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The effect of automation on the labor market: An approach using firm-level microdata

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The effect of automation on the labor market: An approach using firm-level microdata*

Camilo Levenier[1]

Resumen

Este estudio analiza la relación entre máquinas y empleo en los diferentes quintiles de ingresos de los trabajadores, utilizando microdatos a nivel de empresa y trabajador para Chile desde 2009 hasta 2023, considerando un total de 80,000 firmas y 2,900,000 trabajadores. Para investigar esta dinámica, se utiliza una regresión de panel, modelando el empleo como una función de máquinas y un conjunto de otras covariables. Además, se usa un generalized propensity score para abordar el problema de endogeneidad. Los resultados indican que la relación entre máquinas y empleo es predominantemente negativa, especialmente para los trabajadores en los quintiles de ingresos medios y para ciertos sectores económicos como servicios empresariales, transporte e información y comunicación. Además, los resultados sugieren que la relación entre máquinas y empleo en los quintiles de ingresos altos ha sido positiva, apoyando la idea de que el desarrollo tecnológico requiere trabajadores altamente calificados. En general, los resultados sugieren que la automatización en el mercado laboral chileno ha tenido efectos heterogéneos en el empleo, y que dichos efectos serían más pequeños de lo que sugiere la literatura.

Abstract

This study analyzes the relationship between machines and employment across different workers' income quintiles, utilizing firm-level and worker-level microdata for Chile from 2009 to 2023, considering a total of 80,000 firms and 2,900,000 workers. To investigate this dynamic, a panel regression is used, modeling employment as a function of machines and a set of other covariates. Additionally, a generalized propensity score is used to address the endogeneity problem. The results indicate that the relationship between machines and employment is predominantly negative, especially for workers in the middle-income quintiles and for certain economic sectors such as business services, transport, and information & communication. Furthermore, the results suggest that the relationship between machines and employment in high-income quintiles has been positive, supporting the idea that technological development requires highly qualified workers. Overall, the results suggest that automation has had heterogeneous effects on employment in the Chilean labor market, and these effects are smaller than those suggested by the literature.

*The views expressed here are those of the author and do not necessarily reflect the views of the Central Bank of Chile (BCCh). I am grateful to Lucas Bertinatto, Diego Vivanco and an anonymous referee for their valuable comments. Any remaining errors are my own. This study was developed within the scope of the research agenda conducted by the BCCh in economic and financial affairs of its competence. The BCCh has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. The information contained in the databases of the Chilean IRS (SII) are those submitted by the taxpayers and have not been verified by either the Bank or the Service.

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1. Introduction

As with previous industrial revolutions, the current level of technological development allows certain labor tasks previously performed by humans to be partially or totally replaced by machines. A natural consequence of this technological revolution is its impact on the labor market, particularly regarding whether machines act as substitutes for or complements of employment.

In some cases, it seems intuitive to assume a negative relationship between machines and human workers; for example, self-checkout systems have replaced low-income workers in supermarkets. Similarly, chatbots automate customer service, and automated vending machines partially replace some convenience stores. However, positive relationships can also exist. In many cases, capital requires qualified workers for its design, maintenance, and operation. Recently, some artificial intelligence (AI) applications—such as ChatGPT or Copilot—have demonstrated significant utility in supporting labor tasks, such as searching for information, translating texts, programming, resolving bugs, summarizing information, transcribing audio, among many other applications. Recent literature suggests that the use of these applications increases the gap between low- and high-performing workers, favoring the latter (Otis *et al.*, 2023; Roldán-Monés, 2024; Toner-Rodgers, 2024; and Kim *et al.*, 2024). Therefore, it is worthwhile to evaluate how these heterogeneous effects of automation impact on different employment quintiles.

According to the Labor Survey 2023 (ENCLA in Spanish)—which aims to provide information about labor conditions within formal companies in Chile—digitalization and automation are present among Chilean companies, especially in large firms. In fact, nearly 11% of firms implemented some form of automation in their processes during 2023, and only 7% of them dismissed staff because of it. Among the companies interviewed, self-consultation systems were the most adopted innovation (Figure A.1 in the appendix provides additional details). Additionally, digitalization seems to be more popular among Chilean firms. According to ENCLA 2023, about 63% of firms have adopted some form of digitalization (Figure A.2 in the appendix). However, only 1.6% of the firms that adopted digitalization dismissed staff because of its implementation, which makes sense considering that digitalization mainly serves as a facilitation tool for workers, whereas automation could replace their duties. Overall, ENCLA 2023 suggests that a small fraction of firms, mostly big ones, implemented some form of automation, and that the associated loss of employment was marginal during 2023.

Related literature has explored the effects of automation on the labor market. Acemoglu and Restrepo (2020), using U.S. data on exposure to robots, develop a model in which humans and robots compete in the production function, finding a negative relationship between robots and employment. Jackson and Kanik (2020) adopt a similar approach, evaluating labor substitution within a general equilibrium framework and finding that automation reduces the wages of substitutable workers relative to non-substitutable workers, affecting employment across the entire economy. J. De Canio (2016) fits different distributions to cross-sectional data on U.S. productivity, finding that if the elasticity of substitution between human and robotic labor is greater than 1.9, AI will cause a decline in aggregate wages. Gallipoli and Makridis (2018) develop an IT intensity index to estimate industry-specific elasticities of substitution between IT-intensive and non-IT-intensive labor, finding values of 1.6 for manufacturing and 1.3 for services. Berg *et al.* (2018) propose a general equilibrium model finding that automation is good for growth but bad for equality: real wages fall in the short run and eventually rise, but "eventually" can easily take generations. Based on international evidence, Bravo *et al.* (2018) suggest that the rise in the presence of robots correlates with an increase in highly qualified employment at the expense of medium-qualified jobs, applying upward pressure on wages due to a low substitution rate of medium- and low-qualified employment with high-qualified jobs in the short term.

