Automation, Artificial Intelligence, and Labor Market Power

Felipe Balmaceda *
Faculty of Economics and Business
Andrés Bello University
Fernández Concha 700, Santiago, 7591538, Chile
Email: fbalmace@gmail.com

November 4, 2025

*Financial support by the Nucleus Labor Market Mismatch: Causes and Consequences, NCS 2022-045 and the Institute for Research in Market Imperfections and Public Policy, grant ICM IS130002 is gratefully acknowledged.

Abstract

This paper argues that in labor markets with firms that have market power, automation targets low-rent jobs, increasing rents and amplifying wage losses from automation. This implies that fewer jobs are automated as market power rises, and more jobs are automated relative to conditional-allocative efficiency and productive efficiency. Indirectly, the latter results in underadoption of generative artificial intelligence. Automation-induced allocative inefficiency reduces wages and leads to a higher number of displaced workers compared to a competitive labor market. Automation may induce workers to overinvest in skills to avoid being displaced. Taxing automation can restore allocative efficiency, but at the cost of lowering wages and distorting the adoption of generative AI.

JEL: J3, D2, J30

Key Words: Labor market power, automation, generative AI, wages, displaced workers, productive and allocative efficiency, human capital, taxes.

1 Introduction

Why do firms automate some jobs but not others, and how does labor market power shape these decisions? Nearly 150 years ago, Marx (1894) argued that firms invest in labor-saving machines to reduce wage costs, thereby displacing workers and weakening labor's bargaining power. While Marx's framework implicitly assumed non-competitive labor markets, recent empirical evidence suggests that today's labor markets increasingly resemble those conditions (Bessen, 2015).

Labor market power has risen globally, allowing firms to suppress wages below marginal productivity even in ostensibly competitive environments (Manning, 2021). Simultaneously, technological change has accelerated, with automation and artificial intelligence (AI) transforming the nature of work. Some technologies fully substitute for human labor, while others—particularly generative AI—augment it. Empirical evidence shows that automation disproportionately displaces routine and mid-skill workers and contributes to wage inequality (Acemoglu and Restrepo, 2021, Webb, 2020), while AI technologies tend to complement higher-skilled workers and raise productivity (Autor, Chin, Salomons, and Seegmiller, 2022, De Souza and Li, 2023).

This paper studies how labor market power interacts with automation and AI adoption. We ask: When do firms automate jobs? When are workers assign to AI-augmented jobs? How does labor market power distort firms' technology choices and workers' incentives to invest in skills? Should automation be taxed to restore efficiency?

We develop a model with n firms competing in a perfectly competitive product market but exercising market power in the labor market due to horizontal job differentiation. Jobs can be automated, assigned to human workers alone, or enhanced through the use of generative AI. Workers differ in skills and idiosyncratic preferences over firms, which generate wage markdowns and misallocation.

Our model yields three main insights. First, in the presence of labor market power, automation falls as market power rises. Second, there is more automation and work displacement than productive efficiency and constrained allocative efficiency warrant. Third, among jobs that are not automated, AI is adopted efficiently, conditional on the assignment, but market power still distorts overall skill allocation. Fourth, the threat of automation induces heterogeneous human capital investment responses: workers may overinvest in skills to avoid displacement, or underinvest if outside options are attractive or automation productivity thresholds are too high. Fifth, taxing automation can restore efficiency in the automation margin, but at the cost of distorting AI adoption and reducing wages for non-displaced workers. Hence, while taxation may reduce displacement, it introduces new inefficiencies and trade-offs.

This paper builds on several strands of literature spanning labor economics, industrial organization, and the economics of technological change.

An extensive empirical literature studies the impact of automation on employment and wage structures. Acemoglu and Restrepo (2021) show that between 50% and 70% of recent changes in the US wage distribution are due to the declining relative wages of workers performing routine tasks. Webb (2020) finds that previous automation technologies have led to declines in employment and wages, particularly for low- and mid-skill occupations, while AI appears to target high-skill tasks. Similarly, Autor et al. (2022) show that automation reduces employment in exposed occupations, while augmenting technologies expand employment and wages in complementary jobs. Bessen, Goos, Salomons, and van den Berge (2020) find that while automating firms grow faster, they experience short-term job losses at the point of automation.

Dixon, Hong, and Wu (2021), using Canadian firms, find that the robot-adopting firms experience a subsequent increase in employment, but decreases in the total number of managers, and that the employment increase is predominantly from low- and high-skill workers and falls for middle-skill workers. Koch, Manuylov, and Smolka (2021), using Spanish firms, report a similar finding. These studies also find that firms that adopt robots experience higher performance (measured by firm-level total factor productivity or revenue). Interestingly, the studies find that non-adopting firms in the same industry as the robot-adopting firms experience employment declines (Acemoglu and Restrepo, 2020). Eggleston, Lee, and Iizuka (2021) study the effects of robots on workers in Japanese nursing homes and find that robots complement human labor and reduce labor turnover.

Recent studies examine the differential effects of AI and software adoption. Aghion, Antonin, Bunel, and Jaravel (2022) find that automation boosts employment, sales, and profits but does not significantly affect wages or wage inequality within firms. De Souza and Li (2023) find that robots have significantly decreased employment and wages of low-skill workers in operational occupations. However, tools—machines-software that use AI to complement labor have led to an equally large reinstatement of these workers, increasing their employment and wages.

It is increasingly common to examine imperfect competition in labor markets rather than in product markets. Manning (2021) reviews extensive evidence showing that labor market power is pervasive, affecting wage setting and employment decisions. Acemoglu and Restrepo (2024) show that automation is concentrated in high-rent jobs, dissipating worker rents and exacerbating wage losses. However, in their setting, rents arise from worker-side frictions, unlike our model, where firms hold the bargaining advantage.

Theoretical and policy debates increasingly consider whether taxing automation can mitigate displacement and inequality. While few models formally evaluate the equilibrium effects of such taxes, our framework contributes to this literature by showing that taxing technology can restore allocative efficiency in automation—but at a cost to generative AI adoption and wages for non-displaced workers.

Our paper contributes to the literature on innovation, automation, and inequality by modeling technology adoption under imperfect labor markets. It provides a unified explanation for excessive displacement, wage suppression, and skill misallocation, offering a theoretical foundation for ongoing debates over taxing automation and regulating AI in the labor market. By dealing with both allocative and productive inefficiencies, we identify novel margins through which labor market power distorts technological transitions.

The rest of the paper is structured as follows. In the following section, motivational evidence concerning labor market power and AI adoption is provided. In Section 3, we present the model. In the next section, Section 4, we derive the subgame-perfect equilibrium. Then, in Section 5.3, we study taxing technological capital. In Section 6, we examine how labor market power and allocative inefficiency affect individuals' incentives to invest in human capital. In Section 7, we provide concluding remarks.

2 Motivational Evidence

In this section, we provide motivating evidence showing a negative correlation between labor market power and the adoption of automation technologies. This evidence aligns with the prediction of the model in Proposition 7.

We provide two different but complementary pieces of evidence. First, we show a negative correlation between labor market concentration, measured by Herfindahl-Hirschman Index (HHI) of posted vacancies at the commuting-zone level in the U.S. (Choi and Marinescu, 2024), and the presence of robotics-related activity at the commuting-zone level. Second, we report a negative correlation between markdowns for the manufacturing sector and net imports of robots per one thousand workers, at the country level[1] In both cases, we extend the work of Acemoglu and Restrepo (2022), which studies the causal effect of labor force aging on automation at both the commuting-zone and country levels. causal effect of labor force aging on automation at both levels, commuting-zone and country level. Their argument is that middle-aged workers typically perform manual production tasks in a greater proportion, and that the scarcity of such workers generates upward pressure on wages, leading firms to replace them with industrial robots.

2.1 Evidence at the Commuting-Zone Level

In Appendix A.1 there is a complete description of the data, its sources and a more detailed description of the methodology.

Acemoglu and Restrepo (2022) proxy robotics-related activities by the presence of robot integrators in year 2015 -companies that install, program, and maintain robots.

The authors define aging as the difference between the ratio of older workers (above 55 years) to middle-aged workers (21-55 years) in 2015 and 1990.

Data for HHI for vacancies at the commuting-zone level comes from Choi and Marinescu (2024), who provide an upper-bound and a lower-bound estimates described in the appendix.

We reproduce single-IV estimations of section 6 in Acemoglu and Restrepo (2022), but including HHI as an additional regressor.

$$integrators_c = \beta_0 + \beta_1 HHI_c + \beta_2 Aging_c + \Gamma X_{c,1990} + \nu_c,$$

where the subscript c represents the commuting-zone. $integrators_c$ is a dummy variable that indicates the presence of robots integrators. HHI_c is the Herfindahl-Hirschman Index, and we perform separate estimations using the lower bound and the upper bound.

[1] In Figure A6 in Acemoglu and Restrepo (2022), they show a strong positive correlation between log of robot stock variation per one thousand workers and log net imports of robots per one thousand workers.

$Aging_c$ is the labor force aging measure defined by Acemoglu and Restrepo (2022) and described in the appendix. Finally, $X_{c,1990}$ is a set of controls at the commuting-zone level, the majority of them with base levels in 1990, and ν_c is the error term.

Results are presented in Table 1 for the estimations using the upper bound HHI and in Table 2 for the estimations performed using the lower bound for HHI. All estimations instrument aging by the difference in the birth rate between 1950 and 1980 as in the preferred specification in Acemoglu and Restrepo (2022), they argument is that aging could be bias because of migration between commuting-zones.

The standard deviation of the upper bound of the HHI is 0.10; therefore the coefficient from column (4) in Table 1 implies that one standard deviation increase in market concentration reduces the probability of the presence of robots integrator by 7.5%. Similarly, the standard deviation of the lower bound of the HHI is 0.16; therefore the coefficient from column (4) in Table 2 implies that a one-standard-deviation increase in market concentration reduces the probability of the presence of robot integrators by 5.1%.

Figure 1 depicts a scatter plot of the predicted probability of the presence of robots integrators and HHI using the estimations of column (4).

Table 1. Single IV Estimates Location of Robots Integrators vs. Herfindahl–Hirschman Index - Upper Bound

	(1)	(2)	(3)	(4)	(5)
HHI - Upper Bound	-2.2254***	-0.7971***	-0.7146***	-0.7478***	-0.6967***
	(0.1703)	(0.2252)	(0.2159)	(0.2206)	(0.2212)
Aging 1990-2015	0.7395**	0.9105**	0.8530**	0.8632**	0.9281**
	(0.3520)	(0.4109)	(0.3924)	(0.3994)	(0.4027)
Exposure to robots			0.0451**	0.0444**	0.0793***
			(0.0197)	(0.0207)	(0.0207)
log GDP pp 1990		0.0965	-0.0104	-0.0025	-0.0261
		(0.1610)	(0.1270)	(0.1288)	(0.1311)
log Pop 1990		0.0996***	0.1113***	0.1035***	0.1046***
		(0.0192)	(0.0212)	(0.0206)	(0.0212)
Observations	722	722	722	722	712
First-stage F stat.	57.8	62.0	59.0	58.4	60.1

Instruments using average birth rate over 5-years intervals

Robust standard errors in parenthesis clustered by state. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Regressions include Census region dummies

Column (1) only include Census region dummies.

Column (2) includes controls for demographic and economics characteristics in 1990.

Column (3) adds industry controls.

Column (4) adds controls for other shocks affecting US markets.

Column (5) exclude the top 1% commuting zones with the highest exposure to robots.

Table 2. Single IV Estimates Location of Robots Integrators vs. Herfindahl–Hirschman Index - Lower Bound

	(1)	(2)	(3)	(4)	(5)
HHI - Lower Bound	-1.4684***	-0.3449**	-0.3318***	-0.3186**	-0.3037**
	(0.1284)	(0.1559)	(0.1275)	(0.1268)	(0.1300)
Aging 1990-2015	0.8137**	0.9468**	0.8602**	0.8784**	0.9502**
	(0.3554)	(0.4183)	(0.4022)	(0.4153)	(0.4183)
Exposure to robots			0.0504**	0.0497**	0.0888***
			(0.0211)	(0.0222)	(0.0217)
log GDP pp 1990		0.1254	0.0186	0.0258	-0.0016
		(0.1669)	(0.1342)	(0.1363)	(0.1387)
log Pop 1990		0.1084***	0.1158***	0.1112***	0.1104***
		(0.0211)	(0.0200)	(0.0197)	(0.0197)
Observations	722	722	722	722	712
First-stage F stat.	52.8	56.7	55.4	55.4	56.4

Instruments using average birth rate over 5-years intervals

Robust standard errors in parenthesis clustered by state. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Regressions include Census region dummies

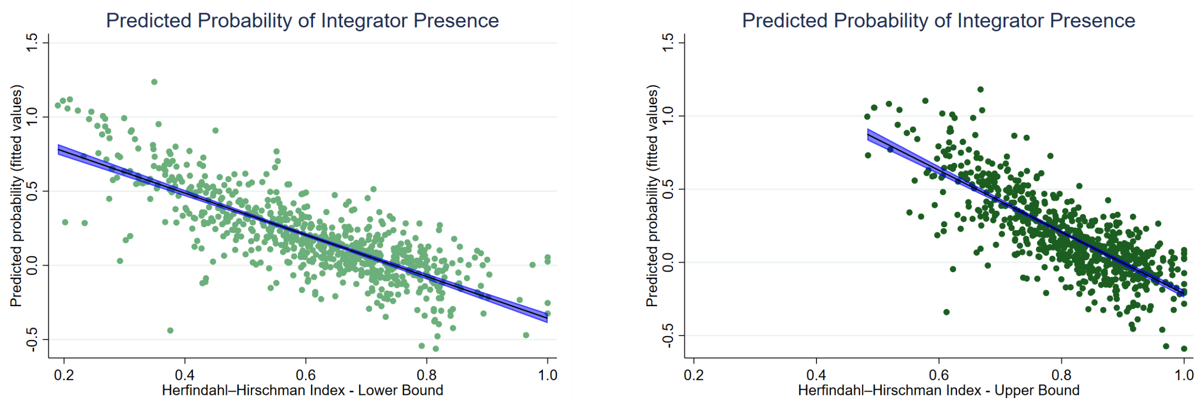
Column (1) only include Census region dummies.

Column (2) includes controls for demographic and economics characteristics in 1990.

Column (3) adds industry controls.

Column (4) adds controls for other shocks affecting US markets.

Column (5) exclude the top 1% commuting zones with the highest exposure to robots.



(a) Predicted Probability Lower Bound HHI. **(b)** Predicted Probability Higher Bound HHI.

