low-productivity sectors and possible complementarity in high-productivity sectors.

8. Impact of Complex Software Use on Additional Firm Outcome Variables

In our last set of results, we address the question of whether in addition to the reallocation of employment from skilled to unskilled production positions the adoption of complex software led firms to change their worker training decisions. Table 9 shows that the use of complex software leads firms to invest in job training. The estimates in columns (1) to (3) show that firms that adopt complex software do not change their behavior regarding training provided to workers but they increase the likelihood of providing ICT-specific training to the manager by approximately 23 percentage points. We also test for the possibility that firms adopting the complex software engage in a reorganization process, for example by outsourcing activities. As an example, one could think of the adoption of complex software that includes the services of workers needed for its implementation. To test this mechanism, we consider as a new dependent variable in Equation (4) an indicator variable for whether the firm engages in outsourcing. Column (4) shows a positive though insignificant effect of complex software on firm outsourcing.

9. Conclusion and Policy Recommendations

A large body of evidence, mainly for developed countries, documents that labor markets are becoming more polarized, with employment and earnings shifting from middle-skilled jobs to both high-skilled and low-skilled jobs. This pattern has given way to several concerns on the extent to which technology adoption could be a core contributing factor, automating routine tasks and potentially displacing middle-skilled occupations. Recently, however, additional concerns arise, as more advanced technologies used by typically more educated workers are increasingly replacing also 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, ultimately lead to an expansion of jobs. The overall impacts of technology adoption on overall employment and on the skills composition of occupation is therefore an empirical question.

To our knowledge, ours is the first paper exploiting a firm-level data set to estimate, in the medium term, the impact of the adoption of more sophisticated technologies on firm-level employment and skills composition of jobs within firms. We exploit a simple reduced-form equation relating adoption of complex software with labor outcomes at the firm level. We mitigate concerns with the potential endogeneity of our measure of firm technology adoption by exploiting changes in technology adoption at the firm level between 2007 and 2013, and instrumenting firm technology adoption with a measure of the local propensity for technological progress whose impact we allow 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 local household use of computers is larger.

Our findings show interesting patterns. First, the level of the managerial human capital is an important driver of complex technological adoption in Chile. In particular, younger, more experienced and more formally educated managers working in younger and larger firms are more likely to perceive benefits in implementing advanced technological changes. Furthermore, following adoption there is evidence that firms invest in the manager's ICT skills. Second, in the *medium run*, this advanced technology adoption is leading to a significant expansion of jobs among administrative workers and unskilled production workers. Furthermore, the adoption of complex software reallocates employment within firms away from skilled production workers. Third, consistent with these employment shifts, the adoption of complex software is linked to an increase in firms' use of routine and manual tasks, and with 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 (e.g., wholesale and retail trade and manufacturing sectors). Our findings shed light on an important policy debate and contribute to a better understanding of the medium-term impacts of firms' advanced technological adoption on firm-level employment decisions and the task content of occupations.

Our findings also have important policy implications. First, our findings are consistent with the view that the adoption of advanced software, especially in the medium-term, can lead to significant “inclusive” employment expansions as firms overcome any short-term rigidities. Second, education and training systems can substantively promote the adoption of more advanced technology adoption, if policies support the development of digital skills especially among employers.

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Table 1. Task Content Measures by Occupation Category in the ELE Survey

	Abstract	Routine-Cognitive	Routine-Manual	Non-routine manual
Managers	+	-	-	-
Administrative workers	-	+	+	-
Skilled production workers	+	-	-	-
Unskilled production workers	-	+	+	+

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC Survey.
Notes: The measures of the task content of occupations are constructed based on Acemoglu and Autor (2011) using Chilean PIAAC survey as described in Appendix A. The table shows whether *each* task content measure of a given occupation category in the ELE survey is above (+) or below (-) the average of that task content across all occupations. For example, the first (+) reported in the first column shows that the abstract task content observed in PIAAC for managers is larger than the average abstract content across all occupations. Shaded fields indicate the most important tasks content for each occupation category. For example, for managers the two most important tasks are abstract and non-routine-manual.

