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Mitigating the Labor Displacing Effects of Automation through a Robot Tax: Evidence from a Survey Experiment[1]

Emanuela Carbonara
University of Bologna, Department of Sociology & Business Law. E-mail: emanuela.carbonara@unibo.it

Chiara N. Focacci
HEC Liège & European University Institute, Robert Schuman Centre. E-mail: cnfocacci@uliege.be

Enrico Santarelli
University of Bologna, Department of Economics. E-mail: enrico.santarelli@unibo.it

Abstract

We examine how taxation might influence the relationship between automation and employment dynamics. The results obtained through a survey experiment with 2,000 entrepreneurs residing in the U.S. show that the implementation of a robot tax leads to a significant decrease in the inclination of entrepreneurs to reduce workforce levels. Conversely, an equal but negative robot tax, functioning as a reward for automation, motivates entrepreneurs to downsize their workforce. Nevertheless, the impact of the former outweighs that of the latter. Among participants who place higher value on automation we observe a 0.174 increase in the log-odds of reducing the workforce and a 0.312 decrease in the log-odds of reducing automation appliances. These changes are statistically significant at the 1% level. With respect to possible gender effects, male entrepreneurs are found to have a greater likelihood of firing employees, regardless of the treatment.

Keywords: Automation; Employment Dynamics; Robots; Taxation; US entrepreneurs.

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JEL Codes: J2, O14, O25.

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Abstract

We examine how taxation might influence the relationship between automation and employment dynamics. The results obtained through a survey experiment with 2,000 entrepreneurs residing in the U.S. show that the implementation of a robot tax leads to a significant decrease in the inclination of entrepreneurs to reduce workforce levels. Conversely, an equal but negative robot tax, functioning as a reward for automation, motivates entrepreneurs to downsize their workforce. Nevertheless, the impact of the former outweighs that of the latter. Among participants who place higher value on automation we observe a 0.174 increase in the log-odds of reducing the workforce and a 0.312 decrease in the log-odds of reducing automation appliances. These changes are statistically significant at the 1% level. With respect to possible gender effects, male entrepreneurs are found to have a greater likelihood of firing employees, regardless of the treatment.

Keywords: Automation; Employment Dynamics; Robots; Taxation; U.S. entrepreneurs.

1. Introduction

This paper draws inspiration from the renewed interest surrounding automation and its impact on employment. In this context, an analysis conducted by Acemoglu and Restrepo (2020) regarding the United States reveals that during the period from 1990 to 2007, the growth in the number of robots in a commuting zone led to a decrease in the average employment-to-population ratio and average wages by 0.39% and 0.77%, respectively, in comparison to a commuting zone with no exposure to robots. On the other hand, focusing on Spain, Koch et al. (2021) report that not only does the adoption of robots result in significant increases in output by 20-25% within a four-year timeframe, but it also leads to a reduction in the labor cost share by 5-7 percentage points and ultimately leads to the creation of new jobs at a rate of 10%. By the same token, Focacci (2021) finds that in both China and Korea the adoption of robots has had the effect of reducing the number of layoffs, primarily due to the training initiatives provided to employees to work alongside their new automated counterparts. Finally, Frey and Osborne (2017) find for the U.S. that some occupations, such as those in transportation and logistics, face a higher likelihood of being displaced by automation.

In summary, the complexity of the relationship between automation and employment suggests that we are likely witnessing the emergence of a new process of creative destruction (Acs et al., 2021). Nevertheless, while researchers are still engaged in the task of exploring the relationship between *automation* on employment, policymakers seem to be mostly focused on the adoption of *compensatory measures* to mitigate the potential job displacement caused by automation. Taxation on robots and automation services has been identified as one of the most suitable measures to mitigate the negative effects of automation not only on low-skilled but also on high-skilled workers. Thus, a way policymakers can compensate for the externalities created by automation technologies and encourage socially optimal levels of investment in them is by implementing taxation (Damijan et al., 2021). The existing literature, however, lacks comprehensive understanding of how and to what extent imposing taxation on robots and other automation services compensates for their externalities. To address this research gap, we conducted a survey experiment in which we examined whether taxing robots and artificial intelligence services used in firms, thus slowing down the adoption of new technologies, has positive effects on employment. 2,000 entrepreneurs residing in the U.S. participated in the survey. The study's results demonstrate that implementing a robot tax to counter automation-driven job loss has a positive impact on human occupation, leading to a significant decrease in the tendency to reduce the size of the workforce. The positive impact of a robot tax on human employment also appears to be greater than the negative impact of automation incentives.

The paper is structured as follows. Section 2 presents a survey of the relevant literature and introduces our research hypotheses. In Section 3 we describe the empirical strategy used, the design of the experiment, and the data. Section 4 illustrates and discusses the main findings, while Section 5 concludes offering managerial and policy implications as well as directions for future research.

2. Literature Review and Research Hypotheses

2.1. Automation and employment

The impact of automation on employment has long been a central theme in the economic debate (for a survey, see Mondolo, 2022). In this regard, the computerization of the 1980s caused a reduction in the number and the wages routine jobs, coupled with a significant shift towards jobs requiring analytical and interactive skills (Berger & Frey, 2016). This skill-biased technological change (SBTC) was driven by the non-neutrality of Information and Communication Technologies (ICTs)-related technological advancements that, by favoring high-skilled labor over low-skilled labor (Piva et al., 2005), contributed to a "mismatch" between the demand for and supply of skilled labor in certain countries (Nickell & Bell, 1995; Machin & Van Reenen, 1998; Barbieri et al., 2020).