Fig. 1. Predicted Probability of the Presence of Robot Integrators.

2.2 Evidence at the Country Level

2.2.1 IFR Data

Figure 2, panel (b), shows a negative correlation between the stock of robots installed per one thousand workers and markdown for the manufacturing sector, for 20 countries above the world average. The data on robots installed is a sample of the 2024 World Robotics Report of the International Federation of Robotics (IFR) and was made publicly available in it web page[2]

2.2.2 Net Imports Robots

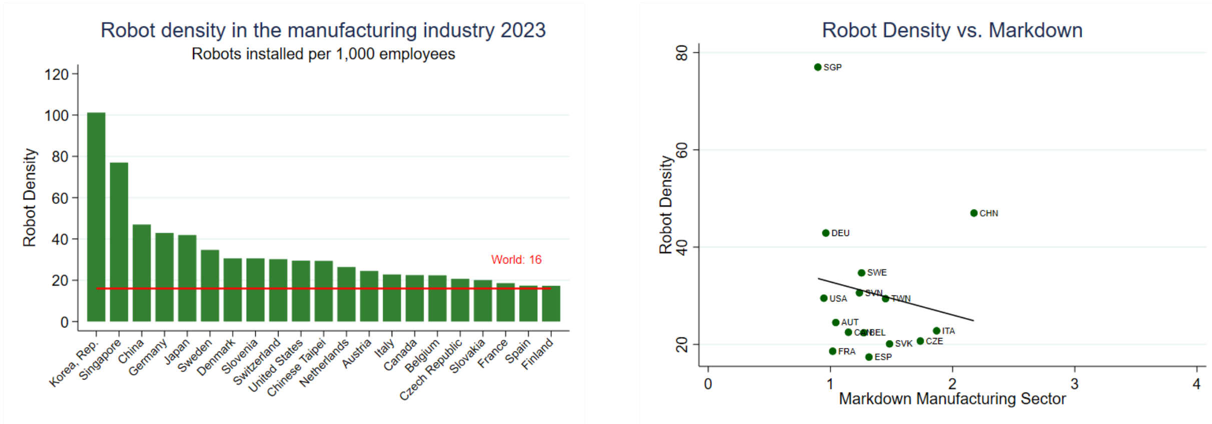
In Appendix A.2 there is a complete description of the data, its sources and a more detailed description of the methodology.

Acemoglu and Restrepo (2022) use data from UN COMTRADE[3] to construct a measure of the accumulated total value of imports of industrial robots between 1996 and 2015, net of re-export, which is publicly available. This measure is then divided by the number of industrial workers in 1995[4], adjusted by hours per worker.

[2] `https://ifr.org/wr-industrial-robots/`

[3] United Nations Commodity Trade Statistics Database

[4] The authors define industrial employment as comprising manufacturing, mining, construction and utilities, which are the sectors adopting robots.



(a) Robot Density Manufacturing Sector 2023 **(b)** Correlation Robot Density and Markdowns

Fig. 2. Robot Density Manufacturing Sector.
Robot Density is defined as robots installed per 1,000 employees in the manufacturing sector for year 2023. The data was taken from the World Robotics Report 2024 of the International Federation of Robotics (IFR)—selected countries published on the IFR's webpage .
Markdowns were estimated following the methodology of Eslava et al. (2023), which employed data from the World Bank Enterprise Surveys (WBES). For countries with multiple country-year observations, we compute the simple average.
Note: The Republic of Korea (KOR) is excluded from panel (b) as an extreme outlier, with 101 robots per 1,000 employees and a markdown of 1.77.

We replicate IV estimations on section 4.2 in Acemoglu and Restrepo (2022), but including markdowns for the manufacturing sector as an additional regressor—estimated using the methodology of Eslava, García-Marín, and Messina (2023)—and using the ratio of net imports of robots between 1996 and 2015 over one thousand industrial workers as the dependent variable[5]. As the WBES survey have multiples waves for some countries, we calculate a simple average of the country-year markdowns observations available by country.

The equation estimated is as follow:

$$\frac{\Delta Im\_R_c^{1996-to-2015}}{L_{c,1995}} = \beta_0 + \beta_1 markdown_c + \beta_2 Aging_c + \Gamma X_{c,1995} + \mu_c$$

where subscript c denotes the country; $Im\_R_c^{1996-to-2015}$ is the accumulated trade value of imports of robots, net of re-exports, between 1996 and 2015; $L_{c,1995}$ is the industrial employment level in 1995 adjusted by hours per worker; $markdown_c$ is the markdown for the

[5] Acemoglu and Restrepo (2022) use accumulated flow of imports of robots relative to other intermediate imports between 1996 and 2015 as the dependent variable. They also perform regressions weighted by manufacturing value added in 1990 (data from UNIDO), instead we perform unweighted regressions.

manufacturing sector estimated using the methodology from Eslava et al. (2023); $Aging_c$ is the aging measure from Acemoglu and Restrepo (2022); $X_{c,1995}$ is a set of controls with levels in 1995; and μ_c is the error term.

Table 3 reports the estimation results. All regressions include region dummies,[6] and all covariates included are displayed in the table. The coefficient on markdown is negative in all specifications and is statistically significant in column (1) and (2). When GDP is added as a covariate in columns (3) and (4), the coefficient remains negative but is no longer statistically different from zero.

Our measure of markdown in the manufacturing sector has a mean of 1.60 and a standard deviation of 0.52. The coefficient on markdown in column (2) of Table 3 implies that an increase of one standard deviation in markdown is associated with a 43.7% reduction in the ratio of net imports robots over one thousand workers. This ratio has a mean of $ 120,630 U.S. dollars over the twenty-year period. A 43.7% decrease of $ 120,630 amounts to approximately $ 52,691—roughly the cost of one industrial robot according to Acemoglu and Restrepo (2022)[7].

Figure 3 shows a negative correlation between markdowns in the manufacturing sector and the (log) of net robot imports per one thousand workers. The solid line depicts the local linear fit obtained using LOESS. The relationship is strongly negative for markdown values between one and two—that is, within one standard deviation below and above the mean.

Figure 4, in Appendix A.3, presents linear correlations between manufacturing-sector markdowns and (log) net robot imports by income group. The negative relationship is clearer and stronger among developing countries—those with log GDP per capita (PPP-adjusted) between 8.00 and 9.50 in 1995.[8] In contrast, the relationship is close to zero among high-income countries—those with log GDP per capita greater than or equal to 9.50 in 1995—and among low-income countries—those with log GDP per capita below 8.00 in 1995.

[6] These comprise seven groups: six groups comprising non OECD countries geographical regions—Africa, East Asia and the Pacific, Europe and Central Africa, Latin America and the Caribbean, Middle East and North Africa and South Asia—and one for OECD countries.

[7] Acemoglu and Restrepo (2022) report that the cost of one industrial robot range from $ 50,000 to $120,000 U.S. dollars.

[8] This definition includes China—the developing country with the lowest value (log($gdp_pc_ppp_9$5) = 8.14)—and all Latin American countries, with Argentina having the highest value in this group (log($gdp_pc_ppp_9$5) = 9.49).

Table 3. Net Robot Imports per Thousand Workers vs. Markdown Manufacturing Sector

	(1)	(2)	(3)	(4)
markdown	-1.2837***	-0.8393**	-0.3938	-0.2829
	(0.3777)	(0.3501)	(0.4270)	(0.2955)
aging 1995-2025		10.4984***	4.8739**	-0.5974
		(1.8441)	(2.3210)	(1.7756)
GDPpc-ppp 1995			1.2269***	-0.8867*
			(0.4109)	(0.5277)
1995 log_pwt_population			0.1663*	-1.7425***
			(0.0912)	(0.4117)
schooling 1995			-0.0998	-0.5839
			(0.5002)	(0.4149)
old-emp-ratio 1995			-0.5570	0.1282
			(1.5335)	(0.9559)
log Mva 1995				0.5762*
				(0.3489)
log-interm-im 1996-2015				1.5991***
				(0.2756)
Observations	100	100	93	93
R-Square	0.631	0.676	0.766	0.859

Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.
Regressions include region dummies.

Figures 5 and 6, in Appendix A.3, display linear correlations between manufacturing-sector markdowns and (log) net robot imports by the regional groups used as dummies in the regressions. The relationship is slightly negative for OECD countries (panel (a) in Figure 5) and more clearly negative across the six non-OECD geographic regions.

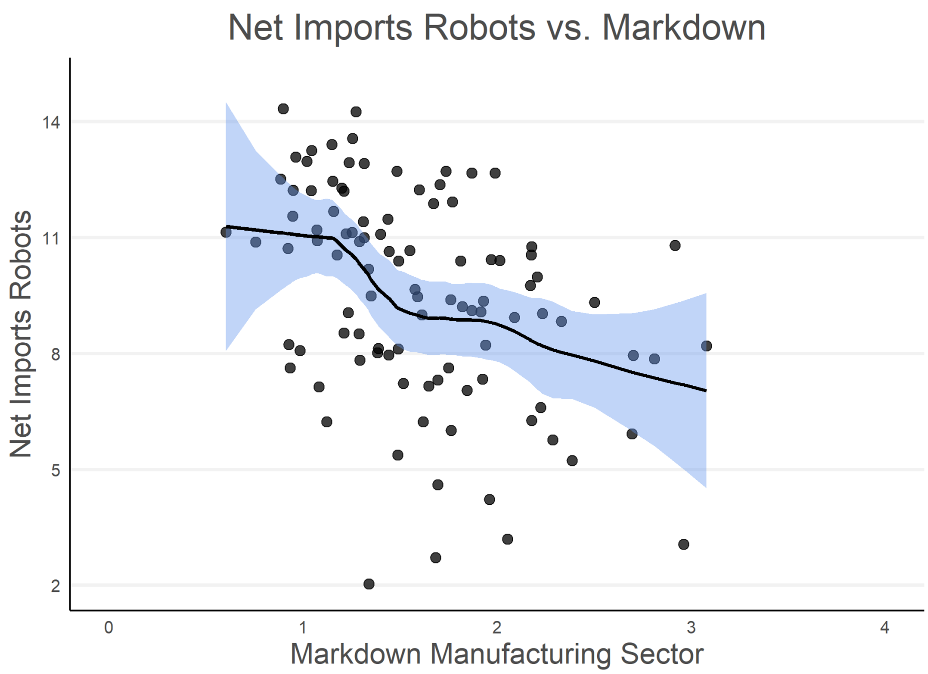


Fig. 3. Markdowns Manufacturing Sector. All regions.
Local linear fit and 95% confidence interval estimated via Local Polynomial Regression (LOESS) with a bandwidth of 0.4.
Markdowns were estimated following the methodology of Eslava et al. (2023), using data from the World Bank Enterprise Surveys (WBES).
Net Imports Robots is defined as robot imports net of re-exports between 1996 and 2015, divided by one thousand industrial workers in 1995, expressed in natural logs. Following Acemoglu and Restrepo (2022).

3 The Model

3.1 Set-Up

Let's consider the following labor-market game. In the first period, firms decide whether or not to automate the job. After that, if the job is not automated, wages are simultaneously chosen. In the third period, individuals learn the firm-specific non-pecuniary preference shocks and the wage for each firm and choose to supply their labor to the firm that offers the higher utility, provided that this is higher than the outside option payoff.

After that, firms learn applicants' skill levels and decide whether to assign the worker to a job that uses both generative AI and human skills or to a job that uses only human skills.

To keep the analysis simple, firms and individuals are risk-neutral and do not discount the future. Firms separate workers into different human capital or credential groups or classes, denoted by s, where s could be, for instance, college degree workers, high-school graduates, etc. Firms believe that workers belonging to class s have a skill level t with cumulative distribution function $F(t|s)$, full and bounded support $\mathcal{T} \subset \Re_+$, and density $f(t|s)$. The class to which a worker belongs and $F(t|s)$ are common knowledge. Workers know their skill level t. A worker from skill class $s' > s$ has distribution $F(t|s')$ that dominates $F(t|s)$ in the sense of first-order stochastic dominance. Thus, $F_s(t|s) < 0$. An s-class worker who cannot find a job or chooses the outside option receives a payoff of $b(s)$, which is non-decreasing in s.

There are n firms horizontally differentiated from individuals' point of view, indexed by $j \in \{1, \ldots, n\}$. Firms produce tradeable goods that are perfect substitutes, and so they trade in a perfectly competitive market at a price p, normalized to one.

We model such occupational differentiation by adopting a random-utility framework in the spirit of Perloff and Salop (1985).[9] Let $\epsilon_l = (\epsilon_l^j, \ldots, \epsilon_n^j)$ be the match-specific utility shock of individual l in each of the $j \in \{1, \ldots, n\}$ possible firm/jobs. Thus, the utility of individual l in job j is given by: $w^j + \epsilon_l^j$. We assume that ϵ_l is i.i.d. across individuals, reflecting idiosyncratic tastes for different jobs, and that, for a given worker, it is also i.i.d. across jobs. These non-wage job characteristics may include hours of work, the distance of the firm from the worker's home, and the social environment in the workplace, among others. In the forthcoming analysis, we will suppress the index l. ϵ^j is distributed $G(\cdot)$ with compact and full support $[\underline{\epsilon}, \bar{\epsilon}] \subset \Re$, zero mean and twice differentiable density $g(\cdot)$.

We assume that there is a local labor market for each worker class s. Within that market, competing firms simultaneously set wages without discriminating among individuals of the same type or class. Because firms know workers' class, a worker from class s cannot apply to a job in class s'. In that sense, the worker class determines the job market in which they can participate. For instance, a lawyer with skill level t will not be hired as a smartphone technician, even though the lawyer's skill level t may exceed that of most

[9] Balmaceda (2025) also studies a Perloff and Salop (1985) in the context of occupational choice and Azar, Berry, and Marinescu (2019) estimate labor market power using a logit model, which is a particular case of Perloff and Salop's (1985) model.

technicians, or vice versa. From now on, we will refer to a worker class s as the labor market of class s.

The next assumption is crucial for characterizing the labor-market equilibrium.