Table 2. Summary Statistics on Employment-Related Outcome Variables, ICT Use Variables and Firm Characteristics

	2007				2013			
	Mean	St. Dev.	10th Perc.	90th Perc.	Mean	St. Dev.	10th Perc.	90th Perc.
Panel A: Employment-Related and Task-Related Variables at Firm Level								
Total employment	53.66	280.39	2.00	89.00	43.59	443.33	1.25	46.00
Shares in total employment of:								
Managers	0.14	0.26	0.00	0.50	0.07	0.16	0.00	0.20
Administrative workers	0.17	0.25	0.00	0.50	0.16	0.23	0.00	0.50
Skilled production workers	0.23	0.32	0.00	0.77	0.19	0.33	0.00	0.82
Unskilled production workers	0.46	0.42	0.00	1.00	0.58	0.39	0.00	1.00
Task indexes								
Abstract task index	-0.38	0.76	-1.30	0.59	-0.64	0.65	-1.30	0.35
Routine-cognitive task index	0.30	0.64	-0.57	0.95	0.52	0.50	-0.19	0.95
Routine-manual task index	0.31	0.68	-0.60	1.06	0.54	0.57	-0.42	1.06
Manual task index	0.40	0.77	-0.54	1.35	0.65	0.66	-0.29	1.35
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	0.08	0.28			0.07	0.25		
Outsourcing	0.10	0.30			0.05	0.22		
Panel B: ICT Use at Firm Level								
Complex software use	0.47	0.50			0.39	0.49		
Panel C: Firm Characteristics								
Firm age	11.76	10.25	2.00	22.00	17.79	9.87	8.00	27.00
Exporter	0.02	0.14			0.01	0.09		
Foreign-owned	0.05	0.21			0.03	0.16		
Credit-constrained	0.06	0.24			0.04	0.19		
Manager age	50.85	11.22	37.00	65.00	56.55	12.30	42.00	75.00
Manager years of experience	21.32	12.15	6	36.00	24.78	13.09	9.00	43.00
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				1,852			

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Note: ELE sampling weights are used for the calculation of the moments of the distribution of each variable.

Table 3. Correlates of Firm Use of Complex Software

	Dependent variable: Firm use of complex software (probit estimation)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Small 1	0.357								0.305
	[0.0135]***								[0.0137]***
Small 2	0.881								0.818
	[0.0124]***								[0.0127]***
Medium	1.845								1.709
	[0.0175]***								[0.0180]***
Large	2.41								2.168
	[0.0290]***								[0.0311]***
Firm age (log)		0.00852							0.0943
		[0.000452]***							[0.00846]***
Exporter			0.767						0.0113
			[0.0218]***						[0.0260]
Foreign-owned				1.799					0.945
				[0.0800]***					[0.0954]***
Credit constrained					-0.278				-0.121
					[0.0249]***				[0.0261]***
Manager less than 50 years old						0.214			0.166
						[0.00983]***			[0.0116]***
Manager with more than 10 years of experience							0.0437		0.142
							[0.0115]***		[0.0132]***
Manager with secondary education								0.768	0.783
								[0.0295]***	[0.0306]***
Manager with college education								1.296	1.058
								[0.0290]***	[0.0300]***
Mining and quarrying	-0.077	0.4	0.373	0.347	0.382	0.318	0.38	0.345	-0.0505
	[0.0544]	[0.0468]***	[0.0466]***	[0.0468]***	[0.0465]***	[0.0466]***	[0.0467]***	[0.0472]***	[0.0567]
Manufacturing	-0.128	0.013	-0.00677	0.0144	0.0202	-0.016	0.00932	0.0164	-0.123
	[0.0188]***	[0.0174]	[0.0175]	[0.0175]	[0.0175]	[0.0174]	[0.0174]	[0.0181]	[0.0194]***
Electricity, gas and water supply	0.941	2.077	2.113	2.076	2.065	2.01	2.084	1.805	0.808
	[0.156]***	[0.141]***	[0.140]***	[0.141]***	[0.141]***	[0.142]***	[0.141]***	[0.139]***	[0.150]***
Construction	-0.0465	0.173	0.182	0.139	0.138	0.11	0.132	0.0575	-0.0595
	[0.0205]**	[0.0192]***	[0.0192]***	[0.0190]***	[0.0191]***	[0.0190]***	[0.0190]***	[0.0192]***	[0.0211]***
Wholesale and retail trade	-0.146	0.109	0.0995	0.0795	0.0844	0.0555	0.0868	0.0913	-0.149
	[0.0180]***	[0.0160]***	[0.0161]***	[0.0160]***	[0.0160]***	[0.0160]***	[0.0160]***	[0.0169]***	[0.0189]***
Hotels and restaurants	-0.431	-0.283	-0.343	-0.311	-0.307	-0.356	-0.31	-0.268	-0.404
	[0.0244]***	[0.0236]***	[0.0238]***	[0.0236]***	[0.0236]***	[0.0236]***	[0.0236]***	[0.0243]***	[0.0252]***
Transport, storage and communications	0.0212	0.31	0.312	0.267	0.28	0.212	0.277	0.241	0.00264
	[0.0233]	[0.0207]***	[0.0207]***	[0.0207]***	[0.0206]***	[0.0208]***	[0.0207]***	[0.0207]***	[0.0237]
Financial intermediation	0.243	1.182	1.183	1.067	1.168	1.101	1.162	0.962	0.046
	[0.0838]***	[0.0659]***	[0.0665]***	[0.0709]***	[0.0655]***	[0.0658]***	[0.0656]***	[0.0659]***	[0.0839]
Real estate and business activities	0.357	0.336	0.303	0.266	0.275	0.178	0.268	0.137	0.388
	[0.0188]***	[0.0178]***	[0.0174]***	[0.0174]***	[0.0174]***	[0.0178]***	[0.0175]***	[0.0179]***	[0.0206]***
Other service activities	0.722	0.453	0.48	0.416	0.432	0.412	0.439	0.283	0.581
	[0.0250]***	[0.0222]***	[0.0222]***	[0.0223]***	[0.0222]***	[0.0222]***	[0.0222]***	[0.0226]***	[0.0252]***
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,704	3,704	3,704	3,704	3,704	3,704	3,704	3,704	3,704
R-squared	0.235	0.071	0.079	0.078	0.070	0.073	0.069	0.108	0.256