On the Chilean economy, Bravo *et al.* (2019) estimate the risk of automation based on workers' skills and their probability of being replaced by machines, showing that middle-income quintiles face the highest risk of automation. Rivera (2019) develops a general equilibrium model and finds that the negative impact on the Chilean labor market depends on whether the change in the price of robots is transitory or permanent. Arriagada (2023) suggests that the effects of automation are heterogeneous and depend on the workers' educational levels. Overall, related literature shows a consensus that the effects of automation on employment depend on the workers' qualifications.

The contribution of this study to the literature is to assess the relationship between machines and employment by leveraging microdata at the firm and worker level for Chile between 2009 and 2023. To the best of my knowledge, no other study has used microdata to address this question. While other studies use general equilibrium models that typically make assumptions about the elasticity between machines and employment, or aggregate indicators of exposure to robots or IT intensity, or the risk of automation as a proxy of the elasticity between machines and employment, this study attempts to estimate these elasticities by using microdata. Moreover, the dataset allows for the estimation of elasticities across different workers' income quintiles and economic sectors, evaluating the heterogeneous effect that automation might have.

The rest of the document is organized as follows: Section 2 describes the data utilized; Section 3 details the methodologies used to estimate the elasticities; Section 4 presents the estimation and results, along with a brief discussion and the study's limitations. Section 5 presents some concluding remarks.

2. The data

This section describes the data and merging process used in the analysis. Three main administrative datasets are used, all provided by the Chilean Tax Authority (SII, in Spanish): (1) the Standard tax form F29, (2) the employment declaration DJ1887, and (3) the Standard income form F22.

The most restrictive data corresponds to employment, given its annual frequency and lag (the latest available information covers up to 2023). Therefore, all microdata is used at annual frequency. The datasets are merged by each firm's identifier and year, resulting in an annual panel dataset of Chilean firms from 2009 to 2023.

1) **F29:** This microdata describes, at a monthly frequency and firm level, the firm's production used for tax purposes. The value added by the firm is constructed using the sales and costs reported in this form.
2) **DJ1887:** This dataset contains information about all formal workers in the Chilean economy. For each worker, the form reports their respective employer, wage, and work modality (full-time or part-time).
3) **F29 + F22:** Combining these two datasets, the BCCh staff has constructed a series of capital stock in machinery for each firm. F29 reports the investment in machinery and equipment, and F22 contains the net capital stock (including all types of assets, not only machinery & equipment). Using the weights published by the National Accounts, the net capital stock is weighted to obtain an initial observation of net capital stock in machinery & equipment by firm. The process of constructing the series of capital follows the perpetual inventory methodology: for each month t, the capital stock corresponds to the previous stock $t-1$ (weighted by 1 minus the depreciation rate) and the investment in t.

To investigate potential evidence of automation in the Chilean labor market, a dataset of the production function at the firm level is compiled. According to Bravo *et al.* (2018), there appear to be heterogeneous effects across different workers' income levels; therefore, employment is divided into three wage-based quintiles. Additionally, the BCCh has access to the economic activity of each firm, allowing an exploration of whether certain economic sectors are more affected by automation than others. Table 1 presents the sectors considered in the analysis.

Table 1: Economic activity sector description

Economic activity
Agriculture & Fishery
Mining
Manufacturing
Electricity, gas, water & waste management (EGW)
Construction
Wholesale and retail trade, restaurants & hotels
Transport, information & communications
Financial services
Dwelling services & real estate
Business services
Personal services

According to Chilean regulations, there are four types of firms based on the number of employees.

Table 2: Firms' size by employment

Firms' size	**# employees**
Micro	0 – 9
Small	10 – 25
Medium-sized	25 – 200
Large	+200

ENCLA 2023 suggests that automation and digitalization are concentrated in large firms. Moreover, considering the limited capital available for investment, data from microenterprises seems to be less reliable than those from small, medium, and large firms. Therefore, it seems reasonable to exclude this group from the analysis. This filter keeps 87% of the employment and 94% of the capital stock in the database, so the results remain representative.

2.1. Variable transformations

All variables of the production function have been deflated using specific prices for each component:

- **Labor market**: Wages are adjusted using the total CPI. Employment is already in real terms.
- **Capital stock of machines**: National Accounts publish prices for the net capital stock by asset types, particularly machinery & equipment.
- **Value added**: GDP deflators by economic activity are used.

2.2. Cleaning procedure

Peña and Prades (2024) emphasize the importance of removing outliers and remaining errors from administrative datasets. Based on previous research, they suggest two steps for data cleaning:

1) Delete observations of firms with negative values in the production functions or values exceeding the maximum reported by the firm with the most employees nationwide.