Recent studies, although they agree in considering AI and robots as part of a new technological revolution (cf., for example, Van Roy et al., 2018; Damioli et al., 2021), do not all align when asked to quantify the impact of this revolution on employment. Analyzing data on online job vacancies in the United States from 2010 onwards, Acemoglu et al. (2022) find that establishments with high exposure to AI reduce their non-AI and overall hiring, whereas establishments with task structures more suitable for AI experience a significant increase in job openings for AI workers.[2]

Conversely, Staccioli & Virgillito (2021) show that the current wave of automation may have an even more pronounced labor-saving effect, affecting both skilled and unskilled labor. This evidence challenges the notion that robots and similar technologies act as substitutes for unskilled labor and complements for skilled labor. For example, analyzing the complete text of over 3.5 million USPTO patent applications published between January 1st, 2009 and December 31st, 2018, Montobbio et al. (2022) recently discovered that labor-saving patents are focused on fields traditionally deemed difficult to automate, including activities requiring social intelligence, cognitive reasoning, and complex problem-solving. From a long-term perspective, the study of Charalampidis (2020) demonstrates that over the period between 1964 and 2016 automation shocks explain approximately half of the fluctuations in the income share of labor in the U.S., while also generating a counter-cyclical labor response.

More cautiously, some studies suggest that automation may have both negative and positive effects on employment and economic growth, depending on competition policy and technological implications (Aghion et al., 2022). Other studies submit that certain industries may initially experience employment gains from automation, but later face job losses as demand becomes less elastic (Bessen, 2019). This alleged graduality of the effects of automation on employment is consistent with the empirical findings on the rapidity of "programmable automation" adoption in the US carried out in the 1980s (Mansfield, 1989), which showed that industrial robots initially spread relatively slowly, causing a negligible labor-saving effect. Reviewing recent literature, Naudé (2021) reaches conclusions not dissimilar to those of Mansfield (1989): The new forms of automation are costly and challenging to adopt, and they do not only displace jobs but also contribute to creating new ones. Studying the impact of automation on the labor market of Chile, a developing country, Katz at al. (2023) find that the impact of automation and digitization of

[2] Results consistent with those of Acemoglu et al. (2022) are also found in studies on wage differentials between workers performing routine jobs and workers performing non-routine jobs that require analytical and interactive skills. In this regard, when examining the impact of technological change on workers, Vannutelli et al. (2022) show that in the context of Italy, non-routine workers consistently earn significantly more than routine workers.

production processes has been largely neutral so far: The number of jobs lost due to automation is roughly equivalent to the number of jobs created by this technology.

Findings on the impact of automation on employment are country-specific, with some studies showing positive effects, such as increased productivity and wages without significant job losses (Morikawa, 2017; Graetz & Michels, 2018; Dinlersoz & Wolf, 2023), and other studies showing that robot adoption can increase inequality in countries with higher initial gender inequality (Aksoy et al., 2021). In Canada, research regarding the impact of automation on employment and organizations indicates that investment in robotics is associated with changes in skill composition within firms, leading to increased employment for low- and high-skilled workers but decreased employment for medium-skilled workers (Dixon et al., 2021). In their study of French firms from 2010 to 2015, Acemoglu et al. (2020a) find that the adoption of robots leads to reduced labor shares, increased value added and productivity, and a smaller share of production workers. However, firms that adopted robots to cut costs may gain market share at the expense of their competitors. This suggests that market-level effects may differ from the firm-level impact of automation, with firms that adopt robots experiencing an overall increase in employment, while firms that do not adopt them may experience employment losses.

Views on the labor-saving impact of automation technologies may be distorted by: *i)* underestimating the fact that the demand for new products made possible by technological change is often the strongest force behind employment creation (Harrison et al., 2014): *ii)* overestimating their use for process innovations rather than product innovations (Carbonara & Santarelli, 2023) ; *iii)* ignoring the possibility that labor could have complementarities with other inputs in the production process (Goel & Nelson, 2022). Extending this interpretation to the case of automation technologies, it cannot be ruled out that, given the challenges incumbents face in handling them, the entry of new firms may have contributed, at least in part, to the initial development and diffusion of such technologies and to a reduction of their negative impact on employment.

2.2. The mitigating effect of robot taxes

The now-classic technology-push literature argues that technological change follows its own trajectory. This implies that it is characterized by absolute cost advantages (Salter, 1966), is “localized”[3] (Atkinson and Stiglitz, 1969; see also Antonelli, 1998), path-dependent (David, 1985), and irreversible (Freeman, 1994). In this context, automation might be considered “Hicks-neutral”, thus increasing productivity at any combination of capital and labor and being advantageous in any case, regardless of its cost (see Acemoglu, 2015). However, it could be hypothesized that an increase in automation costs induced by exogenous factors may slow down its diffusion process. In this scenario, taxation may be seen as a mechanism that could mitigate the potential short-term negative impact of automation technologies on employment by discouraging their adoption.

Nevertheless, the effectiveness of taxation on automation is not so obvious. For example, a survey experiment carried out by Jeffrey (2021) suggests that individuals may not change their preferences for redistributive policies even when feeling vulnerable to automation-induced inequality. However, the same author finds that rhetoric assigning blame to those who are benefiting from automation can have a positive impact on garnering support for redistributive policies.

Following a law and economics perspective, Abbott and Bogenschneider (2018), argued that tax policies should be reformed by adopting a combination of measures that disallow corporate tax deductions for automated workers and grant offsetting tax preferences for human workers. By the same token, identifying in the U.S. tax system a bias against labor and in favor of capital, Acemoglu et al. (2020b) argue that this unbalance has promoted rates of adoption of robots and automation in general above what is socially desirable. The rationale behind their assumption is that marginal automated tasks do not bring substantial productivity gains but rather result in displacement of workers, ultimately reducing employment below its socially optimal level. They recommend adoption of an automation tax that, far from being uniform on all automation technologies, should only be applied to those technologies that automate tasks in which humans hold a significant comparative advantage above a certain threshold. As an alternative, they claim that even a combination of lower labor and capital taxation with increased automation taxes would result in more employment.

[3] The definition of 'localized,' as opposed to 'generic,' technological change identifies a technology that only affects the efficiency of a specific production technique (Antonelli, 1998).

Afonso and Forte (2023) have recently presented a dynamic general equilibrium model in which taxing robots benefits unskilled workers by decreasing firms' inclination to replace them with automation. Following the same reasoning, the study by Damijan et al. (2021) illustrates what types of taxes should be introduced to avoid dramatic displacement effects or wealth inequality. In their report, they suggest 'a VAT tax on robot activities, with a tax rate that decreases with the age of the robots'. However, building on the Skill-Biased Technological Change (SBTC) literature regarding complementarity between high-skilled jobs and automation, Prettner and Strulik (2020) find that a robot tax reduces the potential income gain from higher education, thereby leading to a larger population share of low-skilled individuals. In fact, in reducing demand for machines and growth through less R&D, a robot tax will also induce a decrease in the demand for college education. In this case, the ultimate consequence of taxation would cause a further reduction of the wage of low-skilled workers.