Assumption 1. *$g(\epsilon)$ is log-concave.*

This ensures the existence of an equilibrium and the markdowns go to zero as the number of firms goes to infinity.[10] Firms have access to constant returns to scale technology, i.e., the total output of a firm equals the sum of the outputs of each job.[11]

Jobs are of three different types: automated jobs (a) that fully substitute for human skills; human-skills-only jobs (h) whose only input is human skills; and generative AI-human skills jobs (g) that use both human skills and generative AI. The type of job is denoted by $\tau \in \{a, g, h\}$. There is a finite number of jobs that can be automated.[12]

For a labor market s, the automated output in firm j when automation capital is a is

$$y^j(a;s) = \int_0^{\bar{y}} y dA(y|a,s).$$

where $A(y|k,s)$ is continuous CDF with support $[0,\bar{y}]$ and satisfying $A(y|a',s) \le A(y|a,s)$ for all $a' > a$. Thus, automation capital improves the automation output in the sense of first-order stochastic dominance. The output of a human skills job when the investment in generative AI capital is h in firm j is given by

$$y^j(t,h;s) = \int_0^{\bar{y}} y dH(y|t,h,s).$$

where $H(y|t,h,s)$ is continuous CDF with support $[0,\bar{y}]$ and satisfying $H(y|t',g,s) \le H(y|t,h,s)$ for all $t' > t$, $H(y|t,h',s) \le H(y|t,h,s)$ for all $h' > g$ or all $t > 0$. Thus, generative AI is useful at any level of skill.

The technology satisfies the following properties.

Assumption 2. *For all $j \in \mathcal{J}$,*

[10] See, Gabaix, Laibson, Li, Li, Resnick, and de Vries (2016) for details about markups convergence in random utility models.

[11] This assumption is not as restrictive as it appears at first glance. If the technology is of constant returns to scale and inputs can be freely adjusted, the marginal contribution of a worker will be independent of the other inputs. The reason is that a profit-maximizing firm will maintain a constant ratio between inputs.

[12] This assumption is meant to avoid the solution of firms creating as many automated jobs as they wish whenever the rent from automation is positive. To address this, we could have assumed decreasing returns to automation technology, but that would complicate the algebra without gaining economic intuition.

i) $y^j(a;s)$ *is strictly concave in* a, $\lim_{h\to 0} y^j_a(a;s) > r$, *and* $\lim_{h\to\infty} y^j_a(a,s) < r$.

ii) *For all* $t \in \mathcal{T}$, $y^j(t,h;s)$ *is strictly concave in* h, $y^j(t,0;s) > 0$, *and* $\lim_{h\to\infty} y^j_h(t,h;s) < r$.

iii) *For any* $(t',h') > (t,h)$, *either* $y(t',h',s) + y(t,h,s) \geq y(t,h',s) + y(t',h,s)$ *or the opposite holds.*

These are standard conditions to guarantee the uniqueness of the capital investments. Part ii) also establishes that human skills are productive even when no investment in generative AI is made. Part iii) says that generative AI capital and human skills can be either complements or substitutes.

Rosen (1987) was the first to highlight the importance of non-pecuniary job characteristics in the compensating wage differentials literature. Lamadon, Mogstad, and Setzler (2022) show that worker preferences over non-pecuniary job characteristics lead to imperfect competition in the US labor market. Maestas, Mullen, Powell, von Wachter, and Wenger (2018) find that high-wage workers and college-educated workers have uniformly better job characteristics, and Mas and Pallais (2017) argue that there is evidence that workers in the US are willing to give up part of their income compensation to avoid undesirable working conditions. Sullivan and To (2014) show that there are substantial gains to workers from job search based on non-pecuniary factors, workers sort into jobs with better non-pecuniary job characteristics, and are willing to pay for them. Sorkin (2018) shows a high prevalence of US workers who move to lower-paying firms in a way that cannot be accounted for by layoffs or differences in recruiting intensity to benefit from non-pecuniary job characteristics. He estimates that compensating differentials account for over half of the firm component of the earnings variance. These results provide a foundation for labor-market power driven by the horizontal differentiation of jobs.

In addition, it is highly plausible that individuals with identical productivity may choose different jobs due to their differing tastes. Accounting for job preferences is particularly important to understand differences in job choices between different groups. For example, men and women exhibit different job choice patterns as well as Blacks and Whites.

4 The Equilibrium

4.1 Automation and Generative AI Capital Investments

Let's consider a labor market for worker class s. Because when a worker applies to a job in firm j, both the firm and the worker already know the worker's skill t, firm j chooses generative AI capital to solve the following problem

$$\max_{h \in \Re_+} \{y^j(t, h^j; s) - w^j - rh^j\}. \tag{1}$$

The first-order condition is

$$\int_0^{\bar{y}} y dH_h(t, h^j, s) - r \leq 0.$$

Because of Assumption 2 part ii), if $\lim_{h \to 0} \int_0^{\bar{y}} y dH_h(t, h^j, s) > r$, a unique interior solution exists. Otherwise, the optimal solution is to set it to zero. Let's denote the optimal solution by $h^j(t, r, s)$. Thus, the output when the job is not automated is given by $y(t, r; s) \equiv y^j(t, h^j(t, r, s); s) - rh^j(t, r, s)$.

When the optimal solution is strictly positive, it is easy to check that if generative AI capital and skills are complements, $h^j(t, r, s)$ rises with t, whereas if they are substitutes, $h^j(t, r, s)$ falls with t. Furthermore, it readily follows from the implicit function theorem that $y(t, r; s)$ rises with t and falls with r.

Because the wage is already set, it does not affect the investment decision in generative AI. When $h^j(t, r, s) > 0$, the worker is allocated to a job complemented with generative AI. Otherwise, the job is produced only with human skills. If skills and generative AI are substitutes, if for any t, $h^j(t, r, s) = 0$, then $h^j(t', r, s) = 0$ for all $t' > t$, whereas if they are complements, then $h^j(t', r, s) = 0$ for all $t' < t$.

When the job is automated, firm j chooses automation capital to solve the following problem

$$\max_{a \in \Re_+} \{y^j(a^j; s) - ra^j\}. \tag{2}$$

The first-order condition is

$$\int_0^{\bar{y}} y dA_a(y|a^j;s) - r = 0.$$

Because of Assumption 2 part ii), a unique solution, denoted by $a^j(r,s)$, exists. Thus, the output when the job is automated is given by $y(r,s) \equiv y^j(a^j(r,s);s) - ra^j(r,s)$.

4.2 Equilibrium Wages

Let's consider a labor market for worker class s. Let $d^j \in \{0,1\}$ be firm j's automation decision, where $d^j = 1$ means the job is assigned to human skills and $d^j = 0$ means the job is automated. Then, for any automation profile d, let $\mathcal{J}(d) \subseteq \mathcal{J}$ be the set of firms that opens a vacant and $\mathcal{J}(d^{-j}) \equiv \{k \in \mathcal{J} : k \neq j \text{ and } d^k = 1\}$ be the set of firm j's competitors that open a vacant.

Because workers observe (ϵ, w) before choosing a firm to supply their labor, they will choose the firm that provides the highest expected utility among all those that have a vacant available $j \in \mathcal{J}(d)$ provided that this yields a higher utility than the outside option $b(s)$. Thus, a worker chooses firm $j \in \mathcal{J}(d)$ whenever $w^j + \epsilon^j \geq \max\{b(s), w^{j'} + \epsilon^{j'}\}$.[13] Hence, the probability that a worker chooses firm $j \in \mathcal{J}(d)$ instead of any other firm is given by

$$P^j(w) = P[w^j + \epsilon^j \geq \max_{k \in \mathcal{J}(d^{-j})} \{w^k + \epsilon^k, 0\}] = \int_{\max\{\underline{\epsilon}, b(s) - w^j\}}^{\bar{\epsilon}} \prod_{k \in \mathcal{J}(d^{-j})} G^k\left(w^j + \epsilon^j - w^k\right) dG^j(\epsilon^j),$$

where the equality follows from the independence assumption about the G's distributions.

Proposition 1. *$P^j(w)$ is strictly positive, strictly increasing in w^j, strictly decreasing in $w^{j'}$ for all $j' \neq j$, log-concave in w^j, and log-supermodular in w.*

The log-concavity follows that G is log-concave and the multiplication of log-concave functions is log-concave. The log-concavity of the firm-specific labor supply implies that the price elasticity of supply increases with the wage.

[13]When there is no risk of confusion, we will omit the arguments to keep the notation simpler and we will omit the dependence of distributions and wages on the skill class s.

Because TP-2 functions are preserved under marginalization, the supply is log-supermodular in w. This means that the price elasticity of demand decreases as competitors' prices increase. The latter will imply an increasing best-response correspondence when goods are gross substitutes.

Let's define the marginal product of labor by $\mathbb{E}_t[y^j(t,r,s)] = \mathbb{E}_t[y^j(t,h^j(t,r,s),s)]$. For any given wage profile w, firm j's profits when a vacancy is open are then given by:

$$\Pi^j(w) \equiv \mathbb{E}_t\left[\left(y^j(t,r,s) - w^j\right)P^j(w)\right], \tag{3}$$

Thus, firm j chooses w^j, taken $w^{-j} \equiv (\ldots, w^{j-1}, w^{j+1}, \ldots)$ as given, to solve the following problem

$$\max_{w^j \in \Re_+} \Pi^j(w^j, w^{-j}).$$

In what follows, we will focus on parametric restrictions such that the case in which $\underline{\epsilon} \leq b(s) - w^j$ holds for all j and, therefore, the outside-option payoff is chosen with positive probability for each possible type.[14] From here onwards, let the subindex denote the derivative for the corresponding wage. Because G^k's are identically distributed, the first-order condition is given by

$$(\mathbb{E}_t[y^j(t,r,s)] - w^j)P^j_j(w) - P^j(w) \leq 0, \tag{4}$$

where,

$$\begin{aligned} P^j_j(w) = \int_{b(s)-w^j}^{\bar{\epsilon}} \sum_{h \in \mathcal{J}(d^{-j})} \nu_g\left(w^j + \epsilon^j - w^h\right) \prod_{k \in \mathcal{J}(d^{-j})} G\left(w^j + \epsilon^j - w^k\right) dG(\epsilon^j) + \\ g(b(s) - w^j) \prod_{k \in \mathcal{J}(d^{-j})} G(b(s) - w^k), \end{aligned} \tag{5}$$

where $\nu_g(\cdot) \equiv g(\cdot)/G(\cdot)$ is the of distribution G and the sub-index j denotes the derivative with respect to wage w^j.

Lemma 1. *Firm j's best response $B^j(w^{-j}) \in (0, \mathbb{E}_t[y^j(t,r,s)])$ exists and is unique.*

Profits are log-supermodular in w because the markdown depends only on w^j and

[14] This assumption does not change the results. If we allow for $\underline{\epsilon} > b(s) - w^j$ in some occupations, then the markdown will be a constant depending only on the number of firms.

$P^j(w)$ is log-supermodular in w. The following result readily follows from this and Theorem 6 in Milgrom and Roberts (1990). It also follows from Theorem 5 in Milgrom and Roberts (1990) that each firm has only one serially undominated strategy. Hence, the original game is dominance solvable and the equilibrium is globally stable under any adaptive learning rule satisfying assumption A6 in Milgrom and Roberts (1990).

Proposition 2. *For each labor market s, the equilibrium set has the componentwise largest and smallest elements, given by $w_H(t,r,s)$ and $w_L(t,r,s)$ respectively, with*

$$w_l^j(t,r,s) = \mathbb{E}_t[y^j(t,r,s)]\frac{\xi^j(w_l^j(t,r,s))}{1+\xi^j(w_l^j(t,r,s))},$$

for all $j \in \mathcal{J}(d)$, where $\xi_l^j(w_l^j(t,r,s))$ is the elasticity of the labor supply for $l \in \{H, L\}$.

Hence, a type-s worker is paid a lower wage than his expected marginal product of labor. The markdown as a percentage of the wage is the inverse of the labor-supply elasticity. The higher the elasticity, i.e., the more intense the competition, the higher the wage.

From here onward, we will focus on the symmetric equilibrium for each type, which requires assuming that $\mathbb{E}_t[y^j(t,r,s)] = \mathbb{E}_t[y(t,r,s)],\ \forall\ j \in \mathcal{J}(s)$. Let the cardinality of $\mathcal{J}(d^{-j})$ in the labor market s be $n(s)$. Then, it readily follows from the first-order condition in equation (4) and integration-by-parts that the equilibrium wage $w(b,r,s)$ for an individual of type s is determined by a fixed point of the following equation

$$\begin{aligned}&\mathbb{E}_t[y(t,r,s)] - w = m(b(s)-w) \\ \equiv&\frac{1}{n(s)}\frac{1-G(b(s)-w)^{n(s)}}{\underbrace{G(b(s)-w)^{n(s)-1}g(b(s)-w)}_{\text{exclusion effect}}+\underbrace{\int_{b(s)-w}^{\bar{\epsilon}} g(\epsilon)dG(\epsilon)^{n(s)-1}}_{\text{competition effect}}}.\end{aligned} \tag{6}$$

The numerator in equation (6) is the equilibrium labor supply since the workers choose the outside option with probability $G(b(s)-w)^{n(s)}$ (i.e., when each firm j has a valuation less than $b(s)-w$). The denominator is the slope of the labor supply. This has two terms: (i) the market exclusion effect (equivalent to the exclusion effect in the goods market). When the valuations for all other firms are below $b(s)-w$, which occurs with probability $G(b(s)-w)^{n(s)-1}$, firm j acts as a monopsony. Lowering its wage w by ϵ will exclude $\epsilon g(b(s)-w)$ individuals from paid employment; and (ii) the competition effect (up to the adjustment that the marginal individual's valuation for paid employment is given by $b(s)-w$) considering that a wage increase lowers the probability to be hired, which entails loosing not only the pecuniary benefit of being employed (w) but also the non-pecuniary benefit ϵ. This term represents the density of a firm's marginal workers—those who are indifferent between the corresponding firm and the best outside option for them—times the loss from a lower probability of being hired.

If both sides of equation (6) are divided by $w(b,r,s)$, the left-hand side is the Learner's index, denoted by $L(s) \equiv (e_t[y]-w(b,r,s))/w(b,r,s)$, and the right-hand side is the inverse of the labor-supply elasticity, denoted by $\xi(w)$. Hence, in equilibrium, the Lerner's index is the inverse of the supply elasticity. The Lerner's index ranges from 0 to ∞. A perfectly competitive firm pays $w(b,r,s)=\mathbb{E}_t[y(t,r,s)]$, and therefore $L(y)=0$ –such a firm has no market power. An oligopsonist firm pays $w(b,r,s)<\mathbb{E}_t[y(t,r,s)]$, so its index is $L(s)>0$, but the extent of its markdown depends on the elasticity of labor supply, which in turn depends on the strategic interaction with competing firms as well as the outside option.

Let $w^m(t,r,s)$ be the wage when there is a monopsony ($n=1$). In this case, the elasticity is equal to the hazard rate evaluated at $b(s)-w^m(t,r,s)$ and this increases with $b(s)-w^m$ due to the log-concavity of f. The following is proven in the appendix, where all proofs are placed.