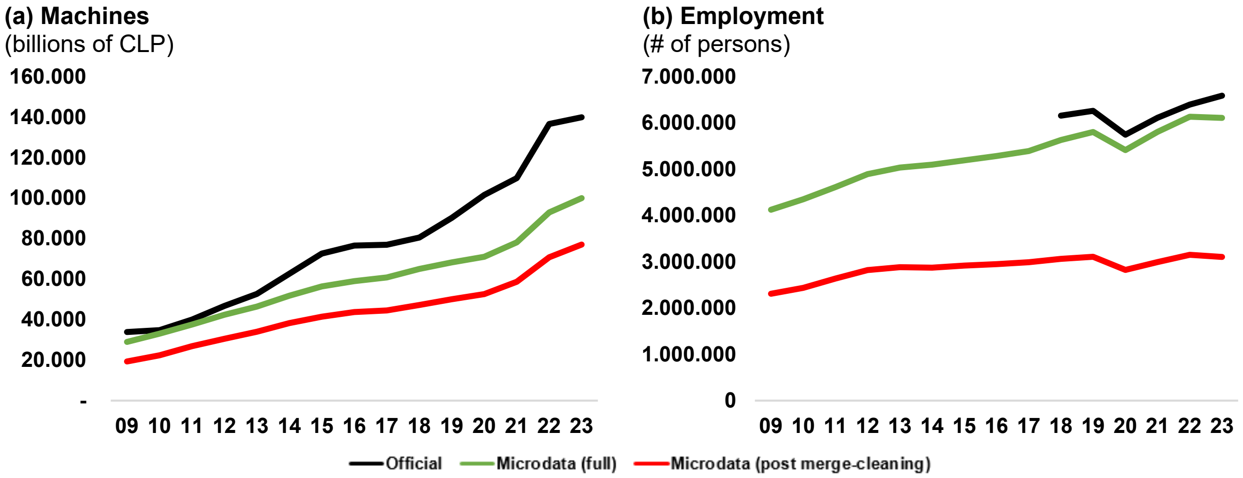
2) Discard observations that imply extreme labor productivity by firms, such as small firms with exceptionally high productivity or large firms with excessively low productivity. Specifically, firms with fewer than 50 employees and whose turnover-to-employees ratio is above the 99.5th percentile in the sample are eliminated. Similarly, firms with more than 50 employees and whose turnover-to-employees ratio is below the 0.5th percentile in the sample are also deleted. Following the same approach, extreme capital productivity is excluded using the turnover-to-capital ratio.

The cleaning procedure retains 99.5% of the original dataset.

2.3. Descriptive statistics

Figure 1 illustrates the evolution of the aggregate capital stock in machines and employment derived from the microdata, comparing it with official statistics.

Figure 1: Machines and employment coverage



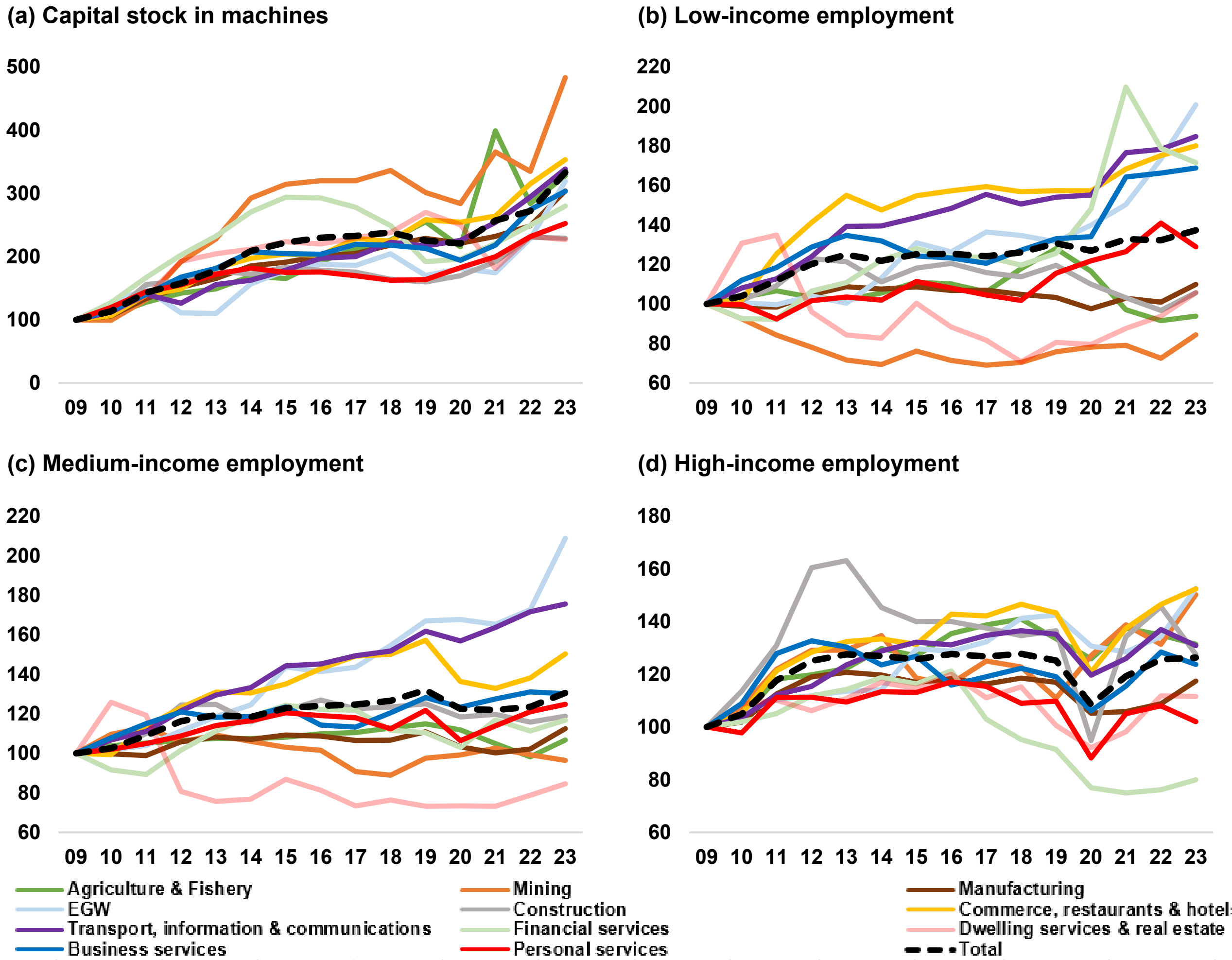
Since 2009, both machinery and employment have shown an upward trend in Chile, although capital has experienced higher growth. In real terms, between 2009 and 2023, the aggregated series obtained from the microdata shows a cumulative growth of 90% for machinery and 50% for employment.