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey.

Notes: Robust standard errors in brackets. ***, **, and * indicate significance at 1%, 5%, and 10% confidence levels, respectively. All variables are defined in Table B1 (Appendix B). The indicator variable for manager less than 50 years old is based on manager age and the indicator variable for manager with more than 10 years of experience is based on the number of years of experience of the manager. The omitted size category are micro firms, the omitted manager education category is primary education, and the omitted sector is agriculture, hunting, fishing and forestry.

Table 4. Firm Complex Software Use, Employment Composition and Task Indexes

Dependent variable:	Panel A: First-stage - Firm complex software use			
	(1)			
Share of hhlds with computer * sector ICT intensity	4.375			
	[1.407]***			
P-value of underid. test	0.002			
F statistic	9.520			
Dependent variable:	**Panel B: Second-stage - Firm employment shares**			
	Managers	Admin. workers	Skilled prod. workers	Unskilled prod. workers
	(1)	(2)	(3)	(4)
Firm complex software use	-0.301	0.277	-0.583	0.607
	[0.249]	[0.209]	[0.267]**	[0.268]**
Dependent variable:	**Panel C: Second-Stage - Firm task indexes**			
	Abstract	Routine-cognitive	Routine-manual	Non-routine-manual
	(1)	(2)	(3)	(4)
Firm complex software use	-1.353	1.242	1.399	1.300
	[0.548]**	[0.519]**	[0.527]***	[0.551]**
Observations	3,704	3,704	3,704	3,704

Source: Authors' calculation based on ELE (INE, 2007 and 2013) survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% confidence levels, respectively. Panel A reports the estimates of the first-stage given by Equation (3) while 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 of the main manager (in logs), number of years of experience of the main manager (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)), as well as region-specific time trends. In Panel A, the under-identification test is based on Sanderson and Windmeijer (2016).

Table 5. Impact of Adoption of Advanced Software on Firm Levels of Employment across Occupations

Dependent variable:	Log of employment			
	Managers	Adm. workers	Skilled prod. workers	Unskilled prod. workers
	(1)	(2)	(3)	(4)
Firm complex software use	-0.810	1.532	-1.270	2.875
	[0.520]	[0.855]*	[0.904]	[1.183]**
Observations	3,704	3,704	3,704	3,704

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% 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 of the main manager (in logs), number of years of experience of the main manager (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)), as well as region-specific time trends.