Looking at the optimization of taxation, the work of Guerreiro et al. (2022) uses an overlapping generations model where the tax system serves the purpose of balancing two objectives. First, it gives young generations an incentive to invest in advanced skills and become non-routine workers. Second, it redistributes income towards routine workers: as their wages reduce, robots become cheaper. Accordingly, they show that it is optimal to tax robots while the current generations of routine workers (unable to move to non-routine occupations) are active in the labor force. On the contrary, optimal robot taxes can be set equal to zero once these workers retire.

Several studies contribute to the development of the paternalistic definition of the workplace as "a place to work and to live" (Leclercq-Vandelannoitte, 2021) when analyzing the interaction between automation and employment. Following interviews with more than three hundred business executives, labor leaders, and professional recruiters, Bewley (1999) develops the belief that employers are usually not prone to cut the jobs or salaries of their employees during recession. This "would hurt morale, which they felt was critical in gaining the cooperation of their employees and in convincing them to internalize the managers' objectives for the company" (Bewley, 1999). By the same token, Baron (2013) defines "empathy wages" the compensation paid to workers who are relatively disadvantaged and in the lower part of the performance distribution, and this has the effect of eliciting gratitude from recipients. Similarly, Baskerville Watkins et al. (2015) claim that corporate social responsibility practices focus on developing compassion inside the organization and are therefore associated to identification of both employers and employees with their company.

Granted that, in a context of potential technological unemployment, taxing automation has a direct negative effect on automation and a direct positive effect on the workforce, one may assume that taxation on automation is likely to induce entrepreneurs to behave in favor of workers. This perspective would represent a departure from the traditional welfare analysis view of entrepreneurs maximizing their productivity gains through the adoption of automation and subsequently redistributing those gains. It would entail a greater ex-ante consideration of the potential short-term negative impact of these technologies on employment. Indeed, in accordance with Rawls' (1971) principle of fairness – which asserts that, to achieve genuine fairness and impartiality in a social agreement or contract, the decision-making process should remain uninfluenced by the biases and inequalities that prevail in society – entrepreneurs may not desire their employees to be in a worse condition (unemployed or at high risk of becoming so) after the adoption of robots. Additionally, by invoking another famous definition by Rawls (1971), that of the principle of punishment, one can attribute to the government the possibility of using a negative incentive to restrict the adoption of robots.

The debate on the usefulness of automation taxes or of robot taxes has mostly remained limited to the U.S. case. One cannot therefore exclude the fact that the same measures might not work or work differently in other countries. Studies conducted for Germany and Scandinavia, for instance, convey a partly different picture, showing that high-corporate tax rates are positively associated with robot density, while automation is discouraged in countries where 'the value of tax deductions for capital investment is zero' (Bogenschneider, 2022).

2.3. Research Hypotheses

Drawing from the literature illustrated in Section 2.2, and under the assumption that the tax framework can influence entrepreneurs' investment choices, we contend that:

H1: An escalation in taxes imposed on automation will heighten entrepreneurs' inclination to curtail the substitution of the workforce with automated systems.

Aligned with Rawls' (1971) principles of fairness and punishment, and with the concepts of empathy wages (Bewley, 1999; Baron, 2013), entrepreneurial compassion (Baskerville Watkins et al., 2015), and entrepreneurial paternalism (Leclercq-Vandelannoitte, 2021), we also formulate the following hypothesis:

H2: The negative effect of an automation reward on the workforce is smaller than the negative effect of an equivalent automation tax on the level of automation.

3. Data & Experimental Design

Following a similar approach to that of Jeffrey (2021), we tested our hypotheses H1 and H2 through a survey experiment conducted on the Qualtrics platform. The experiment involved a random sample of 2,000 entrepreneurs residing in the U.S. who were 18 years of age or older.[4] These entrepreneurs were selected by a third-party organization, Prolific, which specializes in recruiting participants for online experiments. Prolific ensured a carefully curated sample of interviewees and the proper administration of the survey. In our study, the participants selected by Prolific were individuals who had previous or current experience in entrepreneurship or business ownership. As such, they likely encountered the decision of whether to adopt new technologies to automate their businesses or not. As is customary in survey experiments, participants were paid a sum of money to take part. In our case, they received an average reward of £10.06 per hour. Through the survey, we collected information on their gender, age, nationality, and education[5]. We also ask them about the value they attribute to automation on a scale from 1 to 10. An attention check was also presented to participants during the experiment. No other information about the nature and performance of their entrepreneurial activity was collected by Prolific for this survey.

With respect to issues of external validity, we used the Qualtrics sample calculator to ensure high confidence levels and low margin of error. Considering that the US entrepreneurs' population is approximately 54 million, a sample of 1,842 would suffice to guarantee a 99% confidence level, with 3% margin of error. Our sample, which includes 2,000 subjects, increases our external validity with respect to the American entrepreneurial population.

[4] The exact wording of the treatments can be found in Appendix A.
[5] A matrix of pairwise correlations can be found in Table A1 in Appendix B.

Table 1 – Distinctive characteristics of the participants

Variable	Mean	St. Dev.	Min	Max
Age (years)	40.7	12.5	18	68
Gender (%)				
Male=1	50.7	50.0	0	1
Female=1	47.7	50.0	0	1
Other=1	1.6	12.4	0	1
Origin (%)				
Born in the US	96.2	19.1	0	1
Born outside of the US	3.8	19.1	0	1
Education (%)				
Less than high school	0.6	7.7	0	1
High school degree or equivalent	33.4	47.2	0	1
Professional degree (JD, MD)	3.5	18.4	0	1
Bachelor's degree	46.6	49.9	0	1
Master's degree	13.4	34.1	0	1
Doctorate	2.5	15.6	0	1
Value attributed to automation	6.1	2.3	1	10

As regards the data (Table 1), participants are 40.7 years old on average and mostly born in the U.S. (96.2%). The sample is split evenly between males (50.7%) and females (47.7%). With respect to education, our participating entrepreneurs are mostly in possession of a bachelor's degree (46.6%), followed by holders of a high school degree or equivalent (33.4%), and a master's degree (13.4%). With respect to the value attributed to automation on a scale from 1 to 10, we observe that, on average, participants pick a number around 6. This result shows that entrepreneurs are aware of the favorable impact that automation may exert on their business.