The official capital stock series is sourced from the BCCh and represents the net capital stock in machinery & equipment. The official employment statistics are derived from the National Employment Survey (ENE, in Spanish), conducted by the National Statistics Institute of Chile (INE, in Spanish). The distinction between formal and informal employment in the survey began in September 2017. The capital stock microdata covers, on average, 80% of the official statistics, while the employment coverage is higher, averaging 94%. The merging and cleaning processes retain approximately 55% of the employment data and 73% of the machinery data, resulting in a panel database of approximately 500,000 observations, considering a total of 80,000 firms and 2,900,000 workers. Additionally, Figure A.3 in the appendix shows the year-to-year evolution of machinery and employment, and the correlation of these variations between official statistics and microdata is 0.6 for machinery and 0.9 for employment.

Focusing on the microdata post-merging and cleaning procedures, a sectoral analysis reveals some heterogeneity among economic activities (Figure 2). Relative to the overall economy, certain sectors indicate signs of automation:

- **Mining, Agriculture & Fishery:** In these activities, capital experienced significant growth between 2009 and 2023, while low and medium-income employment declined. Meanwhile, high-income employment increased.
- **Industry, Dwelling services & Real estate:** These sectors exhibit a nearly average dynamic in machinery and a weakened evolution in employment.

Figure 2: Machines and employment by economic activity
(index 2009 = 100, real terms)



Note: EGW stands for to electricity, gas, water & waste management.

3. Methodology

Acemoglu and Restrepo (2020) describe the empirical relationship between machines and employment as a linear equation, where L_c represents employment in commuting zone c:

$$d\ln L_c = \beta_L \times US\ exposure\ to\ robots_c + \epsilon_c^L \qquad (1)$$

The authors postulate that equation (1) can be estimated using Ordinary Least Squares (OLS), but endogeneity issues are present. To mitigate these problems, they instrument the U.S. exposure to robots using an analogous measure constructed from the penetration of robots in European countries that are ahead of the United States in robotic technology.

Considering the panel data structure of the available microdata, this work constructs an expanded version of equation (1) by conducting a panel regression where Y represents employment, and X includes the stock of machines and other covariates that could be valuable for employment modeling (value added by firm, the relative price between human labor and machine labor, and fixed effects by firm and year).

However, endogeneity may pose a challenge, as the regressors in the production function could be correlated with the error term. Several econometric methods exist to address the endogeneity problem besides instrumental variables (especially when the instrument is unclear or debatable), such as difference-in-differences, propensity score, matching, and others. Unfortunately, most of these techniques are designed for binary treatment variables (control and treatment groups). In this context, the treatment variable is the stock of machines, which ideally should be treated as continuous, since the intensity of automation likely depends on the magnitude of investment in machines rather than on a binary decision. An extension of the propensity score that can handle a continuous treatment variable is the **generalized propensity score (GPS)**. The main idea of GPS is to expand the notion of treatment and control groups into a continuous framework.

3.1. Panel regression

To quantify the impact of automation across different income levels of workers and economic activities, the panel regression is conducted separately by wage quintile and by economic sector of the firm. This approach aims to group the data into similar categories, allowing the main source of variation to come from the stock of machines. The model also controls for value added, the ratio between wages and machine prices (which can be interpreted as the relative price between human labor and machines), as well as fixed effects by firm and period. Formally:

$$L_{f,t,q_w} = \alpha_{s,q_w} + \beta_{s,q_w} M_{f,t} + \gamma_{s,q_w} VA_{f,t} + \delta_{s,q_w} \left(\frac{wage}{price_M}\right)_{f,t,q_w} + \theta_f + \vartheta_t + \varepsilon_{f,t,q_w} \tag{2}$$

Where:

- f is the firm ID and s is its corresponding economic activity.
- $t \in \{2009, \dots, 2023\}$ is the year.
- q_w is the wage quintile.
- L is employment.
- M corresponds to the stock of machines.
- VA is the value added (sales minus costs).
- $wage$ is the collapsed wage in the firm f at time t in quintile q_w.

All variables are in logarithmic form. The parameter of interest is β_{s,q_w}, which represents the elasticity between employment and machines. If only one panel regression were performed, the potential positive and negative impacts of machines on employment might offset each other. Therefore, it is important to separate the effects across different income levels and sectors.

3.2. GPS

According to Hirano and Imbens (2004), the GPS process is as follows. Let T denote a continuous treatment variable, X represent a set of covariates, and $Y(t)$ the response under exposure to treatment t. In this study, the treatment T corresponds to the level of machines, X includes wages and value added, and Y represents employment. The idea of using wages and value added as X in the GPS is to group similar firms based on these variables, allowing for differences in the treatment (machines).