Table 6. Robustness Tests – Impact of Firm Complex Software Use on Task Indexes

	Second-stage - Firm Task indexes			
Dependent variable:	Abstract	Routine-cognitive	Routine-manual	Non-routine manual
	(1)	(2)	(3)	(4)
	Panel A: Autor & Handel (2013) methodology			
Firm complex software use	-0.582	0.704	0.543	0.598
	[0.240]**	[0.270]***	[0.186]***	[0.227]***
Observations	3,704	3,704	3,704	3,704
	Panel B: IV based on share of households with cell phone			
Firm complex software use	-1.372	1.281	1.432	1.314
	[0.582]**	[0.559]**	[0.565]**	[0.583]**
Observations	3,704	3,704	3,704	3,704
	Panel C: Without weights			
Firm complex software use	-4.428	3.968	4.076	4.462
	[2.547]*	[2.329]*	[2.270]*	[2.608]*
Observations	3,704	3,704	3,704	3,704
	Panel D: With panel-adjusted weights			
Firm complex software use	-1.236	1.235	1.309	1.185
	[0.626]**	[0.614]**	[0.622]**	[0.620]*
Observations	3,704	3,704	3,704	3,704
	Panel E: Complete sample			
Firm complex software use	-2.718	2.065	2.927	2.506
	[1.487]*	[1.130]*	[1.373]**	[1.482]*
Observations	3,984	3,984	3,984	3,984
	Panel F: Ignoring panel structure of the data			
Firm complex software use	-0.588	0.555	0.739	0.508
	[0.444]	[0.324]*	[0.365]**	[0.467]
Observations	3,704	3,704	3,704	3,704
	Panel G: Including sector-specific time trends			
Firm complex software use	-1.414	1.301	1.462	1.358
	[0.630]**	[0.599]**	[0.611]**	[0.630]**
Observations	3,704	3,704	3,704	3,704
	Panel H: Task content measures by occupation and sector			
Firm complex software use	-1.328	1.137	1.237	1.302
	[0.549]**	[0.481]**	[0.512]**	[0.599]**
Observations	3,704	3,704	3,704	3,704

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% 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 of the main manager (in logs), number of years of experience of the main manager (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)), as well as region-specific time trends.

Table 7. Heterogeneity of Impact of Firm Complex Software Use on Employment Composition and Task Indexes across Firm Size

Dependent variable:	Panel A: Second-stage - Firm employment shares			
	Managers	Admin. workers	Skilled prod. workers	Unskilled prod. workers
	(1)	(2)	(3)	(4)
Firm complex software use	-0.0993	0.136	-0.386	0.350
* Micro firm	[0.283]	[0.217]	[0.370]	[0.365]
Firm complex software use	-0.512	0.425	-0.791	0.879
* Non-micro firm	[0.284]*	[0.270]	[0.360]**	[0.413]**
P-value for test of equality of coefficients	0.073	0.317	0.335	0.187
Dependent variable:	**Panel B: Second-Stage - Firm task indexes**			
	Abstract	Routine-cognitive	Routine-manual	Non-routine-manual
	(1)	(2)	(3)	(4)
Firm complex software use	-0.714	0.614	0.727	0.685
* Micro firm	[0.754]	[0.694]	[0.741]	[0.745]
Firm complex software use	-2.026	1.903	2.107	1.946
* Non-micro firm	[0.779]***	[0.674]***	[0.716]***	[0.789]**
P-value for test of equality of coefficients	0.063	0.029	0.038	0.074
Observations	3,704	3,704	3,704	3,704

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% 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 of the main manager (in logs), number of years of experience of the main manager (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)), as well as region-specific time trends. Micro firms are defined in Table B1 (Appendix B1).

Table 8. Heterogeneity of Impact of Firm Complex Software Use on Employment Composition and Task Indexes across Sector's Workforce Education Level

Dependent variable:	Panel A: Second-stage - Firm employment shares			
	Managers	Admin. workers	Skilled prod. workers	Unskilled prod. workers
	(1)	(2)	(3)	(4)
Firm complex software use	-2.506	0.651	1.591	0.264
* High-educated workforce	[1.450]*	[0.470]	[1.107]	[0.452]
Firm complex software use	-0.288	0.274	-0.596	0.609
* Low-educated workforce	[0.243]	[0.210]	[0.265]**	[0.270]**
P-value for test of equality of coefficients	0.134	0.447	0.040	0.517
Dependent variable:	Panel B: Second-Stage - Firm task indexes			
	Abstract	Routine-cognitive	Routine-manual	Non-routine-manual
	(1)	(2)	(3)	(4)
Firm complex software use	-2.583	3.618	2.913	2.526
* High-educated workforce	[1.644]	[2.091]*	[1.714]*	[1.650]
Firm complex software use	-1.346	1.228	1.391	1.293
* Low-educated workforce	[0.548]**	[0.515]**	[0.526]***	[0.551]**
P-value for test of equality of coefficients	0.488	0.279	0.408	0.491
Observations	3,704	3,704	3,704	3,704