Proposition 3. *For each s-type, there exists a unique symmetric equilibrium wage given by* $w(b,r,s)\in[w^m(t,r,s),\mathbb{E}_t[y(t,r,s)]$.

Uniqueness follows from the fact that f is log-concave which makes $m(b(s)-w(b,r,s))$ increasing in $w(b,r,s)$, while the LHS in equation (6) is decreasing in $w(b,r,s)$. Log-concavity implies that the CDF of the second-order highest statistic increases in the sense of first-order stochastic dominance with $b(s)-w(b,r,s)$. This explains why the RHS in equation (6) increases with $w(b,r,s)$ and is bounded. The LHS in equation (6) falls with w. Then by the Intermediate Value Theorem, there is a unique $w(b,r,s)\in[w^m(t,r,s),\mathbb{E}_t[y(t,r,s)]$ that solves equation (6).

Proposition 4. *The equilibrium wage $w(b,r,s)$ increases with $(n, b(s))$, falls with r, and $\lim_{n\to\infty} w(b,r,s) \to y$ and $\lim_{n\to\infty} P(w(b,r,s)) \to 0$.*

The equilibrium wage increases with competition intensity, as workers are more likely to find another paid job that they prefer to the one offered by firm j. This induces firm j to set a higher wage to attract workers. In the limit, as the number of firms approaches infinity, the worker is paid their marginal product of labor. This is because log-concave distributions have either a fat or a thin tail. Otherwise, the wage markdown will not converge to zero as the number of firms approaches infinity (see, Gabaix et al. (2016) for details).

Due to increased competition, holding wages constant reduces the market exclusion effect by increasing the number of jobs available and thereby raising wages. Employment at each firm decreases with competition intensity, and Lerner's index falls.

An increase in the outside-option payoff raises the wage. Wages increase because workers choose the outside option more often when firms keep wages constant. Thus, firms increase wages less than the $b(s)$ increase. The pass-trough from $b(s)$ to wages is equal to $-m'/(1-m')$, which is lower than 1.[15] Thus, a larger outside-option payoff decreases market power because, holding wages constant, the labor-supply elasticity rises as more workers find the outside option more attractive.

4.3 Automation Decision

We will allow for mixed strategies about the automation decision. Let $\alpha^j \in [0,1]$ be firm j's probability to open a vacant, i.e., $d^j = 1$.

Let firm j's expected profits from opening a vacant when competitors choose the mixed strategy α^{-j} be $\mathbb{E}_{\alpha^{-j}} \Pi^j(d^{-j})$, where $\mathbb{E}_{\alpha^{-j}}$ is the expectation with respect to d^{-j} under the mixed-strategy profile α^{-j} and

$$\Pi^j(d^{-j}, s) \equiv \left(\mathbb{E}_t[y^j(t,r,s)] - w^j(b,r,s)\right) \times \\ \int_{b(s)-w^j(b,r,s)}^{\bar{\epsilon}} \prod_{k\in\mathcal{J}(d^{-j})} G\Big(w^j(b,r,s) + \epsilon^j - w^k(b,r,s)\Big) dG(\epsilon^j).$$

[15]If firms could choose non-pecuniary benefits together with wages, they will also use them to compete against self-employment opportunities up to the point where the marginal return of increasing non-pecuniary benefits is equal to that from raising the wage.

Firm j's problem is as follows

$$\max_{\alpha^j \in [0,1]} \{\alpha^j \mathbb{E}_{\alpha^{-j}} \Pi^j(d^{-j}, s) + (1 - \alpha^j) y(r,s)\}.$$

Thus, firm j's best response is given by

$$BR^j(\alpha^{-j}) = \begin{cases} 1 & \text{if } y(r,s) \leq \mathbb{E}_{\alpha^{-j}} \Pi^j(d^{-j}), \\ [0,1] & \text{if } y(r,s) = \mathbb{E}_{\alpha^{-j}} \Pi^j(d^{-j}), \\ 0 & \text{if } y(r,s) > \mathbb{E}_{\alpha^{-j}} \Pi^j(d^{-j}). \end{cases} \tag{7}$$

Firm j chooses to automate the job, provided that competitors do so with probability α_{-j}, whenever this is more profitable than the expected profits of allocating the job to the worker. Thus, what matters to the firm when deciding on automation is the rent a non-automated job produces versus the rent an automated job provides.

The next result readily follows from this and the Nash-equilibrium existence theorem.

Proposition 5. *For each labor market s, there exists a sub-game perfect equilibrium* $(\alpha(b,r,s), w(b,r,s))$.

Let's assume symmetric firms and focus on a symmetric equilibrium. There are three types of symmetric equilibrium: i) one where all firms choose to offer a vacant, and thereby, $\mathbf{d} = \mathbf{1}$; ii) one where all firms choose to automatize their jobs, and thereby, $\mathbf{d} = \mathbf{0}$; and iii) one where all firms use a non-degenerate mixed strategy where they offer a vacant with probability α, and thereby, $\mathbf{d} = \mathbf{1}$ with probability α and $\mathbf{d} = \mathbf{0}$ with probability $1 - \alpha$.

First, let's consider the case where $\mathbf{d^{-j}} = \mathbf{1}$. Using the first-order conditions for wages, we deduce that firm j chooses $d^j = 1$ whenever

$$y(r,s) \leq a(r,s;\mathbf{1}) \equiv m(b(s) - w(b,r,s)) \frac{1 - G(b(s) - w(b,r,s))^n}{n}.$$

Second, let's consider the case in which $d^{-j} = \mathbf{0}$. Using the first-order conditions for wages, we deduce that firm j chooses $d^j = 0$ whenever

$$y(r,s) > a(r,s;\mathbf{0}) \equiv m(b(s) - w(b,r,s))(1 - G(b(s) - w(b,r,s))).$$

This means that the profit from automation exceeds the profit when the firm is a monopoly in the job market.

Thirdly, let's consider the case in which for all $j \in \mathcal{J}$, $d^{-j} = 1$ with probability α and $d^{-j} = 0$ with probability $1 - \alpha$. Let the probability that the cardinality of the set $\mathcal{J}(d^{-j})$ is $v \leq n - 1$ be

$$P(v, n, \boldsymbol{\alpha}) = \binom{n-1}{v} \alpha^v (1-\alpha)^{n-1-v}$$

Observe that $P(v, n, \boldsymbol{\alpha})$ increases with α for all $v > (n-1)\alpha$ and decreases otherwise.

Using the first-order conditions for wages, we deduce that firm j chooses $d^j = 1$ with probability 1 whenever each competitor i is choosing $d^{-j} = 1$ with probability α if and only if

$$y(r,s) = a(r,s;\boldsymbol{\alpha}) \equiv \mathbb{E}_v \left[m(b(s) - w(b,r,s)) \frac{1 - G(b(s) - w(b,r,s))^v}{v} \right]. \tag{8}$$

Because $w(b,r,s)$ rises with the number of firms v and the firm's labor supply falls with the number of firms v, profits decrease with the number of firms that choose to post a vacancy instead of automating the job. This implies that $a(r,s;\mathbf{0}) > a(r,s;\mathbf{1})$. This, together with $P(v,n,\alpha)$ being decreasing in α for v small and increasing for v large, implies that $a(r,s;\alpha)$ falls with α, since as α increases more weight is placed in state where profits are small and less in those with large profits. Thus, we have the following result.

Proposition 6. *For each labor market s, let's consider a symmetric equilibrium.*

i) There exists a threshold $a(r,s;\mathbf{1})$ such that for all $y(r,s) \leq a(r,s;\mathbf{1})$, the equilibrium is given by $d(b,r,s) = \mathbf{1}$. The threshold $a(r,s;\mathbf{1})$ rises with (t,r) and falls with $(n, b(s))$.

ii) There exists a threshold $a(r,s;\mathbf{0})$ such that for all $y(r,s) > a(r,s;\mathbf{0})$, the equilibrium is given by $d(b,r,s) = \mathbf{0}$. The threshold $a(r,s;\mathbf{0})$ rises with (t,r) and falls with $b(s)$.

iii) For all $a(r,s;\mathbf{0}) > y(r,s) \geq a(r,s;\mathbf{1})$, the equilibrium is a mixed strategy equilibrium given by $d(b,r,s) = 1$ with probability $\alpha(b,r,s)$, with $\alpha(b,r,s)$ being the unique solution to $y(r,s) = a(r,s;\alpha)$.

A key empirical question concerning automation is the relationship between its adoption rate and the intensity of competition, as measured by the number of firms

Proposition 7. *For each labor market s, let's consider a symmetric equilibrium. Then, $a(r, s; \mathbf{1})$ rises with (t, r) and falls with $(n, b(s))$, and $a(r, s; \mathbf{0})$ rises with (t, r) and falls with $b(s)$. Thus, automation is less likely to occur as market power increases (n falls), the outside option $b(s)$ falls, and task-specific training and capital costs rise.*

The comparative statics in each part are due to the pass-through from y and $b(s)$ to wages being positive and lower than 1; the equilibrium wage rises with the number of firms that post a vacancy, and the labor supply faced by each firm, holding the wage constant, falls with the number of firms posting a vacancy.

As the number of firms rises, which is our measure of competition intensity, equilibrium wages increase, and thereby, the rents of human-skill jobs fall. Thus, the intense is the competition, the lower the rate of automation adoption. Similarly, as the outside option increases, equilibrium wages rise. This implies a lower rent for a human skill job. This is consistent with the motivational evidence presented in Section 2.

5 Efficiency and Displaced Workers

In this section, we compare: i) the equilibrium job assignments with the productively efficient ones; and ii) the equilibrium job assignments with the welfare-efficient job assignments. To facilitate comparisons, we focus on the symmetric equilibrium.

5.1 Productive Efficiency

Because at the time the automation decision is made, firms do not know the workers' realized skills, and they fully anticipate the productivity of automation, it is productively efficient to automate the job whenever $y(r, s) > \mathbb{E}_t[y(t, r, s)]$. Productive efficiency differs from allocative efficiency because the former does not account for non-pecuniary benefits.

We deduce the following result from this and Proposition 6.

Proposition 8 (Productive Efficiency)**.** *Suppose a symmetric equilibrium.*

i) Suppose that $\mathbb{E}_t[y(t, r, s)] \geq y(r, s)$.

a) If $y(r, s) > a(r, s; \mathbf{0})$, the job is inefficiently automated and workers are inefficiently displaced.

b) If $a(r,s;\mathbf{0}) \geq y(r,s) > a(r,s,\mathbf{1})$, the job is inefficiently automated and workers are inefficiently displaced with probability $1-\alpha$.

c) If $y(r,s) \leq a(r,s;\mathbf{1})$, the job is efficiently assigned to human skills and workers are efficiently employed.

ii) Suppose that $\mathbb{E}_t[y(t,r,s)] < y(r,s)$, the job is efficiently automated and workers are efficiently displaced.

The driving force behind this productive inefficiency is that firms choose automation over human-skill jobs based on the rents they receive from each option, rather than on the actual productivity of each option. Thus, there is too much automation from the perspective of productive efficiency, since the firm shares the revenues from human skills jobs with the worker, whereas it fully appropriates those from automation.

This result also indicates that when $\mathbb{E}_t[y(t,r,s)] > y(r,s)$, workers in the labor market s are inefficiently displaced, as whenever $\mathbb{E}_t[y(t,r,s)] > a(r,s,1)$, firms should post a vacancy and hire workers. Instead, they automate the job with a probability of at least $1-\alpha^*$. In this case, s-type workers either take their best outside opportunity or receive unemployment benefits. In contrast, $\mathbb{E}_t[y(t,r,s)] < y(r,s)$, the job is efficiently automated since the rent from a human-skill job is always lower than the job's productivity.

It is easy to see that the larger the rent the firm gets from human-skill jobs, the lower the productive inefficiency. This leads to the counterintuitive result

Corollary 1. *Labor market power results in inefficient adoption of automation and work displacement relative to productive efficiency when human-skills jobs are more productive.*

Reallocating some jobs to human-skill jobs would increase output by the difference between the productivity in human-skill jobs and that of automation. Displaced workers lose the pecuniary benefits (wages) and the non-pecuniary benefits they would have gotten if those jobs had not been automated. The automation of these jobs creates an inefficiency because the rents the firms would have earned from hiring a worker are lower than the rents earned from automation, even though productivity would have been higher. The lower the rent on human skills, i.e., the more competitive the market, the higher the risk of automation.

There are three reasons why productive inefficiency driven by market power entails a welfare loss for the workers: firstly, they are paid less than the marginal product of labor; secondly, some workers lose the non-pecuniary benefits since they are inefficiently displaced by automation, and thirdly, workers are displaced and end up working in jobs where they are even less productive such as home production, self-employment, or unemployed.

Because $a(r,s;\mathbf{0})$ and $a(r,s;\mathbf{1})$ fall with s, since $F(t|s)$ improves in the sense of FOSD with s and the pass-trough from productivity and the outside option to wages is lower than one, and $y(r,s)$ is non-decreasing in s, we have the following result.

Corollary 2. *Workers of higher classes are more likely to be displaced inefficiently.*

Thus, while it might be the case that high-skilled workers are displaced less often than low-skilled workers, when displacement does occur, it is more likely to be inefficient.

5.2 Constrained Welfare Efficiency

Let's consider a benevolent social planner who chooses automation to maximize profits plus workers' surplus without intervening in the market structure and firms' ability to set wages. Because firms have market power, wages are not equal to the marginal product of labor.

The central planner solve the following problem: $\max_{d\in\{0,1\}^n}\{W(d)\}$, where

$$W(d) = \max\{d(n\Pi + U) + (1-d)(ny(r,s) + b(s))\},$$

$$U \equiv n\int_{b(s)-w(b,r,s)}^{\bar{\epsilon}} (w(b,r,s)+\epsilon)G^{n-1}(\epsilon)dG(\epsilon), \tag{9}$$

and

$$\Pi \equiv (\mathbb{E}_t[y(t,r,s)] - w(b,r,s))\frac{1-G^n(b(s)-w(b,r,s))}{n}.$$

Thus, it is efficient to automate the jobs in labor market s whenever

$$ny(r,s) + b(s) \geq n\int_{b(s)-w}^{\bar{\epsilon}} (\mathbb{E}_t[y(t,r,s)]+\epsilon)G^{n-1}(\epsilon)g(\epsilon)d\epsilon.$$

After integration-by-parts,[16] it is efficient to automate the job if and only if

$$y(r,s) \geq a^*(b,r,s),$$

where

$$a^*(b,r,s) =: \frac{1}{n}\left(\mathbb{E}_t[y] - b + \bar{\epsilon} - (\mathbb{E}_t[y] + b - w)G^n(b-w) - \int_{b-w}^{\bar{\epsilon}} G^n(\epsilon)d\epsilon\right),$$

where this fully accounts for the worker's outside option and non-pecuniary benefits.