For the purposes of the experiment, participants are split into four treatments. These are implemented with the aim of understanding the extent to which taxing automation appliances such as robots and artificial intelligence services in a firm affects the reduction of both robots and the human labor present therein. A control group is utilized for comparison, consisting of entrepreneurs who are not subjected to any positive or negative taxation.[6]

Our main interest is estimating the effect of taxation on the reduction of employment according to the following identification strategy: where *Y* are the outcomes of interest, *TREAT* represents the four treatments of the experiment, and *K* indicates the demographic characteristics of participants.

$$Y_i = \alpha_i + \sum_{t=1}^{3} \gamma_t TREAT_{it} + \beta_i K_i + \eta_{it} \quad (1)$$

We provide participants with information that is common to all treatments. Namely, we describe to them the context that will apply to their decision-making process. All participants are asked how they would act knowing that they are the main employer at a renowned company that currently employs about 500 employees and disposes of 50 robots and several other artificial intelligence software. They also know that their business is going rather well and that paying for their employees' social benefits — this includes pensions and sickness benefits — amounts to circa 20% of the firm's total costs.

During the treatment phase, we inform participants that starting from the following year, the government where their company is located aims to tax each company for automation. Treatments vary according to the additional percentage of costs that entrepreneurs will have to pay for automation (Table 2). In Treatment 1 we inform them that, considering the automation level at their company, projections suggest the robots and the artificial intelligence services used in the company will correspond to circa 20% of total costs. This is in addition to the 20% they already pay for the employees at the company. In Treatment 2, the costs derived from taxation on

[6] The distinctive characteristics of the participants who belong to the control group are outlined in Table A2 in Appendix C.

automation amount to circa 10% of total costs. Accounting for decreasing and negative costs, in Treatment 3 and Treatment 4, taxation on automation will correspond to, respectively, a reward that will reduce the costs of the firm by 20% thanks to the presence of robots and the artificial intelligence services used in the firm and 0% of the firm's total costs — the government will not tax automation.

Table 2 – Treatment groups

Treatment	Mean (%)	St. Dev. (%)	Min	Max	Obs.
20% tax on automation	24.75	43.17	0	1	495
10% tax on automation	24.90	43.25	0	1	498
20% reward on automation	24.95	43.28	0	1	499
No tax, no reward	25.05	43.34	0	1	501

Our outcomes of interest are represented by two dummy variables. The first is equal to 1 if, following treatment, the participant opts for reducing the level of workforce in her company; and 0 otherwise. This includes keeping or increasing the level of the workforce in the company. The second dummy is equal to 1 if, following treatment, the participant opts for reducing the level of automation in her company; and 0 otherwise.

4. Results

Our findings from estimation of a logistic regression model indicate that, when treated with taxation on robots and other automation services, entrepreneurs prefer to safeguard their workforce rather than replace their employees with automation. While several scholars have presented evidence on the effect of rise in automation on jobless growth (Acemoglu & Restrepo, 2020; Spencer et al., 2021) or the coexistence between human and robotic work (Focacci, 2021; Smids et al., 2020; Huang & Naubahar, 2017), we show that positive or negative taxation on automation can also have a direct impact on workers.

Particularly, we find that, compared to our control group, when treating participants with a 20% increase in taxes on automation, there is a 0.467 decrease in the log-odds of opting for a reduction of their workforce, significant at 1% level (Table 3). On the other hand, we observe a 2.282 increase in the log-odds of drastically reducing their robotic and AI equipment. At a lower tax rate (10%) on automation, we find no statistically significant effect on the workforce and a positive, albeit weaker (1.737), impact on the reduction of automation compared to when automation is taxed at 20%. Consistent with our hypothesis **H1**, in the context of potential technological unemployment, taxing automation has a direct negative effect on automation itself. A direct positive effect on the workforce emerges only when the tax rate exceeds a certain threshold.

Table 3 – Regression results for reduction of workforce and automation

Treatment	**Reduction of workforce (Y_1=1)**	**Reduction of automation (Y_2=1)**
20% tax on automation	-0.467*** (0.135)	2.282*** (0.204)
10% tax on automation	-0.033 (0.129)	1.737*** (0.208)
20% reward on automation	0.541*** (0.128)	-0.339 (0.281)
Constant	0.434*** (0.091)	-2.695*** (0.183)
Observations	*2,000*	*2,000*

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<$0.1

Comparing the scenario where no taxes are imposed with one in which a reward for automation that corresponds to a cut in costs of 20% is introduced, we observe that entrepreneurs reduce the level of workforce present in the company. From the third line of Table 3 we see a 0.541 increase in the log-odds of the dependent variable related to the reduction of the level of workforce. Conversely, no statistically significant effect is recorded as regards potentially reducing the automation equipment.

Table 4 – Regression results for reduction of workforce and automation, with controls

Treatment	Reduction of workforce (Y_1=1)	Reduction of automation (Y_2=1)
20% tax on automation	-0.492*** (0.139)	2.486*** (0.215)
10% tax on automation	-0.040 (0.134)	0.218*** (0.218)
20% reward on automation	0.521*** (0.132)	-0.258 (0.288)
Age (years)	0.011** (0.004)	0.005 (0.005)
Male=1	0.409*** (0.098)	-0.042 (0.133)
Born in the US=1	0.415 (0.263)	0.434 (0.400)
High school degree or equivalent	0.246 (0.641)	-0.114 (0.739)
Professional degree (JD, MD)	0.556 (0.683)	0.324 (0.797)
Bachelor's degree	0.424 (0.640)	-0.314 (0.738)
Master's degree	0.305 (0.649)	-0.753 (0.758)
Doctorate	0.225 (0.703)	-0.486 (0.856)
Value to automation	0.174*** (0.023)	-0.312*** (0.030)
Constant	-2.887*** (0.728)	-1.390 (0.883)
Observations	*2,000*	*2,000*

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<$0.1. As regards gender, the baseline for the dummy Male=1 is Male=0, which is when either Female or Other are equal to 1. For country of origin, the baseline for Born in the US, is Born outside of the US. With respect to education, the baseline is Less than high school. The variable Value to automation is defined in a scale from 1 to 10.