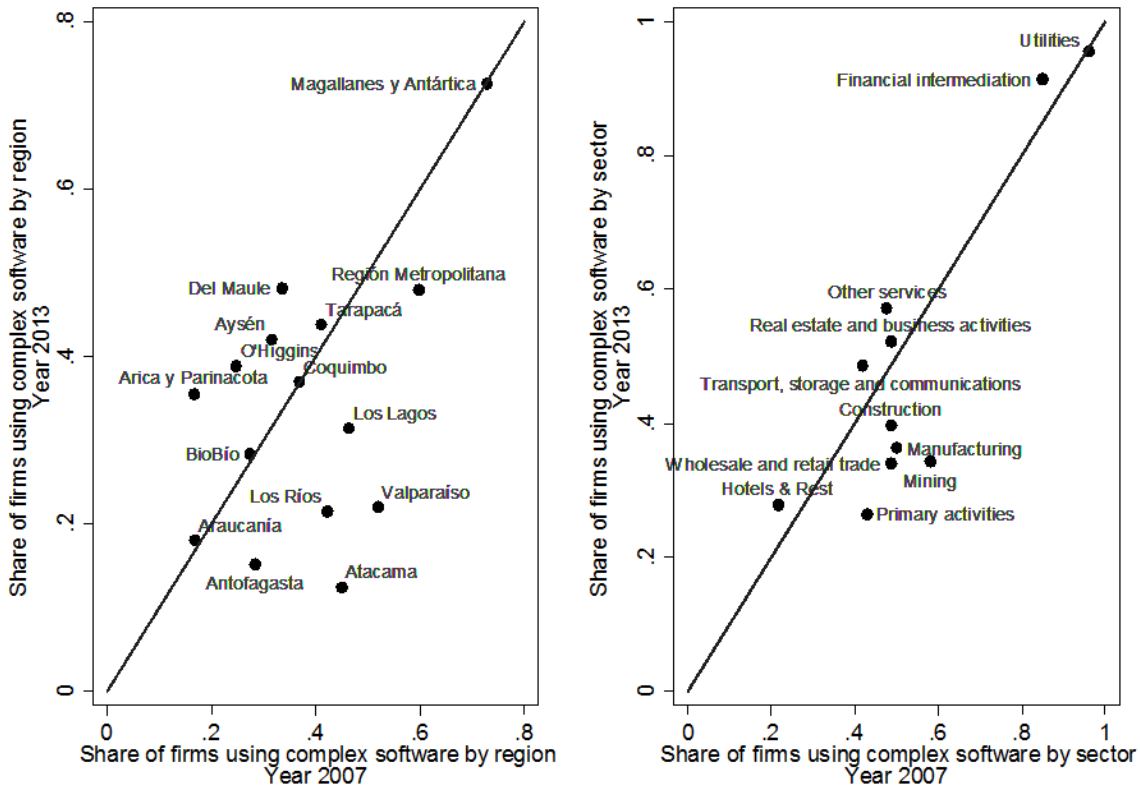
Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% confidence levels, respectively. All regressions control for firm and year fixed effects and include time-varying firm characteristics (size categories, age (in logs), exporter, foreign-owned, and credit constrained indicators, age of the main manager (in logs), number of years of experience of the main manager (in logs) and indicators for the degree of education of the main manager), time-varying region characteristics (average per capita household income in the region (in logs), share of urban households, and average number of years of education of households (in logs)), as well as region-specific time trends. High-educated sectors are those having at least 50% of their workforce with college education in 2007.

Table 9. Impact of Adoption of Advanced Software on Training and Outsourcing

Dependent variable:	Worker training	Manager training	Manager training on ICT	Outsourcing
	(1)	(2)	(3)	(4)
Firm complex software use	0.0185	0.153	0.228	0.143
	[0.356]	[0.258]	[0.115]**	[0.126]
Observations	3,704	3,704	3,704	3,704

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% 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 of the main manager (in logs), number of years of experience of the main manager (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)), as well as region-specific time trends. The dependent variables are defined in Table B1 (Appendix).

Figure 1. Adoption of Complex Software across Regions and Sectors



Source: 2007 and 2013 waves of ELE survey.
Note: ELE sampling weights are used for the shares shown in the two panels of the figure.

Appendix A: Data and Definitions

ELE Survey

The Encuesta Longitudinal de Empresas (ELE survey) was developed by the Sub-secretariat of Economy in the Ministry of Economy, Promotion, and Tourism and the University of Chile (Center of Microdata from the Economics Department) and implemented by the National Statistical Institute. The ELE survey is representative of all economic activities in Chile captured by the International Standard Industry Classification (ISIC) Revision 3 except for public administration, health, education, domestic service, and extraterritorial organizations. The sampling frame from which firms are selected to be surveyed, with a stratification by sector and firm size, is the Directory from INE and a registry from the Chilean internal revenue service. In this study, we use the 2007 and 2013 rounds of the survey and exclude the 2009 wave due to a comparability problem in the definition of occupation categories. In each round of the survey, a panel design is established that selects as many firms as possible from the immediately preceding round. If a threshold of 50% of the cross-section size by sector and firm size cannot be reached with firms included in the immediately previous survey, the missing firms are replaced by firms that were present in the survey round prior to that. Our main firm-level sample is a balanced panel of 1,852 firms observed both in 2007 and in 2013.