The conditional density of the continuous treatment is given by:

$$r(t, x) = f_{T|X}(t|x) \tag{3}$$

Thus, the GPS is represented as $R = r(T, X)$. The conditional density corresponds to a continuous function that models the treatment T as a function of X. While using OLS to model the treatment T based on various observable characteristics is one approach, other functional forms are also allowed. Table 3 describes several alternative functional forms for the GPS:

Table 3: GPS possible functional forms

Model	Description
IPW	Linear regression
CBPS	Developed by Imai and Ratkovic (2014), the method models treatment assignment while optimizing covariate balance. The estimation is performed using the generalized method of moments (GMM) or the empirical likelihood (EL) framework.
weightIt	Greifer (2025) developed an R package that can estimate propensity scores by enhancing or extending the functionality of other R packages. In the continuous treatment framework, kernel density estimation can be implemented, estimating the numerator and denominator densities for the weights. In this work, two approaches were implemented for kernel estimation: • Linear kernel. • Kernel using a Bayesian additive regression tree (BART[3]).

Covariate balance is the usual criterion to determine the functional form of the GPS. Given a specific functional form of the GPS, the next step is to estimate of the dose-response function, which represents the average response when subjects receive the treatment $T = t$:

$$\mu(t) = E[Y_i(t)] \tag{4}$$

One approach to estimating the dose-response function is use the inverse probability weight (IPW) derived from the generalized propensity score (GPS). Zhang *et al.* (2012) define the weights as follows:

$$\frac{W(T_i)}{r(T_i|X_i)}, \tag{5}$$

where $W(T_i)$ is selected to stabilize the weight when $r(T_i|X_i)$ is very small for certain observations. Equation (5) suggests that subjects with exposure levels closer to the conditional mean will have higher conditional density and, consequently, lower weights. Once the weights are estimated, the dose-response function can be derived by calculating the mean probability of occurrence of the outcome across all levels of exposure.

Finally, the average treatment effect is estimated using the IPW to weigh the regressors in a linear model, such as an OLS regression.

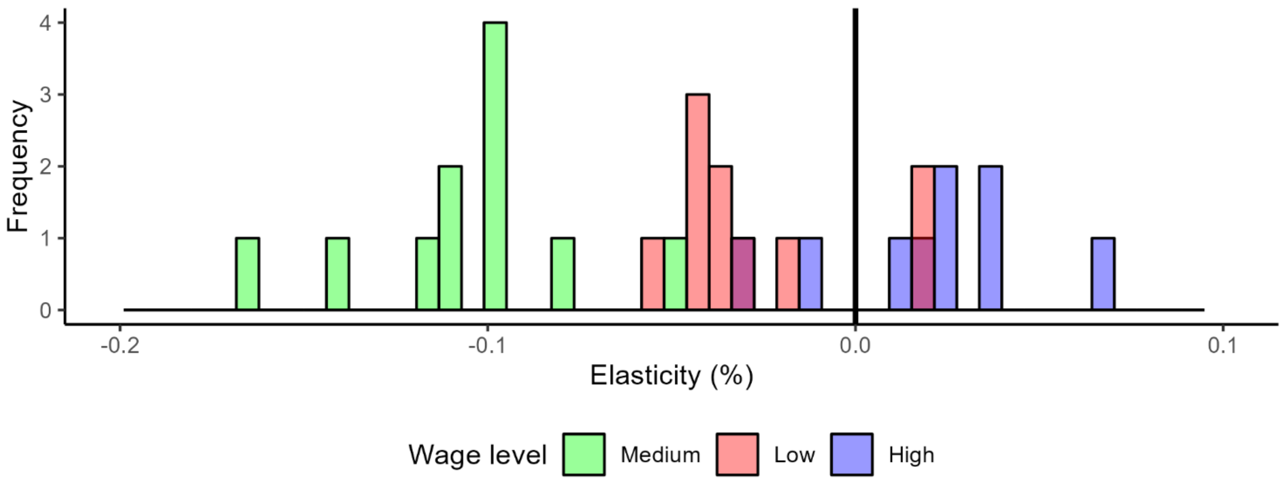
[3] More details about this methodology can be found in Chipman *et al.* (2010).

4. Estimation, results and discussion

4.1. Panel regression

This study estimated a panel regression with fixed effects, as it is the best approach according to the Hausman and F tests[4]. Equation (2) facilitates the estimation of elasticities between employment and machines, by wage quintiles and economic sector. Specifically, the data allows for the identification of 11 economic sectors and three wage quintiles, resulting in a total of 33 panel regressions.

Figure 3: Panel regression estimation
Elasticities between machines and employment by wage quintile
(%)