It readily follows that firms' automation decisions overlook workers' non-pecuniary benefits and the value of the outside option, which are only partially captured by the equilibrium wage. Thus, we conclude the following.

Proposition 9 (Constrained Welfare Efficiency)**.** *Suppose a symmetric equilibrium.*

i) If $y(r,s) \geq a^*(b,r,s)$, the job is efficiently automated and workers are efficiently displaced.

ii) If $a^*(b,r,s) \geq y(r,s) > a(r,s,\mathbf{0})$, the job is inefficiently automated and workers are inefficiently displaced.

iii) If $a(r,s,\mathbf{0}) \geq y(r,s) > a(r,s;\mathbf{1})$, the job is inefficiently automated with probability $1-\alpha(b,r,s)$ and efficiently assigned to human skills with probability $\alpha(b,r,s)$. Workers are inefficiently displaced with probability $1-\alpha(b,r,s)$.

iv) If $y(r,s) < a(r,s;\mathbf{1})$, the job is efficiently assigned to human skills and workers are efficiently employed.

Let's define $a^*(b,r,s)|_{w=y}$ as the threshold above which the productivity of automation must be for this to be welfare efficient when workers are paid their marginal product of labor. Notice that $a^*(b,r,s)|_{w=y} > a^*(b,r,s)$.

Corollary 3. *There is more automation and work displacement than allocative efficiency and constrained allocative efficiency warrant when human-skills jobs are more productive.*

[16] Integration-by-parts implies the following

$$n\int_{b(s)-w}^{\bar{\epsilon}} \epsilon G(\epsilon)^{n-1} g(\epsilon)d\epsilon = \bar{\epsilon} - (b(s)-w)G^n(b(s)-w) - \int_{b(s)-w}^{\bar{\epsilon}} G(\epsilon)^n d\epsilon.$$

5.3 Taxing Automation

Keynes (1929) predicted that the rapid spread of technologies would bring "technological unemployment". Leontief made a similar prediction: "Labor will become less and less important... . Machines will replace more and more workers. I do not see that new industries can employ everybody who wants a job". These ideas are echoed by business people and politicians, who argue about the potential benefits of taxing automation based on the belief that it will lead to significant job losses and lower wages.

Because automation is inefficiently high, levying a tax $\tau \in \Re$ on automated jobs could mitigate productive and allocative inefficiencies, thereby avoiding the inefficient displacement of workers.[17] This policy is known as a "robot tax," a proposed policy under which companies would pay a tax for using robots or automated systems that replace human workers. This proposal was made by the European Parliament and by entrepreneurs, including Bill Gates. South Korea has indirectly addressed the issue by reducing the tax credit, leading to lower automation investment and increased employment. Namely, Kang, Lee, and Quach (2024) find, using Korean data, that a reduction in the tax credit reduces investments in automation and increase employment, lowers wage inequality due to slower wage growth in the upper half of the income distribution, and has a positive fiscal externality, implying that behavioral responses to reductions in the tax credit increased the government's revenue beyond the direct mechanical impact of the policy.

When $\mathbb{E}_t[y(t,r,s)] \geq y(r,s)$, then a tax satisfying $y(r,s) - \tau = a(r,s,\mathbf{1})$ re-establishes productive efficiency. In contrast, when $\mathbb{E}_t[y(t,r,s)] < y(r,s)$, no tax is required.

When $y(r,s) \in [a(r,s,\mathbf{1}), a^*(b,r,s))$, re-establishing allocative efficiency requires again finding a tax so that $y(r,s) - \tau = a(r,s,\mathbf{1})$ so that all firms prefer to open a vacancy instead of automating the job. In contrast, when $y(r,s) > a^*(b,r,s)$, no tax is needed since $a^*(b,r,s) > a(r,s,\mathbf{1})$ and, thereby, firms automate the job as efficiency requires.

To the extent that automation cannot be taxed directly, the alternative is to tax technological capital; however, this has the drawback of lowering the marginal product of labor, as adopting generative AI becomes more burdensome and as automated jobs that can be

[17]The same result can be obtained by taxing the investment in robots a. This will result in the capitalization of automation decreasing with the tax rate τ. However, an investment tax will result in inefficient investments for jobs that can be efficiently automated.

efficiently automated become less productive. The tax also reduces the equilibrium wage; therefore, the outside option is taken more often, resulting in a corresponding extra loss in expected non-pecuniary benefits. To see this, let's suppose that a tax τ is levied on technological capital. Then, the optimal investment in artificial intelligence will be lower. Let the output in a human skill job be $\mathbb{E}_t[y(t,r,s,\tau)]$ and that in an automated job be $y(r,s,\tau)$. Observe that

$$\frac{\partial \mathbb{E}_t[y(t,r,s,\tau)]}{\partial \tau} = -r\mathbb{E}_t h(t,r,s,\tau) \text{ and } \frac{\partial y(r,s,\tau)]}{\partial \tau} = -ra(r,s,\tau).$$

Because $\mathbb{E}_t h(t,r,s,\tau)$ rises with s, the impact of technological capital tax on human skill jobs is larger in labor markets when more advanced skills are needed.

If $\mathbb{E}_t[y(t,r,s)] > y(r,s) > a(r,s,\tau;\mathbf{0})$, then to reestablish productive efficiency requires that $y(r,s,\tau)$ to fall with τ at a faster rate than $a(r,s,\tau;\mathbf{0})$, while if $a(r,s,\tau;\mathbf{0}) \geq y(r,s) > a(r,s,\tau;\mathbf{1})$, $y(r,s,\tau)$ must fall with τ at a faster rate than $a(r,s,\tau;\mathbf{1})$. Thus, for $v \in \{1,n\}$, the following must hold

$$-ra(r,s,\tau) < \frac{1}{v}\frac{r\mathbb{E}_t h(t,r,s,\tau)}{1-m'(b-w)}\Big(vm'(b-w)(1-G(b-w)^v) - m(b-w)G(b-w)^{v-1}g(b-w)\Big). \tag{10}$$

If $a^*(b,r,s) > y(r,s) > a(r,s,\tau;\mathbf{0})$, reestablishing allocative efficiency requires the condition in equation 10 to hold.

When $a(r,s,\tau;\mathbf{0}) \geq y(r,s) > a(r,s,\tau;\mathbf{1})$, the central planner choose the tax to maximize total welfare

$$\alpha(b,r,s,\tau)n\int_{b(s)-w}^{\bar{\epsilon}}(\mathbb{E}_t[y(t,r,s)]+\epsilon)G^{n-1}(\epsilon)g(\epsilon)d\epsilon + (1-\alpha(b,r,s,\tau))(ny(r,s)+b(s)),$$

where $\alpha(b,r,s,\tau)$ be the mixed strategy when the tax rate is τ.

Because $\mathbb{E}_t[y(t,r,s,\tau)]$ falls with τ, and the pass-through from $\mathbb{E}_t[y(t,r,s,\tau)]$ to wages is lower than 1, the rent from human-skill jobs falls with τ. This implies that $a(r,s,\tau;\alpha(b,r,s))$ falls, holding $\alpha(b,r,s)$ constant, with τ. Thus,

$$\frac{\partial \alpha(b,r,s,\tau)}{\partial \tau} = \frac{y_\tau(r,s,\tau) - a_\tau(r,s,\tau;\alpha)}{a_\alpha(r,s,\tau;\alpha)}\Big|_{\alpha=\alpha(b,r,s)} \lesseqgtr 0,$$

where $a(r,s,\tau;\alpha)$ is defined in equation (8) and is increasing in α.

The first-order condition is as follows

$$
\begin{aligned}
&-\alpha(b,r,s,\tau)nr\mathbb{E}_t[h(t,r,s,\tau)])\Bigg(\int_{b-w}^{\bar{\epsilon}} G^{n-1}(\epsilon)g(\epsilon)d\epsilon+\\
&\frac{1}{1-m'(b-w)}\big(\mathbb{E}_t[y]+b-w\big)G^n(b-w)g(b-w)\Bigg)-(1-\alpha(b,r,s))nra(r,s,\tau)+\\
&\alpha_\tau(b,r,s,\tau)n\big(a^*(b,r,s,\tau)-y(r,s,\tau)\big)\leq 0
\end{aligned}
$$

Because $a(r,s,\tau;\alpha)$ falls with α, if $y_\tau(r,s,\tau) > a_\tau(r,s,\tau;\alpha)$, an increase in τ rises the probability that the job is assigned to human skills. This increases welfare since $a^*(b,r,s,\tau) > y(r,s,\tau)$. Whereas, if $y_\tau(r,s,\tau) < a_\tau(r,s,\tau;\alpha)$, an increase in τ lowers the probability that the job is assigned to human skills. This decreases welfare.

In addition, an increase in the technological capital tax lowers wages and productivity in both automated and human-skill jobs due to the inefficient investment in artificial intelligence. Thus, holding the probability that the job is assigned to human skills constant, welfare falls with the tax rate.

Thus, taxing capital results in the following trade-off. On the one hand, it improves the allocation of workers to jobs by reducing inefficient automation whenever $y_\tau(r,s,\tau) > a_\tau(r,s,\tau;\alpha)$. Therefore, firms are more likely to open a vacancy when it is efficient to do. On the other hand, those who keep their job are paid a lower expected wage than before since generative AI capital falls with the tax rate. This also induces more workers to take their outside options, harming efficiency. Thus, welfare falls. The optimal tax rate balances this trade-off.

In contrast, when$y_\tau(r,s,\tau) \leq a_\tau(r,s,\tau;\alpha)$, taxing capital worsens the allocation of workers to jobs by increasing inefficient automation. This reinforces the effect on wages and productivity, making automation capital taxes a poor instrument for improving welfare. In this case, a subsidy on automation capital will be needed.

6 Artificial Intelligence and Skill Acquisition

In this section, we study how labor market power and automation influence workers' incentives to invest in skills. We will assume that workers can invest in human capital (skills) before firms make decisions about automation. Namely, workers ca choose their labor market class s at a cost $c(s)$. This is an increasing, convex function, and $c(0) = 0$. We can think of s as being the high-school graduation, college graduation, post graduates, as well as degrees in different fields arts, astronomy, physics, etc. To facilitate tractability, we make s a continuous variable.

First, we will focus on the case in which the continuation equilibrium is in mixed strategy. Workers choose s to maximize expected utility; that is, solve

$$\max_{s\in\Re_+}\{\alpha(b,r,s)U(w(b,r,s) + (1-\alpha(b,r,s))b(s) - c(s)\}.$$

Because $\mathbb{E}_t[y(t,r,s)]$ rises with an increase in s since this implies a FOSD improvement in $F(t|s)$, and the pass-through from $\mathbb{E}_t[y(t,r,s)]$ and $b(s)$ to wages is lower than 1, the rent from human-skill jobs increases with s. This implies that $a(r,s;\alpha(b,r,s))$ rises, holding $\alpha(b,r,s)$ constant, with s. Thus,

$$\frac{\partial\alpha(b,r,s)}{\partial s} = \frac{y_s(r,s) - a_s(r,s;\alpha)}{a_\alpha(r,s;\alpha)}\Big|_{\alpha=\alpha(b,r,s)} \lesseqgtr 0,$$

where $a(r,s,\tau;\alpha)$ is defined in equation (8) and is increasing in s, since $b_s(s) \geq 0$ and $w_s(\cdot) > 0$.

The first-order condition is as follows

$$\begin{aligned}&\alpha(b,r,s)\left(\frac{\mathbb{E}_{ts}[y(t,r,s)] - m'(b(s)-w(b,r,s))b_s(s)}{1-m'(b(s)-w(b,r,s))}\int_{b(s)-w(b,r,s)} G^n(\epsilon)g(\epsilon)d\epsilon + \right. \\ &\left.\frac{\mathbb{E}_{t,s}[y(t,r,s)]b_s(s)}{1-m'(b-w)}b(s)G^n(b(s)-w(b,r,s))g(b-w(b,r,s))\right) + \\ &(1-\alpha(b,r,s))b_s(s) + \alpha_s(b,r,s)(U(w(b,r,s)) - b(s)) - c_s(s) \leq 0.\end{aligned} \tag{11}$$

Let's denote the solution to the first-order condition by $s(r)$. The first-order condition reveals two effects that can be either opposing or complementary. First, a worker chooses paid employment with probability $1 - G^n$, and the pass-through from y to wages is $1/(1-m') < 1$. Hence, he does not fully internalize the full return to his investment. Because of this, the worker's incentives to improve his skills are, ceteris paribus, lower than they are in a competitive market. This happens because the worker is the full residual claimant to his investment's return when the market is competitive. Thus, market power creates a hold-up problem from the workers' perspective.

Second, an increase in investment in skills may increase or decrease the probability that firms open vacancies. When it decreases, the hold-up problem intensifies, leading to even weaker incentives to invest. In contrast, when the likelihood that the firm opens a vacancy in the corresponding market rises with s, workers have stronger incentives to upgrade their skills, since this increases the likelihood of paid employment. This counterweighs the hold-up problem.

If we assume that $y_s(r,s) < a_s(r,s,\alpha)$, then $\alpha(b,r,s)$ rises with s, which means that firms are more prone to open a vacancy for workers in higher labor markets than for workers in low ones. In this case, incentives to advance up the skill ladder are more effective. If the opposite holds, those are less strong. An increasing $\alpha(b,r,s)$ with s seems more plausible, as the evidence suggests that automation is less effective at substituting for workers in labor markets that require more advanced skills (high-skilled labor markets).

Second, let's consider the equilibrium in pure strategies. In this case, the third term in the first-order condition (11) is zero, except for inframarginal worker classes, i.e., those for which $y(r,s) = a(r,s,\mathbf{0})$ or $y(r,s) = a(r,s,\mathbf{1})$.