PIAAC Survey and Definition of Task Measures

We define the task content of occupations for abstract, routine-cognitive, routine-manual, and (non-routine) manual tasks, identifying in the PIAAC survey the questions that are very similar to those used by other studies relying on the DOT, PDII, O*NET or STEP surveys. Abstract comprises abstract problem-solving and creative, organizational and managerial tasks which are associated with the following variables in the PIAAC survey: the frequency of reading material and of writing material at work; the frequency of math tasks involving at least high-school mathematics; the frequency of problem-solving tasks requiring at least 30 minutes to be solved; the frequency of interaction with other people at work; the frequency of learning at work; the frequency of making presentations or giving speeches, and an indicator for the supervision of other workers.[22] Routine-cognitive and routine-manual involve codifiable cognitive and manual tasks that follow explicit procedures. Routine-cognitive tasks are associated with the following variables in the PIAAC survey: rigidities in the adjustment of the sequence of tasks at work; the rigidities in the adjustment of working hours at work; and the rigidities in the adjustment of the speed or rate of work.[23] These variables capture the degree of autonomy a worker has in performing his job. Routine-manual tasks are associated with a variable in the PIAAC survey on the frequency of using accuracy with hands or fingers. Finally, manual comprises tasks that require physical adaptability and are associated with a variable in the PIAAC survey on the frequency of working physically for a long period.

In order to construct the task content of occupations based on the PIAAC survey we focus on 1,624 adult workers that are wage employees in the private sector employed in any of the sectors

[22] Variables measuring the frequency of a particular activity are expressed on a scale ranging from 1 (indicating very low frequency) to 5 (indicating very high frequency).

[23] Variables measuring the rigidity of a particular activity are expressed on a scale ranging from 1 (indicating little rigidity) to 5 (indicating strong rigidity). Our definition of routine-cognitive and routine-manual tasks follows the definition used by other papers using the PIAAC surveys (Marcolin et al.,2016; Pouliakas and Russo, 2015).

covered by the ELE survey. Then, we match the 262 detailed occupations in our PIAAC sample (classified at the 4-digit level of the International Standard Classification of Occupations (ISCO) 2008) to the four occupation categories in the ELE survey: managers, administrative workers, skilled production workers and unskilled production workers.[24] Finally, we combine the variables associated with each type of task in the PIAAC survey (shown in Table B2 in Appendix B) into a single task content measure for each occupation category in the ELE survey following the approach of Acemoglu and Autor (2011). We proceed in three steps:

1) For each variable associated with any of the four types of tasks we calculate the mean and standard deviation across the sample of 1,624 workers so as to be able to standardize the variable by subtracting the mean and dividing by the standard deviation.

2) For each worker, we obtain scores for each of the four types of tasks by adding all the standardized variables obtained 1) associated with abstract tasks (8 variables), associated with routine-cognitive (3 variables), and by considering the standardized routine-manual tasks and manual tasks obtained in 1) themselves (since they only have one standardized variable associated). For all final task scores to have a zero mean and standard deviation of one, we do one additional standardization of the abstract task score and the routine-cognitive task score by subtracting their mean and dividing by their standard deviation.

3) For each of the four occupation categories in the ELE survey, we calculate a weighted average of the value of each of the four final standardized task scores obtained in 2) using as weights the contribution of each detailed occupation mapped to that occupation category to total hours of work in the previous week, as reported in the PIAAC survey.[25] Since the resulting task content measures cannot be compared across occupation categories, we standardize them using the mean and standard deviation taken across the four occupation categories. These normalized task content measures are an input for the firm-level task indexes.

The key advantage of this methodology is that the scale of the abstract, routine-cognitive, routine-manual, and manual task content measures is comparable across tasks and across occupations in the ELE survey. Panel A of Table B3 in Appendix B provides for each occupation in the ELE survey the average of each task content measure. Higher values of the task content measure indicate that that type of tasks is more important for that occupation. For managers, the most important tasks are abstract, followed by non-routine manual and routine-manual tasks, while routine-cognitive tasks are the least important. This ranking is very intuitive as managers are expected to perform the problem-solving tasks included in the definition of abstract tasks. The relative importance of non-routine-manual tasks for managers is in line with Messina et al. (2016) who find that occupations with a high content of non-routine-manual tasks include high-level occupations like database and network professionals, managing directors and chief executives. As expected, routine-cognitive tasks are of lesser relevance for managers, who typically have more freedom to decide the way they work. For administrative workers, the most important tasks are routine-cognitive and routine-manual, which again is a finding in line with expectations. For skilled production workers, the most important tasks are abstract, followed by routine-cognitive tasks – these are the set of tasks we expect to be replaced by the complex software. Finally, for unskilled production workers the most important tasks are non-routine manual followed by routine-manual.