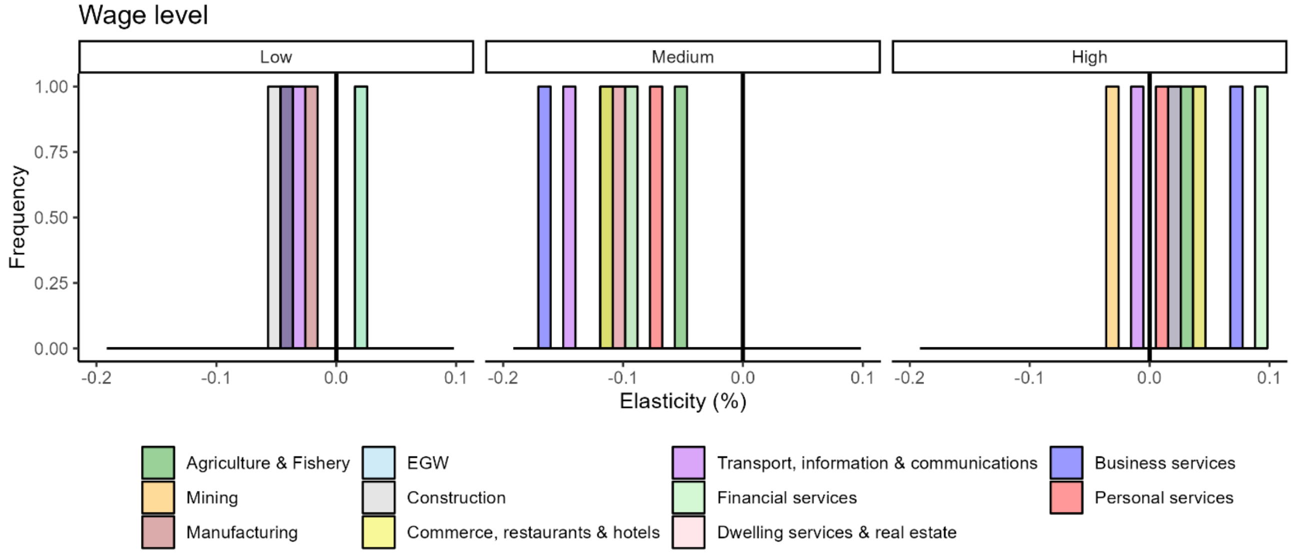
Note: only statistically significant coefficients are plotted.

In Figure 3, each bar corresponds to the (economic activity, wage quintile) group defined in equation (2). The results suggest that, on average, the level of machines was negatively correlated with employment in Chile between 2009 and 2023. Consistent with Bravo *et al.* (2018), middle-income quintiles exhibit the highest negative association. Low-income quintiles also show a negative relationship with machines. In contrast, high-income quintiles tend to exhibit positive relationships with machines, suggesting greater complementarity between capital and highly skilled workers.

Regarding economic activities, Figure 4 shows that business services, transportation, information & communication exhibit a higher negative association between machines and middle-income workers. Conversely, business and financial services show a higher positive correlation between machines and high-income workers.

[4] The F test suggests that fixed effects are preferred to pooling (p-value < 0.05). The Hausman test suggests that fixed effects are preferred to random effects (p-value < 0.05).

Figure 4: Panel regression estimation
Elasticities between machines and employment by economic sector
(%)



Note: only statistically significant coefficients are plotted. EGW stands for to electricity, gas, water & waste management.

Table A.1 in the appendix provides additional details about the elasticity estimation for each economic activity and wage quintile group, including the p-values and adjusted R-squared values for each panel regression (the R-squared of the panel regressions is, on average, nearly 92%).

4.2. GPS

To determine which continuous function to use, it is necessary to assess covariate balance. This evaluation is typically conducted through adjusted correlations, with a tolerance threshold set at 0.1. Lower adjusted correlations indicate better latent groupings. The model that meets this threshold and minimizes the adjusted correlations for the two covariates (wages and value added) is the kernel estimation using Bayesian additive regression trees (BART):

Table 4: Adjusted correlations of covariate balance

Covariate	Adjusted correlation
Value added	0.009
Wages	0.027

Table A.2 in the appendix provides the adjusted correlations for the other models described in Table 4. Unfortunately, CBPS could not be applied due to the high computational demand required, given the high-dimensional data utilized in this work.

Using inverse probability weighting (IPW) derived from the GPS, it is possible to quantify the average treatment effect (ATE) of machines on employment and calculate this effect for each wage quintile:

Table 5: Average Treatment Effect

Wage quintile	ATE
Low	-0.18
Medium	-0.23
High	+0.33

4.3. Discussion

Previous methods have both advantages and disadvantages. Panel regression accommodates the panel structure of the data, but endogeneity issues may still arise. The GPS attempts to mitigate endogeneity problems by using control and treatment groups within a continuous framework; however, it is limited by its cross-sectional nature.

Nevertheless, similar conclusions are obtained: automation has heterogeneous effects on employment depending on workers' qualifications, and the relative order of these elasticities[5] remains consistent irrespective of the methodology employed. This supports the literature on automation, which suggests that middle-income workers are the most negatively affected, while high-income workers tend to benefit:

$$\hat{\beta}_{medium}(-) < \hat{\beta}_{low}(-) < \hat{\beta}_{high}(+) \tag{6}$$

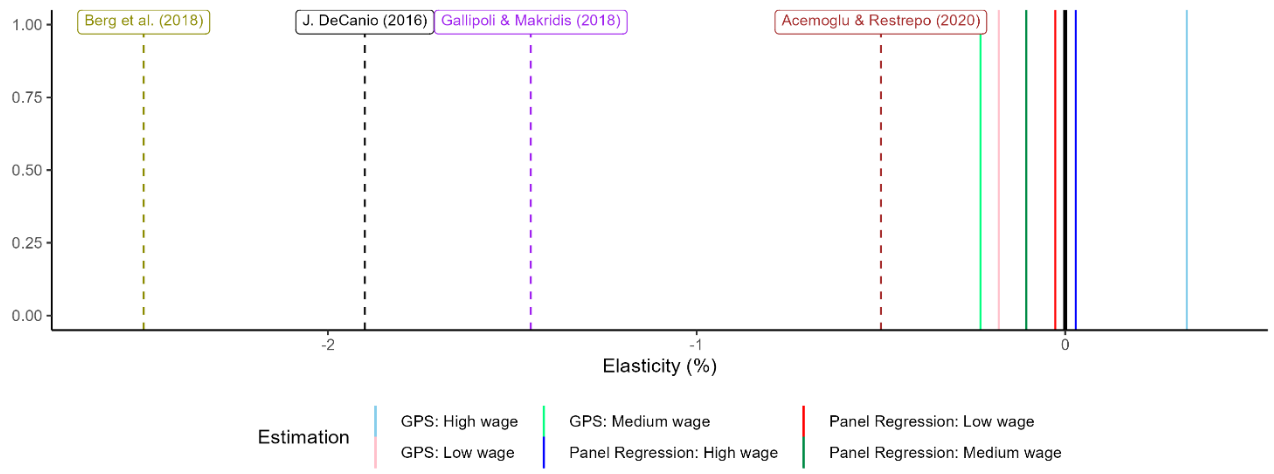
Bravo *et al.* (2018), based on a model developed by Autor *et al.* (2003), suggest that medium-skilled jobs correspond to precise and sequentially defined processes that can be easily codified by computational algorithms and performed by machines. In contrast, high-skilled jobs are associated with tasks that require problem-solving skills, intuition, creativity, and persuasion. This implies that technology negatively affects workers performing routine tasks and positively affects those performing non-routine tasks, a phenomenon known as Routine-Biased Technological Change (RBTC). Thus, automation primarily impacts medium-skilled jobs and pressures wages due to the low substitution of employment in the short run.