If $y(r,0) > a(r,0,\mathbf{d})$ and $y_s(r,s) < a_s(r,s,\mathbf{d})$ for all s, then there is class threshold $s(\mathbf{d})$ such that $y(r,s) \leq a(r,s,\mathbf{d})$ for all $s \geq s(\mathbf{d})$. Thus, if a worker invests $s(\mathbf{1})$, he can belong to a labor market class where workers are not displaced by automation. If a worker invests $s(\mathbf{0})$, he can belong to a labor market class where workers are not displaced with probability $\alpha(b,r,s)$. Thus, a worker invests $s(r)$ only if

$$\alpha(b,r,s(r))\big(U(w(b,r,s(r)) - b(s(r))\big) + b(s(r)) - c(s(r)) \geq U(w(b,r,s(\mathbf{0})) - c(s(\mathbf{0})). \tag{12}$$

Let $s_b \equiv \text{argmax}_{s\in\Re_+}\{b(s) - c(s)\}$.

Proposition 10. *Suppose that $\alpha(b,r,s)\big(U(w(b,r,s) - b(s)\big) + b(s) - c(s)$ is quasi-concave in s and $U(w(b,r,s(\mathbf{0})) - c(s(\mathbf{0})) \geq b(s_b) - c(s_b)$. Then a worker invest $\max\{s(\mathbf{0}), s(r)\}$ to avoid being displaced by automation whenever the condition (12) holds. Otherwise, it invests $s = 0$. The investment in skills is sub-optimal relative to the welfare-maximizing skill level.*

Because workers are not full residual claimants on the return to skills, they underinvest relative to the level consistent with allocative efficiency. This happens because the minimum investment required to escape displacement is larger than the one under allocative efficiency, and the worker acquires skills based solely on wage impacts. In contrast, allocative efficiency requires choosing s based on the surplus from skills when the vacancy is open.

The evidence points to an increase in human capital investment among those more exposed to automation. However, by increasing training, they might not stop firms from automating jobs, but instead induce more hiring in other jobs where the acquired skills are productive. For instance, HeB, Janssen, and Leber (2023) find that workers exposed to substitution by automation are 15 percentage points less likely to participate in training than those not exposed to it. In addition, workers who leave occupations highly exposed to automation increase their training participation, while those who enter them train consistently less. The automation training gap is particularly pronounced among medium-skilled and male workers and is driven primarily by the lack of training in ICT and soft skills. Moreover, workers in exposed occupations receive less financial and non-financial training support from their firms, and this training gap is almost entirely due to a shortfall in firm-financed training courses.

Dauth, Findeisen, Suedekum, and Woessner (2021) find that robots' adoption is associated with displacement effects in manufacturing, but these are fully offset by new jobs in services. The most affected are young workers just entering the labor force. Automation is associated with more stable employment within firms for incumbents, driven by workers taking on new tasks in their original plants. However, young workers change their human capital investment strategy away from vocational training and towards colleges and universities.

Innocenti and Golin (2022) find, using data from representative samples of working individuals in 16 countries, that workers' intentions to invest in training outside their workplace–controlling for other behavioral traits– increase with the fear of automation. They also report that fear of automation reinforces the effect that internal locus of control exerts on retraining intentions.

7 Conclusions

This paper argues that when labor markets are non-competitive, i) firms' automation adoption rate falls as market power rises, and ii) firms automate more jobs than productive and allocative efficiency requires when human-skills jobs are more productive. Conditional on automation not taking place, the adoption of generative AI aligns with productive efficiency; that is, when generative AI has a comparative advantage over solo human-skill jobs. However, due to excessive automation, there is insufficient adoption of generative AI. This occurs because firms with market power choose automation by comparing the cost of hiring a worker to the cost of automating the job.

Because automation is adopted more frequently than efficiency demands, we argue that a tax on technological capital can address the productive and welfare inefficiencies caused by automation. However, it gives rise to productive and welfare inefficiency in the adoption of generative AI and lowers wages. Thus, taxing technological capital must be done by balancing the inefficiency caused by excessive automation against the inefficiency resulting from the induced shortage of jobs when generative AI is adopted, along with the concurrent wage loss.

Last but not least, we argue that workers who anticipate being displaced may overinvest in human capital to increase the rent from human-skill jobs, making automation relatively less profitable. However, workers from low-skill classes might be completely discouraged from investing in skills, as they anticipate their jobs will be automated even when they acquire human skills.

References

Acemoglu, D. and Restrepo, P. Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244, 2020. doi: 10.1086/705716.

Acemoglu, D. and Restrepo, P. Tasks, Automation, and the Rise in US Wage Inequality. NBER Working Papers 28920, National Bureau of Economic Research, Inc, June 2021.

Acemoglu, D. and Restrepo, P. Demographics and automation. *The Review of Economic Studies*, 89(1):1–44, 2022. doi: None.

Acemoglu, D. and Restrepo, P. Automation and rent dissipation: Implications for wages, inequality, and productivity. Technical report, National Bureau of Economic Research, 2024.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. The effects of automation on labor demand. *Robots and AI: A new economic era*, pages 15–39, 2022.

Autor, D., Chin, C., Salomons, A. M., and Seegmiller, B. New Frontiers: The Origins and Content of New Work, 1940–2018. NBER Working Papers 30389, National Bureau of Economic Research, Inc, August 2022.

Azar, J., Berry, S., and Marinescu, I. E. Estimating labor market power. *Available at SSRN 3456277*, 2019.

Balmaceda, F. Market Power and Occupational Mismatch. *Journal of Development Economics*, R&R, 2025.

Bessen, J. Learning by doing: The real connection between innovation, wages, and wealth. In *Learning by Doing*. Yale University Press, 2015.

Bessen, J., Goos, M., Salomons, A., and Bergevan den , W. Firm-level automation: Evidence from the netherlands. *AEA Papers and Proceedings*, 110:389–93, May 2020. doi: 10.1257/pandp.20201004.

Choi, H. and Marinescu, I. Data for labor market concentration using lightcast (formerly burning glass technologies). *Data in Brief*, 55:110647, August 2024. ISSN 23523409. doi: 10.1016/j.dib.2024.110647.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153, 05 2021. ISSN 1542-4766. doi: 10.1093/jeea/jvab012.

De Loecker, J. and Warzynski, F. Markups and firm-level export status. *American Economic Review*, 102(6):2437–71, May 2012. doi: 10.1257/aer.102.6.2437.

De Souza, G. and Li, H. Robots, Tools, and Jobs: Evidence from Brazilian Labor Markets. Technical report, 2023.

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

Eggleston, K., Lee, Y. S., and Iizuka, T. Robots and labor in the service sector: Evidence from nursing homes. NBER Working Papers 28322, National Bureau of Economic Research, Inc, 2021.

Eslava, M., García-Marín, A., and Messina, J. Inequality and Market Power in Latin America and the Caribbean. IDB Publications (Working Papers) 13192, Inter-American Development Bank, October 2023.

Gabaix, X., Laibson, D., Li, D., Li, H., Resnick, S., and Vriesde , C. The impact of competition on prices with numerous firms. *Journal of Economic Theory*, 165(C):1–24, 2016.

Hall, R. E., Blanchard, O. J., and Hubbard, R. G. Market structure and macroeconomic fluctuations. *Brookings papers on economic activity*, 1986(2):285–338, 1986.

HeB, P., Janssen, S., and Leber, U. The effect of automation technology on workers' training participation. *Economics of Education Review*, 96:102438, 2023. ISSN 0272-7757. doi: https://doi.org/10.1016/j.econedurev.2023.102438.

Innocenti, S. and Golin, M. Human capital investment and perceived automation risks: Evidence from 16 countries. *Journal of Economic Behavior Organization*, 195:27–41, 2022. ISSN 0167-2681. doi: https://doi.org/10.1016/j.jebo.2021.12.027.

Kang, D., Lee, J. H., and Quach, S. The welfare effects of a robot tax: Evidence from a tax credit for automation technologies in korea. October 2024. Available at SSRN: `https://ssrn.com/abstract=5005128` or `http://dx.doi.org/10.2139/ssrn.5005128`.

Koch, M., Manuylov, I., and Smolka, M. Robots and Firms. *Economic Journal*, 131(638): 2553–2584, 2021.

Lamadon, T., Mogstad, M., and Setzler, B. Imperfect competition, compensating differentials, and rent sharing in the us labor market. *American Economic Review*, 112(1):169–212, January 2022. doi: 10.1257/aer.20190790.

Maestas, N., Mullen, K. J., Powell, D., Wachtervon , T., and Wenger, J. B. The value of working conditions in the united states and implications for the structure of wages. Working Paper 25204, National Bureau of Economic Research, October 2018.

Manning, A. Monopsony in labor markets: A review. *ILR Review*, 74(1):3–26, 2021. doi: 10.1177/0019793920922499.

Marx, K. *Das Capital Bd. 3*. Verlag von Otto Meissner, 1894.

Mas, A. and Pallais, A. Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–59, December 2017. doi: 10.1257/aer.20161500.

Milgrom, P. and Roberts, J. Rationalizability, learning, and equilibrium in games with strategic complementarities. *Econometrica*, 58(6):1255–77, November 1990.

Perloff, J. M. and Salop, S. C. Equilibrium with Product Differentiation. *Review of Economic Studies*, 52(1):107–120, 1985.

Rosen, S. The theory of equalizing differences. In Ashenfelter, O. and Layard, R., editors, *Handbook of Labor Economics*, volume 1 of *Handbook of Labor Economics*, chapter 12, pages 641–692. Elsevier, 1987.

Sorkin, I. Ranking firms using revealed preference. *The Quarterly Journal of Economics*, 133 (3):1331–1393, 2018.

Sullivan, P. and To, T. Search and nonwage job characteristics. *Journal of Human Resources*, 49(2), 2014.

Webb, M. The impact of artificial intelligence on the labor market. *Available at SSRN: https://ssrn.com/abstract=3482150*, pages 15–39, 2020.

Yeh, C., Macaluso, C., and Hershbein, B. Monopsony in the us labor market. *American Economic Review*, 112(7):2099–2138, July 2022. doi: 10.1257/aer.20200025.

Zhou, J. Competitive bundling. *Econometrica*, 85(1):145–172, 2017. doi: 10.3982/ECTA14251.

A Appendix

A.1 Methodology and Data: Evidence at the Commuting-Zone Level

A.1.1 Data: Herfindahl-Hirschman Index

We use data from Choi and Marinescu (2024). They use job vacancy data from Lightcast covering 2007Q1 to 2021Q2 and measure labor market concentration by using Herfindahl-Hirschman Index (HHI) at the six-digit SOC occupation, commuting-zone-2000 (cz-2000), and quarter levels. HHI is calculated using posted vacancy shares by market (occupation x commuting zone) and quarter. The share of vacancies of a firm in a given market and quarter is calculated as the number of vacancies posted by the firm in the market and quarter divided by total vacancies posted by all firms in that market and quarter. HHI by market m and quarter t is defined as the sum of squared shares.

$$HHI_{m,t} = \sum_{j \in J} S^2_{j,m,t}$$

where $S_{j,m,t}$ is the share of vacancies of firm j in market m and quarter t.

The authors provide a lower bound for the HHI, where they assume that all missing employer names are different from one another and from those correctly identified, and an upper bound, where they assume that all missing employer names correspond to a single firm.

The authors provide data scaled by a factor of 1000, but we re-scale the data to have HHI between 0 and 1. Additionally, we aggregate HHI by markets defined only by commuting zone. Since vacancies shares by occupations within commuting zones is not publicly available, we do so using a simple average.

Furthermore, we merge this dataset with data from Acemoglu and Restrepo (2022) on robot integrators, exposure to robots, and demographics and economic characteristics by commuting-zone-1990 (cz-1990). As the definition of commuting zones in both datasets is not the same, and the crosswalk between cz-2000 and cz-1990 is not one-to-one, we therefore calculate a weighted average of HHI at the cz-1990 level, weighted by the number of counties shared between cz-2000 and cz-1990.

A.1.2 Data: Robot Integrators and Controls

Estimations performed by Acemoglu and Restrepo (2022) include the following controls:

i) Census region dummies.

ii) Demographic and economic controls, including the male share of the labor force in 1990, the urban share in 1990, the ratio of older to middle-aged workers in 1990, log GDP in 1990, log Population in 1990, the share of workers by five educational levels in 1990, and the share of workers by five racial groups in 1990. These variables come from NHGIS (**?**) (as cited in Acemoglu and Restrepo (2022)).

iii) Employment shares for 5 broad industrial categories in 1990: Agriculture, Mining, Construction, Manufacturing, and Financial and Real State, using data from NHGIS (**?**) (as cited in Acemoglu and Restrepo (2022)).

iv) The measure of exposure-to-robots between 1993 and 2007 from **?**, which captures the extent to which a commuting-zone houses industries that are adopting robots at higher rates and it is defined as:

$$exposure - to - robots_c^{t_0,t_1} = \sum_{i \in \mathcal{I}} l_{ci}^{1970} \overline{APR}_i^{t_0,t_1}$$

where $exposure - to - robots_c^{t_0,t_1}$ represents the exposure-to-robots in commuting-zone c between years t_0 and t_1. It is a weighted average of the adjusted-penetration-of-robots in industry i between years t_0 and t_1 ($\overline{APR}_i^{t_0,t_1}$), weighted by the labor share of industry i within commuting zone c in 1970 (l_{ci}^{1970}). In turn, the adjusted-penetration-of-robots in industry i between years t_0 and t_1 is defined as,

$$\overline{APR}_i^{t_0,t_1} = \frac{1}{5} \sum_{j \in \mathcal{J}} \left[\frac{M_{i,t_1}^j - M_{i,t_0}^j}{L_{i,1990}^j} - g_{i,(t_0,t_1)}^j \frac{M_{i,t_0}^j}{L_{i,1990}^j} \right]$$

where $M_{i,t}^j$ is the stock of industrial robots in industry i in country j in year t, $L_{i,1990}^j$ is the employment level in industry i in country j in 1990, and $g_{i,(t_0,t_1)}$ is the output growth rate of industry i in country j between years t_0 and t_1. The set of countries $\mathcal{J}$ is comprised by five European countries—Denmark, Finland, France, Italy, and Sweden—that were ahead from the U.S. in the adoption of robots. The authors use this European countries instead of the United States in order to avoid variations arising from idiosyncratic U.S. factors. They use data from the International Federation of Robotics (IFR) for the stock of industrial robots, which is proprietary, and data from the EU KLEMS dataset for output growth and employment levels (as cited in **?**)). For the employment share by industry and commuting-zone in the United States in 1990, they use data from the 1970, 1990, and 2000 Censuses and the American Community Survey (ACS (**?**); as cited in **?**). The disaggregated data of the stock of robots by industry and country is not available, but the authors made publicly available the data for the adjusted-penetration-of-robots by industry in several intervals and exposure-to-robots by industry and commuting-zone in several intervals.

v) Exposure to Chinese imports and the labor share in routine occupations by commuting-zone from **?** (as cited in **?**)

A.1.3 Methodology

Acemoglu and Restrepo (2022) study the causal effect of labor-force aging on the presence of robotics-related activity at the commuting-zone-1990 level. They proxy robotics-related activities by the presence of robot integrators in year 2015—companies that install, program, and maintain robots—using data originally compiled by **?** (as cited in Acemoglu and Restrepo (2022)).