[24] A matrix with the matches between detailed occupations and occupation categories is available upon request.

[25] Total hours of work in the previous week are obtained as the sum of hours of work in the previous week by all existing detailed occupations (regardless of which occupation category in the ELE survey they are mapped to).

Appendix B: Tables

Table B1. Definition of Variables taken from the ELE Survey

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, organize, 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.
Skilled production workers	Professionals and technicians working directly related 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, economic and commercial services.
Unskilled production workers	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.
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-cognitive task index	Weighted average of a routine-cognitive task measure for each employment category obtained from PIAAC survey. Weights are defined as the share of each employment category in firm total employment.
Routine-manual task index	Weighted average of a routine-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.
Non-routine 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 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 variable for whether the firm uses client management, production or 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.
Firm size	Firm size is captured by the firms' annual sales and is measured in promotion units ("*UF*"). One UF corresponds to 23,309.56 Chilean peso, as December 31 2013. Micro firms are those with [0.1; 2400] UF of annual sales in 2007; and [800; 2,400] in 2013; small category 1 firms are those with (2,400; 5,000] UF of annual sales; small category 2 firms are those with (5,000; 25,000] UF of annual sales; medium firms are those with (25,000; 100,000] UF of annual sales; and large firms are those with 100,000 or more UF of annual sales. This definiton is used by the Subsecretary of the Economy and the University of Chile.
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 a 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.

Table B2. Variables Associated with Four Types of Tasks in the PIAAC Survey

Tasks measures	Variables
Abstract	(1) Frequency of reading material (1 to 5)
	(2) Frequency of writing material (1 to 5)
	(3) Frequency of math tasks involving at least high school mathematics (1 to 5)
	(4) Frequency of problem solving tasks requiring at least 30 min to be solved (1 to 5)
	(5) Frequency of interaction with other people (1 to 5)
	(6) Frequncy of learning at work (1 to 5)
	(7) Frequency of making presentations or giving speeches (1 to 5)
	(8) Supervising other employees (Yes/No)
Routine-cognitive	(1) Rigidities in adjustment of sequence of tasks (1 to 5)
	(2) Rigidities in adjustment of working hours (1 to 5)
	(3) Rigidities in adjustment of speed or rate of work (1 to 5)
Routine-manual	(1) Frequency of using accuracy with hands or fingers (1 to 5)
Non-routine manual	(1) Frequency of working phisically for a long period (1 to 5)

Source: 2014 Chile PIAAC Survey.

Notes: Variables measuring the frequency of a particular activity are expressed on a scale ranging from 1 (indicating very low frequency) to 5 (indicating very high frequency). Variables measuring the rigidity of a particular activity are expressed on a scale ranging from 1 (indicating little rigidity) to 5 (indicating strong rigidity).

Table B3. Task Content Measures based on the PIAAC Survey by Occupation in the ELE Survey

Panel A. Following Methodology of Acemoglu and Autor (2011)

	Abstract	Routine-Cognitive	Routine-Manual	Manual
Managers	0.883	-0.940	-0.504	-0.709
Administrative workers	-0.052	0.121	-0.046	-0.215
Skilled production workers	0.358	-0.473	-0.482	-0.502
Unskilled production workers	-0.154	0.185	0.203	0.249

Panel B. Following Methodology of Autor and Handel (2013)

	Abstract	Routine-Cognitive	Routine-Manual	Non-routine manual
Managers	0.883	-0.940	-0.504	-0.709
Administrative workers	-0.052	0.121	-0.046	-0.215
Skilled production workers	0.358	-0.473	-0.482	-0.502
Unskilled production workers	-0.154	0.185	0.203	0.249

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.

Table B4. Sectoral and Size Composition of the ELE Panel Sample

Size category by value of annual sales	
Micro	29.77
Small 1	20.87
Small 2	28.83
Medium	13.03
Large	7.51
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 2007 and 2013 waves of ELE survey.
Notes: Size categories are defined in Table B1.