It's necessary to highlight that this work uses the capital stock in machines as a proxy for the level of automation. This type of capital is mostly related to physical labor; however, automation of other types of tasks (e.g., verbal or intellectual tasks) also exists. Therefore, the estimated elasticities could represent a lower bound, especially considering that AI currently performs verbal or intellectual tasks (e.g., synthesizing texts, translating text and searching for information, among others).

Figure 5 shows the elasticities between machines and employment for this work and other studies. The literature suggests a range between 0.5% and 2.5%, a higher range of elasticities compared to those estimated in this work. The reasons may lie in: 1) access to microdata related to the production function of firms, while other works must make more assumptions in modeling (structural models) and others use the risk of being automated as a proxy for elasticities, where the calculations may still yield overestimated results; and 2) the data in this work corresponds to an emerging economy, where technological development is still behind the levels of advanced economies.

[5] Doesn't indicate differences statistically significant.

Figure 5: Literature Comparison
Elasticities between machines and employment
(%)



5. Concluding remarks

This paper contributes to the literature on automation and the effects of machines on employment. It also complements the existing literature in Chile—which primarily focuses on general equilibrium models and the estimation of automation risk—by introducing an empirical approach using firm-level microdata on employment and machines. The objective is to provide empirical elasticities that could be valuable for future research.

The methodology employed involves using panel regressions to estimate elasticities, complemented by the generalized propensity score (GPS), a tool that mitigates endogeneity issues. The results suggest that, on average, there is a negative correlation between employment and machines, particularly concentrated among middle-income workers and in certain economic activities such as business services, transportation, information & communication. Additionally, high-income quintiles have a positive association with machines, supporting the idea that highly qualified workers are necessary to design and maintain machines in the automation process of firms.

This study uses the capital stock in machines as a proxy for the level of automation, although this type of machinery is mostly related to physical labor. Other types of automation, such as verbal or intellectual tasks, are not captured in the estimated elasticities of this work, making these elasticities potentially a lower bound of the real effect of automation in Chile.

The elasticities estimated in this study are lower in magnitude than those suggested by the international literature, which may be due to: 1) the use of firm-level microdata—providing more accurate information on the production function of each firm—rather than using indicators of automation risk or general equilibrium models, which often make more assumptions about the relationship between machines and employment; and 2) the data used in this study correspond to an emerging economy, where technological development is still behind the level of advanced economies.

Nevertheless, although the substitution elasticities between machinery and employment currently seem small for the Chilean context, the rapid advancement of AI and its potential to automate not only physical tasks but also verbal and intellectual tasks could amplify its impact on employment in the future.

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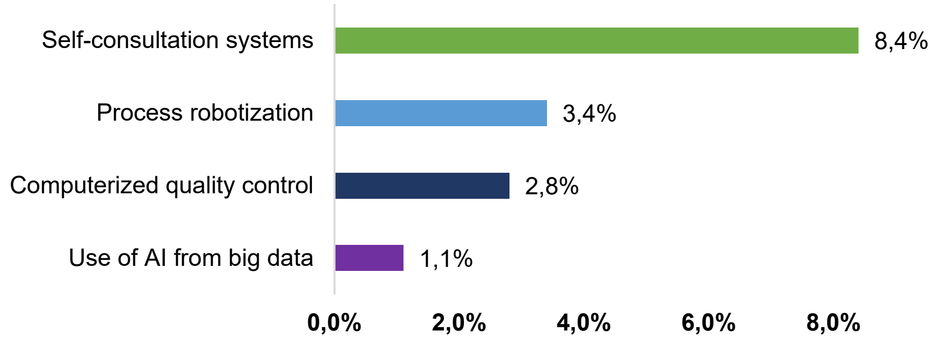
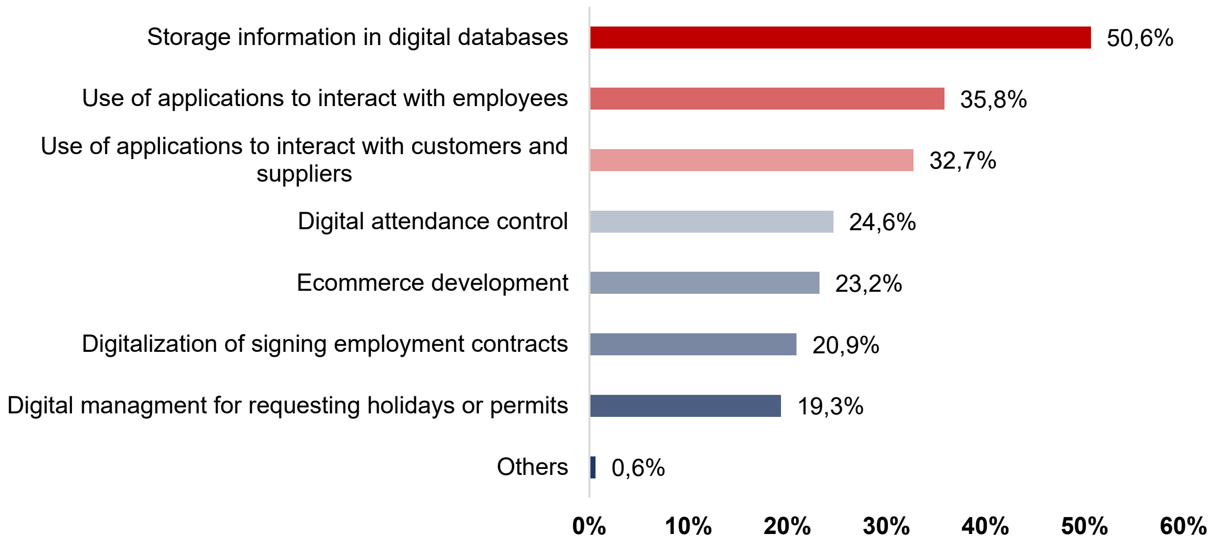
Appendix