The most interesting results are those presented in Table 4, where all controls for demographic characteristics and the value attributed by entrepreneurs to automation are included.

For participants who value automation to a larger extent on a scale from 1 to 10 (line 12 in Table 4), we observe a 0.174 increase in the log-odds of reducing the workforce and a 0.312 decrease in the log-odds of reducing automation appliances, significant at 1% level. With both coefficients being statistically significant at 1% confidence level. This confirms our hypothesis **H2**, aligning with the previously discussed principles of punishment and fairness, empathy wages, entrepreneurial compassion, and entrepreneurial paternalism[7] Taxing automation, a form of punishment, encourages pro-worker behavior, while ensuring that workers are not disadvantaged by new additions of robots.

As regards the tendency to opt for reduction of the workforce, we observe that a one-year increase in age corresponds to a 0.011 increase in the log-odds of the dependent variable. The effect is stronger and equal to 0.409 for entrepreneurs who identify as males, significant at 1% level. This may be explained by the lower levels of corporate empathy registered for male entrepreneurs, opting for a thinking-over-feeling approach (Mueller, 2007), or the higher perception of entrepreneurial success (Ngah & Salleh, 2015).

On the other hand, the participants' country of origin and level of education do not affect the propensity to terminate employees.

5. Conclusions, limitations, and directions for future research

This research stems from the necessity to acquire policy insights relevant to handling the effects of automation within labor markets. Our study aims to enhance the literature concerning fiscal policy frameworks, entrepreneurial decision-making models, and trends in labor market configurations. In particular, an assessment was conducted to gauge the influence of tax policy on

[7] In a second collection of data, we hire 501 participants through Prolific, following the same selection procedures and ensuring participants have not taken part in our previous survey experiment. Here, too, we propose taxation on automation equal to 20% of the company's costs. However, as a variation of Treatment 1, we make explicit that by using automation services, the company could experience a high likelihood of registering an increase in the total factor productivity. Findings remain consistent with the main model.

entrepreneurs' strategic choices regarding workforce size in relation to the implementation of artificial intelligence and robotic technologies in their respective businesses.

The results obtained from estimating a logistic regression model indicate that imposing a robot tax — i.e., taxing machine inputs — positively impacts human employment, resulting in a significant decrease in the entrepreneurs' inclination to downsize the workforce. Turning to the case of adopting an equivalent but negative robot tax, i.e., a reward for automation, we find that it strongly encourages entrepreneurs to reduce their workforce. However, for entrepreneurs who value automation the most, we find that the direct effect of an automation incentive in reducing the workforce is much less pronounced than its negative effect on reducing automation. Accordingly, when they are highly committed to automation, entrepreneurs maintain a relatively pro-worker behavior.

In terms of its implications for policy making, our research indicates that the government plays a decisive role in addressing the employment disruption arising from the ongoing and rapidly advancing technological revolution. If policymakers are contemplating taxing automation, they must also consider the potential displacement of human labor in favor of automation. To address this concern, when automation is taxed, an equal positive subsidy should be provided to firms to cover costs related to their existing workforce. Alternatively, workers could share ownership of robots and other automated software present in their firm so as to discourage their dismissal. In parallel, firms should be prepared to invest in the reskilling of their workforce to guarantee efficient use of automation and consequent surplus gained from workers working with robots and not in place of them (Focacci and Perez, 2020). In connection with this, governments are urged to financially support firms in providing *ad hoc* active labor market policies for their workers, ultimately benefiting their firm. Finally, by introducing taxation on automation, firms are obliged to select quality over quantity when it comes to what automated products and services to implement as these will represent a significant cost. This proactive approach aims to prevent the adoption of 'so-so' technologies (as defined by Acemoglu & Restrepo, 2019) that could lead to employment disruption and worker displacement without contributing to enhanced productivity and improved service quality.

The methodological limitations of this experimental study are primarily associated with the online nature of the experiment. While they offer convenience and scalability, we acknowledge that online experiments can be challenging to monitor, which may lead to some participants misunderstanding questions or providing inaccurate responses. Thus, one cannot exclude that certain categories of entrepreneurs may be either overrepresented or underrepresented.

While our research focused on a U.S. sample, our findings offer valuable insights to policymakers worldwide who are interested in managing the balance between safeguarding employment and promoting economic growth through automation. Future research should investigate the labor market effects of taxation on automation for countries where automation is well advanced, including Singapore, South Korea, and Japan. An interesting perspective would also include comparisons for Germany, Sweden, and Denmark, where economic growth is high but so is welfare assistance in the labor market. In other words, one may question whether taxing automation has direct links to the country's institutional context, especially as regards the general taxation framework and employment protection, as well as its main economic sectors. Additional analyses may look at what the implications of taxing automation are for achieving a smart green growth based on innovation, on the one hand, and sustainable economic choices, on the other.

References

Abbott, R., and Bogenschneider, B. (2018). Should robots pay taxes? Tax policy in the age of automation. *Harvard Law & Policy Review*, 12(1): 145-175.

Acemoglu, D. (2015). Localized and biased technologies: Atkinson and Stiglitz's new view, induced innovations, and directed technological change. *The Economic Journal*, 125(583): 443–463.

Acemoglu, D., and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128(6): 2187-2244. DOI: 10.1086/705716.

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and Jobs. Evidence from online vacancies. *Journal of Labor Economics*, 40(S1): S293–S340. DOI: 10.1086/718327S293.

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020b). Competing with robots: Firm-level evidence from France. *AEA Papers and Proceedings*, 110: 383-388. DOI: 10.1257/pandp.20201003.