Table B5. Firms Switching Complex Software Adoption Status between 2007 and 2013

	Share of firms using complex software in 2007	Share of firms switching software use status between 2007 and 2013
Overall panel sample	46.7%	25.4%
By firm size		
Micro	16.5%	26.8%
Small 1	29.5%	23.9%
Small 2	35.5%	35.4%
Medium	80.0%	12.1%
Large	92.6%	1.5%
By sector		
Agriculture, hunting, fishing and forestry	27.3%	8.5%
Mining and quarrying	40.4%	0.7%
Manufacturing	45.4%	15.8%
Electricity, gas and water supply	95.3%	0.1%
Construction	39.4%	12.9%
Wholesale and retail trade	33.6%	30.0%
Hotels and restaurants	18.3%	4.8%
Transport, storage and communications	36.1%	7.7%
Financial intermediation	88.3%	0.1%
Real estate and business activities	57.2%	12.4%
Other service activities	61.1%	7.1%

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey.

Table B6. Summary Statistics on Regional Variables from the CASEN Survey

	Computer		Cell Phone	
	2006	2013	2006	2013
	(1)	(2)	(5)	(6)
Tarapacá	35.10	61.62	63.80	90.94
Antofagasta	43.56	72.23	68.42	93.86
Atacama	36.72	58.16	64.75	92.88
Coquimbo	26.37	54.25	59.12	92.16
Valparaíso	32.91	59.45	61.78	89.85
O'Higgins	24.81	51.26	59.40	89.84
Del Maule	20.74	43.24	58.82	90.36
BioBío	28.33	55.54	56.53	88.77
Araucanía	23.83	43.28	56.34	89.16
Los Lagos	23.74	51.13	63.82	89.37
Aysén	26.27	59.05	62.68	92.53
Magallanes y Antártica	46.75	68.48	57.69	89.36
Región Metropolitana	43.47	63.99	62.86	89.21
Los Ríos	23.79	47.79	53.22	88.75
Arica y Parinacota	32.40	59.56	52.61	87.48
Country Avg.	31.25	56.60	60.12	90.30

Source: 2006 and 2013 waves of CASEN survey.

Table B7. OLS Estimated Impact of Complex Software Use on Firm Occupation Shares and Task Indexes

Dependent variable:	Panel A. Firm employment shares			
	Managers	Admin. workers	Skilled prod. workers	Unskilled prod. workers
	(1)	(2)	(3)	(4)
Firm complex software use	0.0182	0.0216	-0.0022	-0.0377
	[0.0156]	[0.0302]	[0.0277]	[0.0345]
Dependent variable:	**Panel B. Firm task indexes**			
	Abstract	Routine-cognitive	Routine-manual	Non-routine-manual
	(5)	(6)	(7)	(8)
Firm complex software use	0.0653	-0.0476	-0.0488	-0.0694
	[0.0528]	[0.0410]	[0.0467]	[0.0543]
Observations	3,704	3,704	3,704	3,704

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Notes: Robust standard errors in brackets clustered by region-sector. ***, **, and * indicate significance at 1%, 5%, and 10% confidence levels, respectively. All regressions control for firm and year fixed effects and include time-varying firm characteristics (firm size categories, firm age (in logs), exporter, foreign-owned, and credit constrained indicators, age of the main manager (in logs), number of years of experience of the main manager (in logs) and indicators for the degree of education of the main manager), time-varying region characteristics (average per capita household income in the region (in logs), share of urban population, average number of years of education of population in the region (in logs)), as well as region-specific time trends.

Table B8. Task Content Measures based on the PIAAC Survey by Occupation and Sector of Activity in the ELE Survey

	Abstract	Routine-Cognitive	Routine-Manual	Non-routine manual
Managers	**1.081**	**-1.320**	**-1.180**	**-1.051**
Primary sector	0.935	-1.239	0.090	0.610
Manufacturing sector	1.174	-1.218	-0.757	-1.038
Services ssector	1.073	-1.346	-1.300	-1.145
Administrative workers	**-0.127**	**0.556**	**0.546**	**-0.007**
Primary sector	-0.215	0.136	-0.383	-0.201
Manufacturing sector	-0.331	0.672	0.508	0.318
Services ssector	-0.091	0.621	0.591	-0.015
Skilled production workers	**0.347**	**-0.191**	**-0.427**	**-0.288**
Primary sector	0.593	-0.096	-1.038	-1.324
Manufacturing sector	0.340	-0.404	-0.910	-0.523
Services ssector	0.333	-0.156	-0.242	-0.134
Unskilled production workers	**-1.302**	**0.955**	**1.061**	**1.346**
Primary sector	-1.314	1.199	1.330	0.914
Manufacturing sector	-1.182	0.950	1.158	1.243
Services ssector	-1.315	0.882	0.950	1.293

Source: Authors' calculations based on 2007 and 2013 waves of ELE survey and 2014 Chile PIAAC survey.
Note: Reported values correspond to Autor and Acemoglu (2011) methodology.