Figure A.1: Which of the following forms of automation does this company use?



Source: ENCLA 2023.

Figure A.2: Which of the following forms of digitalization does this company use?



Source: ENCLA 2023.

Figure A.3: Machines and employment coverage

(%, YoY)

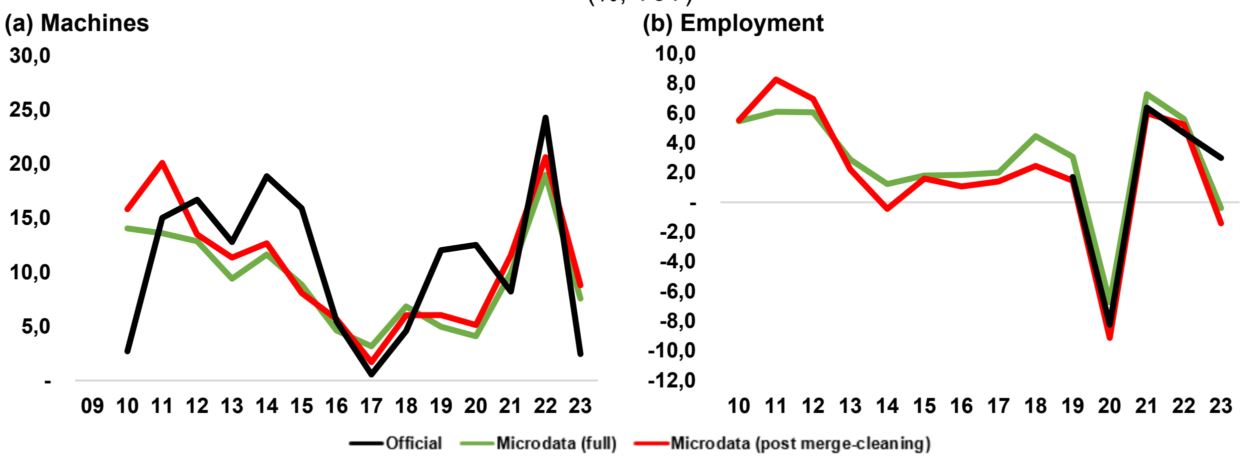


Table A.1: Panel regression elasticities by economic activity and wages quantiles

Economic activity	Wage level	$\hat{\beta}$		$Adj. R^2$
Agriculture & Fishery	Low	-0.04	***	0.92
	Medium	-0.05	***	0.95
	High	0.03	***	0.92
Mining	Low	-0.04	***	0.84
	Medium	-0.11	***	0.92
	High	-0.03	***	0.97
Manufacturing	Low	-0.02	***	0.88
	Medium	-0.10	***	0.96
	High	0.02	***	0.95
Electricity, gas, water & waste management	Low	0.02	*	0.88
	Medium	-0.11	***	0.96
	High	0.02	**	0.94
Construction	Low	-0.06	***	0.93
	Medium	-0.10	***	0.95
	High	0.04	***	0.95
Wholesale and retail trade, restaurants & hotels	Low	-0.04	***	0.88
	Medium	-0.12	***	0.95
	High	0.04	***	0.93
Transport, information & communications	Low	-0.03	***	0.84
	Medium	-0.14	***	0.94
	High	-0.01	***	0.93
Financial services	Low	0.02	***	0.82
	Medium	-0.10	***	0.95
	High	0.10	***	0.89
Dwelling services & real estate	Low	-0.04	***	0.84
	Medium	-0.10	***	0.93
	High	0.00		0.90
Business services	Low	-0.04	***	0.90
	Medium	-0.16	***	0.96
	High	0.07	***	0.92
Personal services	Low	0.00		0.87
	Medium	-0.08	***	0.96
	High	0.01	***	0.96

Note: elasticities from equation (2), employment by wage quantile and by economic sector as a function of machines and other covariates, modelled as 33 panel regressions with fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.2: Adjusted correlation of covariate balance

Covariate	IPW	weightIt lineal	weightIt BART
Value added	0.034	0.035	0.009
Wages	0.040	0.056	0.027

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