Acemoglu, D., Manera, A., and Restrepo, P. (2020b). Does the US tax code favor automation?. *Brookings Papers on Economic Activity*, 1: 231-300. DOI: 10.1353/eca.2020.0003.

Acemoglu, D., Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor'. *Journal of Economic Perspectives* 33(2): 3-30. DOI: 10.1257/jep.33.2.3.

Acs, Z. J., Song, A. K., Szerb, L., Audretsch, D. B., and Komlósi, É. (2021). The evolution of the global digital platform economy: 1971–2021. *Small Business Economics* 57(4): 1629-1659. DOI: 10.1007/s11187-021-00561-x.

Afonso, O., and Forte, R. (2023). How powerful are fiscal and monetary policies in a directed technical change model with humans and robots?. *International Journal of Finance and Economics*, 28(3): 3008-3032. DOI: 10.1002/ijfe.2581.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2022). The effects of automation on labor demand. A survey of the recent literature. In Ing, L. Y., and Grossmann, G. M. (Eds.). *Robots and AI. A New Economic Era*. New York: Routledge, 15-39.

Aksoy, C. G., Özcan, B., and Philipp, J. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, (134): 103693. DOI: 10.1016/j.euroecorev.2021.103693.

Antonelli, C. (1998). The dynamics of localized technological changes. The interaction between factor costs inducement, demand pull and Schumpeterian rivalry. *Economics of Innovation and New Technology*, 6(2-3): 97-120. DOI: 10.1080/10438599800000016.

Atkinson, A. B., and Stiglitz, J. E. (1969). A new view of technological change. *The Economic Journal*, 79(315): 573–578.

Barbieri, L., Mussida, C., Piva, M., and Vivarelli, M. (2020). Testing the employment and skill impact of new technologies. In: Zimmermann, K. F. (Ed.). *Handbook of Labor, Human Resources and Population Economics*. Springer, Cham: pp. 1-27. DOI: 10.1007/978-3-319-57365-6_1-1.

Baron, J. M. (2013). Empathy wages? Gratitude and gift exchange in employment relationships, *Research in Organizational Behavior,* 33(1): 113-134. DOI: 10.1016/j.riob.2013.10.006.

Baskerville Watkins, M., Ren, R., Umphress, E. E., Boswell, W. R., del Carmen Triana, M., and Zardkoohi, A. (2015). Compassion organizing: Employees' satisfaction with corporate philanthropic disaster response and reduced job strain, *Journal of Occupational and Organizational Psychology*, 88(2): 436-458. DOI: 10.1111/j.2044-8325.2011.02050.x.

Berger, T., and Frey, C. B. (2016). Did the computer revolution shift the fortunes of U.S. cities? Technology shocks and the geography of new jobs. *Regional Science and Urban Economics*, 57(1): 38–45. DOI: 10.1016/j.regsciurbeco.2015.11.003.

Bessen, J. (2019). Automation and jobs: when technology boosts employment. *Economic Policy*, 34(100): 589–626. DOI: 10.1093/EPOLIC/EIAA001.

Bewley, T. F. (1999). *Why Wages Don't Fall During a Recession*. Cambridge (MA): Harvard University Press.

Bogenschneider, B. (2022). Empirical evidence on robot taxation: Literature review and technical analysis. *American University Business Law Review*, 11(1): 1-41.

Carbonara, E., and Santarelli, E. (2023). Artificial intelligence and robots: A threat or an opportunity for SMEs and entrepreneurship?. In: Carbonara, E., and Tagliaventi, M. (Eds.). *SMEs* *in the Digital Era: Opportunities and Challenges of the Digital Single Market*. Cheltenham: Edward Elgar, 104-121.

Charalampidis, N. (2020). The U.S. Labor income share and automation shocks. *Economic Inquiry*, 58(1): 294-318. DOI: 10.1111/ecin.12829.

Damijan, J. P., Damijan, S., and Vrh, N. (2021). *Tax on Robots: Whether and How Much*. GROWINPRO Working Paper Series, 39.

Damioli, G., Van Roy, V., and Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, 11: 1-25. DOI: 10.1007/s40821-020-00172-8.

David, P. A. (1985). Clio and the economics of QWERTY. *American Economic Review*, 75(2): 332-337.

Dinlersoz, E., and Wolf, Z. (2023). Automation, labor share, and productivity: plant-level evidence from U.S. manufacturing. *Economics of Innovation and New Technology*, forthcoming. DOI:10.1080/10438599.2023.2233081.

Dixon, J., Hong, B., and Wu, L. (2021). The robot revolution: Managerial and employment consequences for firms. *Management Science*, 67(9): 5586-5605. DOI: 10.1287/mnsc.2020.3812.

Domini, G., Grazzi, M., Moschella, D. & Treibich, T. (2021). Threats and opportunities in the digital era: Automation spikes and employment dynamics. *Research Policy*, 50(7): 104137. DOI: 10.1016/j.respol.2020.104137.

Domini, G., Grazzi, M., Moschella, D. & Treibich, T. (2022). For whom the bell tolls: The firm-level effects of automation on wage and gender inequality. *Research Policy*, 51(7): 104533.

Focacci, C. N. (2021). Technological unemployment, robotisation, and green deal: A story of unstable spillovers in China and South Korea (2008–2018). *Technology in Society*, 64: 101504. DOI: 10.1016/j.techsoc.2020.101.504.

Focacci, C. N., & Perez, C. (2022). The importance of education and training policies in supporting technological revolutions: A comparative and historical analysis of UK, US, Germany, and Sweden (1830–1970). *Technology in Society*, 70: 102000. DOI: 10.1016/j.techsoc.2022.102000.

Freeman, C. (1994). The economics of technical change. *Cambridge Journal of Economics*, 18(5): 463-514. DOI: 10.1093/oxfordjournals.cje.a035286.

Frey, C. B., and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological Forecasting and Social Change* 114: 254–280. DOI: 10.1016/j.techfore.2016.08.019.

Goel, R. K., and Nelson, R. A. (2022). Employment effects of R&D and process innovation: Evidence from small and medium-sized firms in emerging markets. *Eurasian Business Review*, 12(1): 97-123. DOI: 10.1007/s40821-022-00203-6.