The authors define aging as the difference between the ratio of older workers (above 55 years) to middle-aged workers (21-55 years) in 2015 and 1990, using data from the NBER Survey of Epidemiology and End Results dataset (NBER-SEER), as cited in Acemoglu and Restrepo (2022). Their argument is that middle-aged workers typically perform manual production tasks in a greater proportion, and that the scarcity of such workers generates upward pressure on wages, leading firms to replace them with industrial robots. Furthermore, they use the change in ratios because investment in robots is forward-looking and robots have a life-span of about 12 years; therefore, purchases made in 2003 would already reflect expectations of labor-force aging through 2015.

We reproduce single-IV estimations of section 6 in Acemoglu and Restrepo (2022), but including HHI as an additional regressor.

$$integrators_c = \beta_0 + \beta_1 HHI_c + \beta_2 Aging_c + \Gamma X_{c,1990} + \nu_c$$

where the subscript c represents the commuting-zone. $integrators_c$ is a dummy variable that indicates the presence of robots integrators. HHI_c is the Herfindahl-Hirschman Index, and we perform separate estimations using the lower bound and the upper bound. $Aging_c$ is the labor force aging measure defined by Acemoglu and Restrepo (2022) and described in the previous section. Finally, $X_{c,1990}$ is a set of controls at the commuting-zone level, the majority of them with base levels in 1990, and ν_c is the error term.

A.2 Methodology and Data: Evidence at the Country Level

A.2.1 Data: Markdowns by Country

We estimate markdowns using the methodology of Eslava et al. (2023). They follow the production approach used by Hall, Blanchard, and Hubbard (1986) and De Loecker and Warzynski (2012) to estimate markups, which has been extended to markdowns by several authors (Yeh, Macaluso, and Hershbein (2022) among others).

Using the same notation as in Eslava et al. (2023). The De Loecker and Warzynski (2012) markup formula for firm i at time t is given by:

$$\mu_i \equiv \frac{P_i}{MC_i} = \left(\frac{\partial F(.)}{\partial X_i^{k'}} \frac{X_i^{k'}}{Q_i}\right) \left(\frac{V_i^{k'} X_i^{k'}}{P_i Q_i}\right)^{-1}$$

where $X_i^{k'}$ is the amount of input k' used. It is assumed that input k' is fully flexible, static, and not subject to monopsony forces. $V_i^{k'}$ denotes the unit price of input k' for firm i.

If it is assumed that labor is a fully flexible input and not subject to adjustment costs (hiring or firing costs), firm i has monopsony power. The F.O.C implies that the wage markdown for firm i at time t is given by:

$$\nu_i \equiv \frac{MPL_i}{w_i} \equiv \left[\frac{\partial \omega_i(l_i)}{\partial l_i} \frac{l_i}{\omega_i(l_i)} + 1\right] = \frac{1}{\mu_i} \left[\left(\frac{\partial F(.)}{\partial l_i} \frac{l_i}{Q_i}\right) \left(\frac{\omega_i l_i}{P_i Q_i}\right)^{-1}\right]$$

The methodology allows for calculating markdowns using only accounting data about a firm's input, labor, and sales costs. We require labor and input costs and production function input(labor) elasticities at the firm level to estimate markups and markdowns. Costs are taken directly from the WBES data. To estimate elasticities, Eslava et al. (2023) assume that all firms within a given economic sector share the same CRS production function regardless of the country.[18] [19] These assumptions enable the calculation of input elasticities as the average cost share across all firms in the WBES dataset:

$$\hat{\eta}_{sector} \equiv \frac{1}{N} \sum_{i \in sector} \frac{\omega_i l_i}{P_i Q_i} = \left(\frac{\partial F(.)}{\partial l} \frac{l}{Q}\right)$$

[18] Economics sectors are defined by 2-digit ISIC Rev 3 groups.

[19] Defined by 2-digit ISIC Rev 3 groups.

The World Bank Enterprise Surveys (WBES) is the only data source for estimating markups and markdowns. WBES has a stratified sample designed to be representative of the manufacturing sector (Group D ISIC Rev 3) and the retail sector (ISIC 32 Rev 3) for all countries. We estimate firm markdowns and calculate weighted country-year averages[20].

We follow the data cleaning and imputation procedures described in Eslava et al. (2023): we filter out non-representative data[21]. When labor or input costs are missing, they are imputed using the predictions of a weighted country-specific regression of costs on sales, including (two-digit)industry-year fixed effects. Additionally, we drop outlier observations of cost shares in sales by removing those below the 5th percentile and above the 95th percentile. Moreover, we truncate costs that exceed sales while keeping the ratio between labor and input costs constant. Finally, we drop country-year with less than 250 firms in the sample.

The procedure described above allow us to estimate markdowns for 108 unique countries with surveys performed between 2006 and 2024[22], resulting in 202 country-year observations.

A.2.2 Data: Imports of Robots and Controls

We use data of imports of industrial robots and country-level controls from Acemoglu and Restrepo (2022):

i) Data of imports of industrial robots comes from UN COMTRADE. Industrial robots are included in the HS-1996 code 847950, which was introduced in 1996. Since imports is a flow variable, the authors calculate the accumulated total value of imports of industrial robots between 1996 and 2015, net of re-export. The authors restrict the sample to those countries with net imports of robots greater than zero. Furthermore, they exclude Germany, which is a major robot producer, and Luxembourg, a major entry port to the European community.

ii) The authors use data of population and birth rates from the UN World Population Prospects for 2015, which provides estimations on population by age up to 2050.

[20] Using expansion factors as weights.

[21] We only use observations in which managers declare that the data are taken directly from books or closely estimated from book records.

[22] 2020 is excluded to avoid non-representative data due to the Covid-19 Pandemic.

Their measure of aging is the difference between the ratio of older workers (above 55 years) to middle-aged workers (21-55 years) in 2025 (projected) and 1990. They instrument aging using birth rates by thousand people in seven five years intervals between 1950 and 1985.

iii) Data for industrial employments comes from ILO Modelled Estimates and it is adjusted by hours per worker from the Penn World Tables, version 9.0. The authors define industrial employment as comprising manufacturing, mining, construction and utilities, which are the sectors adopting robots.

iv) Country co-variates includes log GDP per capita (PPP adjusted) in 1995, log population in 1995, and average years of schooling in 1995 (originally from the Barro-Lee dataset). All these variables comes from the Penn World Tables, version 9.0.

v) Additional co-variates includes the manufacturing value added in 1995 (expressed in constant 2015 U.S. dollars) from UNIDO and the log of the total value of intermediate imports between 1996 and 2015, which are defined as products by goods whose two-digit HS codes is given by 82 (Tools), 84 (Mechanical machinery and appliances), 85 (Electrical machinery and equipment), 87 (Tractors and work trucks), and 90 (Instruments and apparatus).

A.2.3 Methodology

Acemoglu and Restrepo (2022) study the causal effect of labor-force aging on the variation of the stock of robots between 1993 and 2014 and also compare their results using net imports of robots relative to other intermediate imports between 1996 and 2015 as dependent variable. They use data from the IFR to measure the variation in the stock of robots, which is proprietary, and use data from UN COMTRADE[23] to measure net imports of robots and intermediate imports, which is publicly available. In Figure A6 in Acemoglu and Restrepo (2022) they show a strong positive correlation between log of robot stock variation per one thousand workers and log net imports of robots per one thousand workers.

[23] United Nations Commodity Trade Statistics Database

We replicate IV estimations on section 4.2 in Acemoglu and Restrepo (2022), but including markdowns for the manufacturing sector as an additional regressor and using the ratio of net imports of robots between 1996 and 2015 over one thousand industrial workers (level in 1995 and adjusted by hours per worker) as the dependent variable[24]. As the WBES survey have multiples waves for some countries, we calculate a simple average of the country-year markdowns observations available by country.

The equation estimated is as follow:

$$\frac{\Delta Im\_R_c^{1996to2015}}{L_{c,1995}} = \beta_0 + \beta_1 markdown_c + \beta_2 Aging_c + \Gamma X_{c,1995} + \mu_c$$

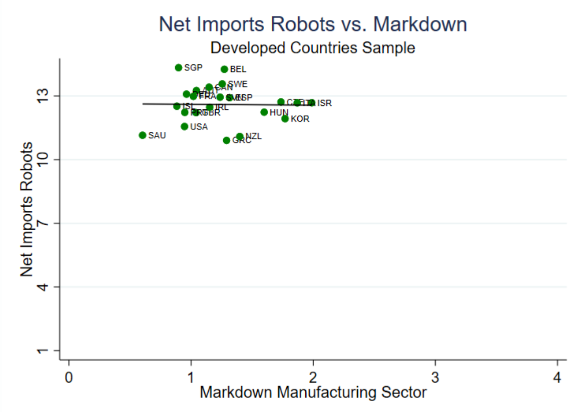
where subscript c denotes the country; $Im\_R_c^{1996-to-2015}$ is the accumulated trade value of imports of robots, net of re-exports, between 1996 and 2015; $L_{c,1995}$ is the industrial employment level in 1995 adjusted by hours per worker; $markdown_c$ is the markdown for the manufacturing sector estimated using the methodology from Eslava et al. (2023); $Aging_c$ is the aging measure from Acemoglu and Restrepo (2022); $X_{c,1995}$ is a set of controls with level in 1995; and μ_c is the error term.

We exclude India of the estimation, because considering this country an outlier with markdown of 3.14 and log of net imports of robots per one thousand industrial workers of 9.10. This was produced because India has a large value of net imports of robots, also has a large labor force, but a small level of industrial workers; additionally, has a low amount of hours per worker. We consider that the amount of hour per workers does not correspond to the hours worked in the industrial sector and that the imports of robots could be bias.

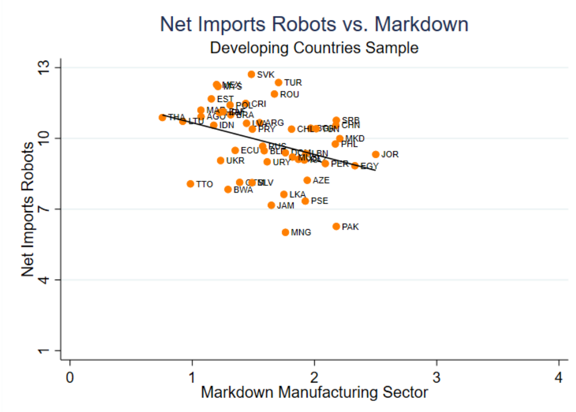
[24] Acemoglu and Restrepo (2022) use accumulated flow of imports of robots relative to other intermediate imports between 1996 and 2015 as the dependent variable. They also perform regressions weighted by manufacturing value added in 1990 (data from UNIDO), instead we perform unweighted regressions.

A.3 Graphs Net Imports Robots

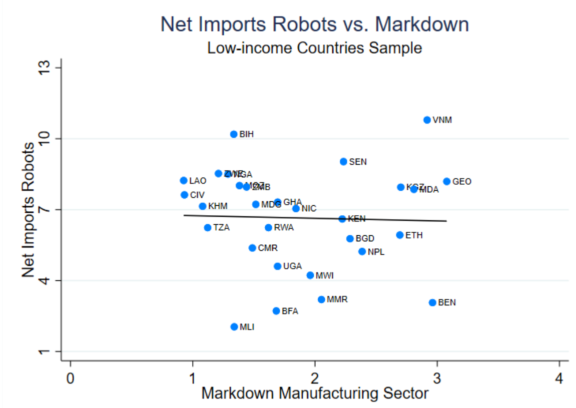
A.3.1 By Income Group



(a) Markdowns Manufacturing Sector. Developed Countries.



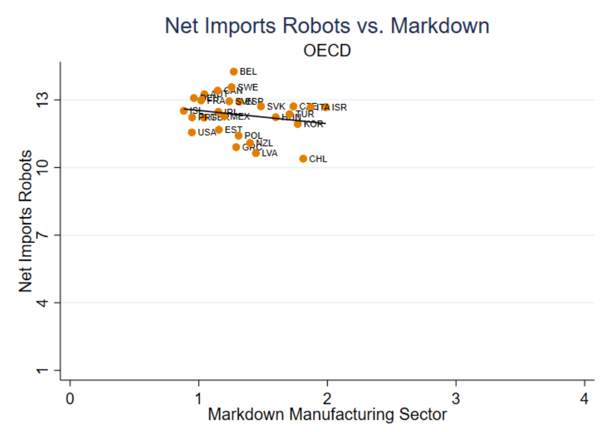
(b) Markdowns Manufacturing Sector. Developing Countries.



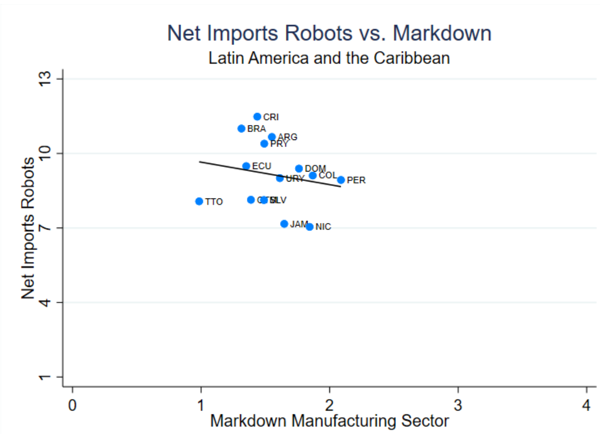
(c) Markdowns Manufacturing Sector. Other Countries.

Fig. 4. Markdowns manufacturing sector by income group.
Markdowns were estimated following the methodology of Eslava et al. (2023), using data from the World Bank Enterprise Surveys (WBES). Net Robot Imports is defined as robot imports net of re-exports, divided by one thousand workers, expressed in natural logs (Acemoglu and Restrepo, 2022).