Goldin, C., and Katz, L. F. (2007). The race between education and technology: The evolution of U.S. educational wage differentials, 1890 to 2005. In: *The Race between Education and Technology*, pp. 287-324. Cambridge (MA): Harvard University Press.

Graetz, G., and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5): 753-768. DOI: 10.1162/rest_a_00754.

Guerreiro, J., Rebelo, S., and Teles, P. (2022). Should robots be taxed?. *The Review of Economic Studies*, 89(1): 279– 311. DOI: 10.1093/restud/rdab019.

Hamdan, A., Hassanien, A. E., Razzaque, A., and Alareeni, B. (2021). *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success*. Heidelberg: Springer.

Harrison, R., Jaumandreu, J., Mairesse J., and Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, 35(1): 29-43. DOI: 10.1016/j.ijindorg.2014.06.001

Huang, Y., and Sharif, N. (2017). From ‘labour dividend’ to ‘robot dividend’: technological change and workers' power in South China. *Agrarian South: Journal of Political Economy*, 6(1): 53-78. DOI: 10.1177/2277976017721284.

Katz, R., Callorda, F., and Jung, J. (2023). The impact of automation on employment and its social implications: evidence from Chile. *Economics of Innovation and New Technology*, 32(5): 646-662. DOI:10.1080/10438599.2021.1991798.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638): 2553-2584. DOI: 10.1093/ej/ueab009.

Krenz, A., Prettner, K., and Strulik, H. (2021). Robots, reshoring, and the lot of low-skilled workers. *European Economic Review*, (136). 103744. DOI: /10.1016/j.euroecorev.2021.103744.

Innocenti, S., and Golin, M. (2022). Human capital investment and perceived automation risks: Evidence from 16 countries. *Journal of Economic Behavior and Organization*, 195: 27-41. DOI: doi.org/10.1016/j.jebo.2021.12.027.

Jeffrey, K. (2021). Automation and the future of work: How rhetoric shapes the response in policy preferences. *Journal of Economic Behavior and Organization*, 192: 417-433. DOI: 10.1016/j.jebo.2021.10.019.

Leclercq-Vandelannoitte, A. (2021) The new paternalism? The workplace as a place to work—and to live. *Organization*, 28(6): 949-975. DOI: 10.1177/13505084211015374.

Machin, S., and Van Reenen, J. (1998). Technology and changes in the skill structure: evidence from seven OECD countries. *Quarterly Journal of Economics*, 113(4): 1215–1244. DOI: 10.1162/003355398555801.

Mansfield, E. (1989). The diffusion of industrial robots in Japan and the United Staes. *Research Policy*, 18(4): 183-192.

Mondolo, J. (2022). The composite link between technological change and employment: A survey of the literature. *Journal of Economic Surveys*, 36(4): 1027–1068. DOI: 10.1111/joes.12469.

Montobbio, F., Staccioli, G., Virgillito, M. E., and Vivarelli, M. (2022). Robots and the origin of their labour-saving impact. *Technological Forecasting and Social Change*, 174, 121122. DOI: 10.1016/j.techfore.2021.121122.

Morikawa, M. (2017). Firms' expectations about the impact of AI and robotics: Evidence from a survey. *Economic Inquiry*, 55(2): 1054–1063. DOI: 10.1111/ecin.13056.

Mueller, S.L. (2007), Gender-based income disparity among self-employed professionals, *Journal of Enterprising Communities: People and Places in the Global Economy*, 1(4): 293-307. DOI: 10.1108/17506200710833809.

Naudé, W. (2021). Artificial intelligence: neither utopian nor apocalyptic impacts soon. *Economics of Innovation and New Technology*, 30(1): 1-23. DOI: 10.1080/10438599.2020.1839173.

Ngah, R., Salleh, Z. (2015). Emotional intelligence and entrepreneurs' innovativeness towards entrepreneurial success: A preliminary study. *American Journal of Economics*, 5(2): 285-290. DOI: 10.5923/c.economics.201501.37.

Nickell, S., and Bell, B. (1995). The collapse in demand for the unskilled and unemployment across the OECD. *Oxford Review of Economic Policy*, 11(1): 40–62. DOI: 10.1093/oxrep/11.1.40.

Paolillo, A., Colella, F., Nosengo, N., Schiano, F., Stewart, W., Zambrano, D., Chappuis, I., Alive, R., Floreano, D. (2022). How to compete with robots by assessing job automation risks and resilient alternatives. *Science Robotics*, 7(65): eabg5561. DOI: 10.1126/scirobotics.abg5561.

Piva, M., Santarelli, E., and Vivarelli, M. (2005). The skill bias effect of technological and organisational change: Evidence and policy implications. *Research Policy*, 34(2): 141-157. DOI: 10.1016/j.respol.2004.11.005.

Prettner, K., and Strulik, H. (2020). Innovation, automation, and inequality: Policy challenges in the race against the machine. *Journal of Monetary Economics*, 116: 249-265. DOI: 10.1016/j.jmoneco.2019.10.012.

Rawls, J. (1971). *A Theory of Justice*. Cambridge (MA): Harvard University Press.

Salter, W. E. G. (1966). *Productivity and Technical Change*. Cambridge University Press: Cambridge.

Santarelli, E., Staccioli, J., and Vivarelli, M. (2023). Automation and related technologies: A mapping of the new knowledge base. *Journal of Technology Transfer*, 48(2): 779 - 813. DOI: 10.1007/s10961-021-09914-w.

Shome, P. (2022). Taxation of Digital economy. In: Shome, P. (2022). *Taxation History, Theory, Law and Administration*. Springer: Heidelberg, pp. 387–404.

Smids, J., Nyholm, S., and Berkers, H. (2020). Robots in the workplace: a threat to—or opportunity for—meaningful work?. *Philosophy and Technology*, 33(3): 503-522. DOI: 10.1007/s13347-019-00377-4.

Spencer, D., Cole, M., Joyve, S., Whittaker, X., and Stuart, M. (2021). *Digital Automation and the Future ow Work*. EPRS Panel for the Future of Science and Technology, 656.311.

Staccioli, J., and Virgillito, M. E. (2021). Back to the past: the historical roots of labor-saving automation. *Eurasian Business Review*, 11(1): 27-57. DOI: 10.1007/s40821-020-00179-1.

Van Roy, V., Vertesy, D., and Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research Policy*, 47(9): 1762–1776. DOI: 10.1016/j.respol.2018.06.008.

Vannutelli, S., Scicchitano, S., and Biagetti, M. (2022). Routine-biased technological change and wage inequality: do workers' perceptions matter?. *Eurasian Business Review*, 12(3): 409-450. DOI: 10.1007/s40821-022-00222-3.

APPENDIX A

Experimental Instructions

PLEASE READ THIS TEXT CAREFULLY

You're the main employer at a renowned company that currently employs about 500 employees and disposes of 50 robots and several other artificial intelligence softwares.

Currently, using automation appliances does not cost anything to the company. On the other hand, paying for your employees 'social benefits amounts to circa 20% of your firms 'total costs.

In the screens that follow, you will be asked to think about a strategic choice that could influence the future of your company.

Please take the time you need to read and fully understand the text.

Treat1

Next year, the government of the country where your company is located aims to TAX each company for automation.

Considering the automation level at your company, projections suggest the robots and the artificial intelligence services you use will increase your total costs by 20%.

You already pay 20% of your total costs for the employees at your company.

Treat2

Next year, the government of the country where your company is located aims to TAX each company for automation.

Considering the automation level at your company, projections suggest the robots and the artificial intelligence services you use will increase your total costs by 10%.

You already pay 20% of your total costs for the employees at your company.

Treat3

Next year, the government of the country where your company is located will keep NOT TAXING any of the companies for automation.

You currently pay 20% of your total costs for the employees at your company.

Treat4

Next year, the government of the country where your company is located aims to REWARD each company for automation.

Considering the automation level at your company, projections suggest the total costs of your company will be reduced by circa 20% thanks to the presence of robots and the artificial intelligence services you currently own.

You currently pay 20% of your total costs for the employees at your company.

Outcomes

In order to keep the firm competitive, you need to take action, considering the current level of automation used in your company and the proportion of employees that work there.

Knowing this information, what would you do with the **LEVEL OF WORKFORCE** present in your company?

- **INCREASE** it
- **REDUCE** it
- **KEEP** the same level

What would you do with the **LEVEL OF AUTOMATION** present in your company?

- **INCREASE** it
- **REDUCE** it
- **KEEP** the same level

Now that you have made your choice, suppose you are forced to deactivate a proportion of robots and AI services.

Also know that efficient secondary markets exist, allowing you to recover most value from the initial investment.

The original value of this equipment was equal to $100,000.

Any of the actions proposed has the same fixed cost.

- **SELL** the proportion of automation equipment deactivated in your firm to buyers in the market. Having used the equipment in your firm for a long time, you would lose $50,000 as their value has dropped by half.

- **RENT OUT** the proportion of automation equipment deactivated in your firm to other firms. Finding the right buyers and coordinate with them would cost you $50,000.

- **USE** the proportion of automation equipment deactivated in your firm for other business purposes abroad. The relocation costs would be equal to $50,000.

Questionnaire

How much do you value automation on a scale from 0 to 10?

Not so much   0 1 2 3 4 5 6 7 8 9 10 Very much

With which gender do you identify most with?

- Male
- Female
- Prefer not to say

What is the highest level of education you have completed?

- Less than high school degree
- High school degree (or equivalent including GED) Professional degree (JD, MD)
- Bachelor's degree
- Master's degree
- Doctorate

Please type in your age below.

____

Where were you born?

- In the US
- Outside the US

APPENDIX B

Table A1 — Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Work reduction (1)	**1**													
Automation reduction (2)	-0.3082	**1**												
Tax=20% (3)	-0.1290	0.2938	**1**											
Tax=10% (4)	-0.0158	0.1193	-0.3302	**1**										
Reward=20% (5)	0.1511	-0.2175	-0.3316	-0.3329	**1**									
Age (6)	0.0472	0.0230	0.0218	-0.0348	-0.0065	**1**								
Male (7)	0.1348	-0.0629	-0.0074	0.0145	0.0225	-0.0734	**1**							
Born in the US (8)	0.0338	0.0384	0.0049	0.0298	0.0063	-0.0027	0.0291	**1**						
Bachelor's degree (9)	0.0433	-0.0196	0.0263	-0.0257	0.0082	-0.0044	0.0221	0.0494	**1**					
Doctorate (10)	0.0069	-0.0141	-0.0176	0.0041	-0.0039	0.0473	0.0681	0.0151	-0.1496	**1**				
High school degree (11)	-0.0531	0.0555	-0.0205	-0.0205	0.0262	-0.0277	-0.0662	0.0132	-0.6615	-0.1134	**1**			
Master's degree (12)	-0.0028	0.0367	0.0043	-0.0090	0.0029	0.0277	0.0135	-0.1061	-0.3675	-0.0630	-0.2786	**1**		
Professional degree (13)	-0.0028	-0.0639	-0.0011	-0.0025	0.0233	0.0580	-0.0088	0.0236	-0.1779	-0.0305	-0.1349	-0.0749	**1**	
Value given to automation (14)	0.2055	-0.2591	-0.0354	-0.0056	0.0447	-0.0198	0.2334	-0.0254	0.0471	0.0222	-0.0711	0.0200	0.0055	**1**

APPENDIX C

Table A2 – Distinctive characteristics of the control group

Variable	Mean	St. Dev.	Min	Max
Age (years)	40.9	12.4	18	67
Gender (%)				
Male=1	48.9	50.0	0	1
Female=1	49.5	50.0	0	1
Other=1	1.6	12.4	0	1
Origin (%)				
Born in the US	94.8	22.2	0	1
Born outside of the US	5.2	22.2	0	1
Education (%)				
Less than high school	0.6	7.7	0	1
High school degree or equivalent	35.5	47.9	0	1
Professional degree (JD, MD)	3.6	18.7	0	1
Bachelor’s degree	45.5	49.8	0	1
Master’s degree	12.4	33.0	0	1
Doctorate	2.8	16.5	0	1
Value attributed to automation	6.0	2.3	1	10