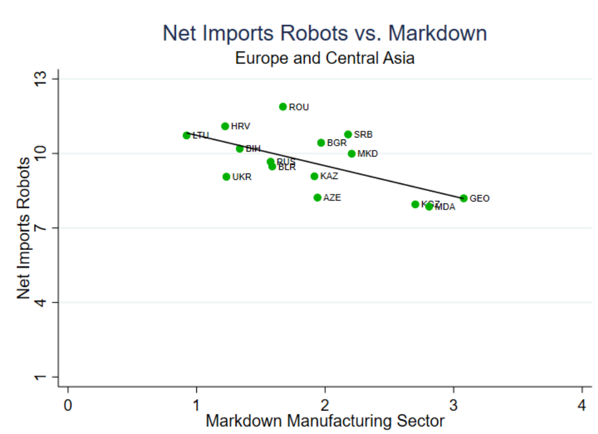
A.3.2 By Region



(a) OECD.

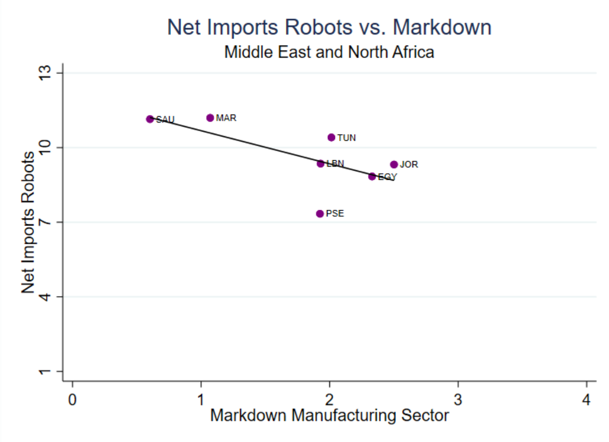


(b) Latin America and the Caribbean.

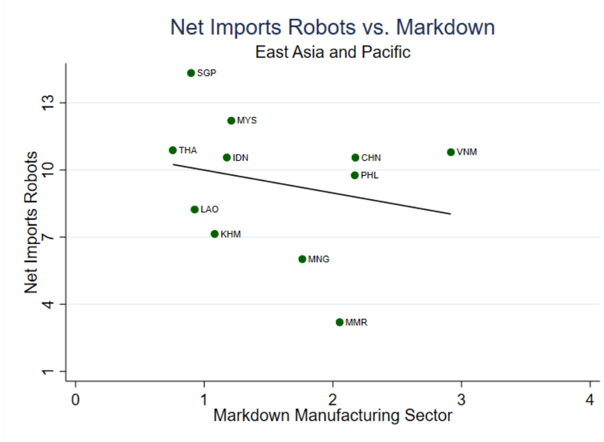


(c) Europe and Central Asia.

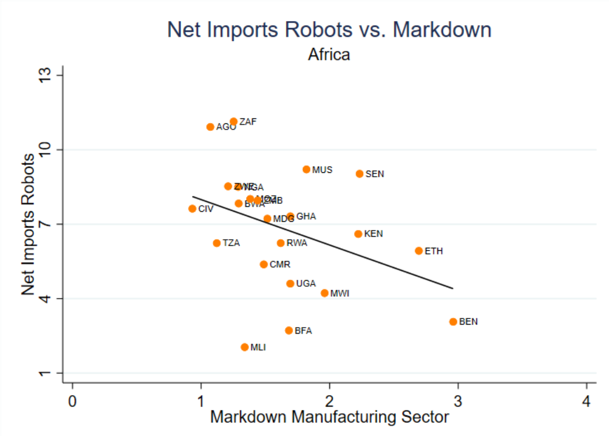
Fig. 5. Markdowns manufacturing sector by region.
Markdowns were estimated following the methodology of Eslava et al. (2023), using data from the World Bank Enterprise Surveys (WBES). Net Robot Imports is defined as robot imports net of re-exports, divided by one thousand workers, expressed in natural logs (Acemoglu and Restrepo, 2022).



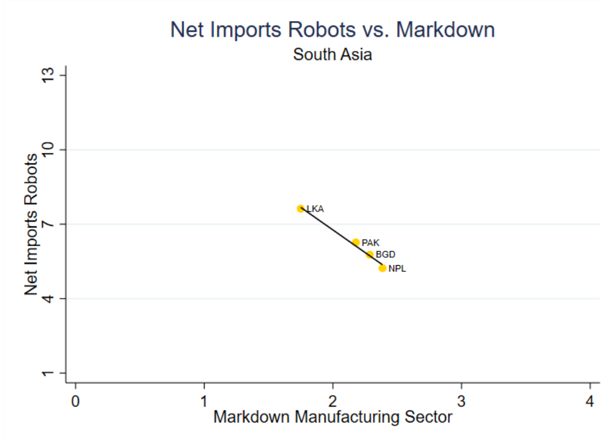
(a) Middle East and North Africa.



(b) East Asia and Pacific.



(c) Sub-Saharan Africa.



(d) South Asia.

Fig. 6. Markdowns manufacturing sector by region.
Markdowns were estimated following the methodology of Eslava et al. (2023), using data from the World Bank Enterprise Surveys (WBES). Net Robot Imports is defined as robot imports net of re-exports, divided by one thousand workers, expressed in natural logs (Acemoglu and Restrepo, 2022).

Proof of Lemma 1. Existence follows from Weiertress' Theorem and uniqueness from the log-concavity of the profit functions: the best response is the solution to

$$P^j_j(w) - \frac{1}{y^j(t,r,s) - w^j} = 0. \tag{A1}$$

It follows from this that profits are log-concave whenever

$$\frac{P^j(w)P^j_{jj}(w) - (P^j_j(w))^2}{(P^j(w))^2} - \frac{1}{(y^j(t,r,s) - w^j)^2} \leq 0, \tag{A2}$$

where the inequality follows from the fact that $P^j(w)$ is log-concave in w □

Proof of Proposition 3. The proof of this result follows closely Zhou (2017).

Recall that the first-order condition is given by

$$y(h,g) - w = \frac{1}{n(s)} \frac{1 - G(b(s) - w)^{n(s)}}{G(b(s) - w)^{n-1} g(b(s) - w) + \int_{b(s)-w}^{\bar{\epsilon}} g(\epsilon) dG(\epsilon)^{n-1}}. \tag{A3}$$

Lets define CDF of the second-highest order statistics by

$$G_{n-1}(b(s) - w) = G(b(s) - w)^{n(s)} + nG(b(s) - w)^{n-1}(1 - G(b(s) - w))$$

Observe that at $w = y$, the right-hand side equation (A3) is greater than the left-hand side since it is strictly positive. Let $\lambda_g(\cdot) \equiv g(\cdot)/(1 - G(\cdot))$ be the hazard rate. Let's define $w^m(y)$ as the wage when there is only one firm. It is easy to check that this is the unique (due to log-concavity of $g(\cdot)$) solution to the following equation

$$y - w^m = \frac{1}{\lambda_g(y - w^m)}.$$

Observe that at $w = w^m$, the LHS is larger than the RHS. To see this notice that

$$
\begin{aligned}
m(b(s) - w) =& \frac{1 - G(b(s) - w)^{n(s)}}{nG(b(s) - w)^{n-1} g(b(s) - w) + \int_{b(s)-w}^{\bar{\epsilon}} \lambda_g(\epsilon) dG_{n-1}(\epsilon)} \\
<& \frac{1 - G(b(s) - w)^{n(s)}}{nG(b(s) - w)^{n-1} g(b(s) - w) + \lambda_g(b(s) - w)(1 - G_{n-1}(b(s) - w))} \\
=& \frac{1}{\lambda_g(b(s) - w)},
\end{aligned}
$$

where the inequality follows from the fact λ_g is increasing. One deduces from this and the definition of $w(b, r, s)$, that the left-hand side is greater than the right-hand side at $w(b, r, s) = w^m(y, b(s))$. Thus, the first-order condition in equation (A3) has a solution $w \in [w^m(y, b(s)), y]$.

Because the left-hand side of the first-order condition in equation (A3) falls with w at rate equal to -1, the solution is unique if $m'(y - w) < 0$. To show that this is the case observe that

$$
m'(b(s) - w) = -n \frac{G(b(s) - w)^{n-1} g(b(s) - w)}{1 - G(b(s) - w)^{n(s)}} m(b(s) - w) \left(1 + m(b(s) - w) \frac{h'(b(s) - w)}{g(b(s) - w)} \right).
$$

Thus, $m'(b(s) - w) < 0$ if and only if

$$
ng(b(s) - w) \Big(G(b(s) - w)^{n-1} g(b(s) - w) + \int_{b(s)-w}^{\bar{\epsilon}} g(\epsilon) dG(\epsilon)^{n-1} \Big) + (1 - G(b(s) - w)^{n(s)}) h'(b(s) - w) >
$$

Using the fact that log-concavity implies that $(1 - G)h' + g^2 > 0$, one deduces that the inequality above holds if

$$
{}^{n}(s) \int_{-w}^{\bar{\epsilon}} g(\epsilon) dG(\epsilon)^{n-1} > (1 - G(b(s) - w)^{n(s)}) \lambda_g(b(s) - w) - nG(b(s) - w)^{n-1} g(b(s) - w).
$$

Using the definition of G_{n-1}, we re-write this as follows

$$
\int_{-w}^{\bar{\epsilon}} \lambda_g(\epsilon) dG(\epsilon)_{n-1} > (1 - G_{n-1}(b(s) - w)) \lambda_g(b(s) - w).
$$

The inequality holds because the hazard rate is increasing.

□

Proof of Proposition 1. Because G^k are identically distributed, for all $j \in \mathcal{J}(d)$

$$P^j(w) = \int_{b(s)-w^j}^{\bar{\epsilon}} \prod_{k \in \mathcal{J}(d^{-j})} G^k\Big(w^j + \epsilon^j - w^k\Big) dG^j(\epsilon^j),$$

and for all for all $j \in \mathcal{J}(d)$,

$$P^j_j(w) = \int_{b(s)-w^j}^{\bar{\epsilon}} \sum_{h \in \mathcal{J}(d^{-j})} \nu_g\Big(w^j + \epsilon^j - w^h\Big) \prod_{k \in \mathcal{J}(d^{-j})} G\Big(w^j + \epsilon^j - w^k\Big) dG(\epsilon^j) +$$
$$g(b(s) - w^j) \prod_{k \in \mathcal{J}(d^{-j})} G(b(s) - w^k),$$

where $\nu_g(\cdot) \equiv g(\cdot)/G(\cdot)$,

$$P^j_h(w) = -\int_{b(s)-w^j}^{\bar{\epsilon}} \nu_g\Big(w^j + \epsilon^j - w^h\Big) \prod_{k \in \mathcal{J}(d^{-j})} G\Big(w^j + \epsilon^j - w^k\Big) dG(\epsilon^j) < 0.$$

$P^j(w)$ is strictly increasing in w^j and is strictly decreasing in $w^{j'}$.

$P^j(w)$ is log-concave in w^j if and only if the following holds

$$\frac{1}{P^j(w)} P^j_{j,j}(w) - \frac{1}{(P^j(w))^2} (P^j_j(w))^2 \leq 0$$

This holds because the multitplication of log-concave functions is log concave and $G()$ is log-concave in w^j.

Also observe that for all $j \in \{1, \ldots, n\}$, we have that for all $j \in \mathcal{J}(d)$

$$P^j_{jj}(w) = \int_{b(s)-w_j}^{\bar{\epsilon}} \left(\sum_{h \in \mathcal{J}(d^{-j})} \nu'_g\Big(w_j + \epsilon_j - w_h\Big) + \left[\sum_{h \in \mathcal{J}(d^{-j})} u_g\Big(w_j + \epsilon_j - w_h\Big) \right]^2 \right) \times$$
$$\prod_{k \in \mathcal{J}(d^{-j})} G\Big(w_j + \epsilon_j - w_k\Big) dG(\epsilon_j) - h'(b(s) - w_j) \prod_{k \in \mathcal{J}(d^{-j})} G(b(s) - w_k).$$

Observe that for all $j, h \in \mathcal{J}(d)$, log-supermodularity implies

$$\frac{1}{P^j(w)} P^j_{j,j'}(w) - \frac{1}{(P^j(w))^2} P^j_j(w) P^j_{j'}(w) \geq 0.$$

Observe that

$$P^j_{jh}(w) = \int_{b(s)-w_j}^{\bar{\epsilon}} \left(-\nu'_g\Big(w_j+\epsilon_j-w_h\Big) - \nu_g\Big(w_j+\epsilon_j-w_h\Big) \sum_{h\in\mathcal{J}(d^{-j})} \nu_g\Big(w_j+\epsilon_j-w_h\Big)\right)\times$$
$$\prod_{k\in\mathcal{J}(d^{-j})} G\Big(w_j+\epsilon_j-w_k\Big)dG(\epsilon_j) + \nu_g\big(b(s)-w^h\big) \prod_{k\in\mathcal{J}(d^{-j})} G\big(-w^k\big)g(b(s)-w^j)$$

since $\nu'_h < 0$ because $g(\cdot)$ is log-concave.

□

Proof of Proposition 4. It follows from the first-order condition in equation (6) and uniqueness that the equilibrium wage increases with $x \in (y, b(s))$ if and only if

$$\frac{\partial w}{\partial x}(1-m'(b(s)-w)) = \frac{\partial y}{\partial x} - m'(b(s)-w)\frac{\partial b(s)}{\partial x} > 0. \tag{A4}$$

Because $m'(\cdot) < 0$, we deduce that $w(b,r,s)$ rises with $(y, b(s))$.

Next, we show that $w(b,r,s)$ increases with n and converges to y as n goes to infinity. Observe that (6) rewrites as follows

$$\begin{aligned}\frac{1}{y-w} &= \frac{g(\bar{\epsilon}) - \nu_g(b(s)-w)G(b(s)-w)^{n(s)} - \int_{b(s)-w}^{\bar{\epsilon}} h'(\epsilon)G(\epsilon)^{n-1}d\epsilon}{(1-G(b(s)-w)^{n(s)})/n} \\ &= n\frac{g(\bar{\epsilon}) - \nu_g(b(s)-w)G(b(s)-w)^{n(s)}}{1-G(b(s)-w)^{n(s)}} - \int_{b(s)-w}^{\bar{\epsilon}} \frac{h'(\epsilon)}{g(\epsilon)} d\frac{G(\epsilon)^{n(s)} - G(b(s)-w)^{n(s)}}{1-G(b(s)-w)^{n(s)}},\end{aligned}$$

where the first step follows from integration by parts. One can show that the first term rises with n. Second, log-concavity of $g(\cdot)$ implies that $-\frac{h'}{g}$ is increasing. Third, $\frac{G(\epsilon)^{n(s)}-G(b(s)-w)^{n(s)}}{1-G(b(s)-w)^{n(s)}}$ is the distribution of the highest order statistics conditional on this being greater than $b(s)-w$ and, therefore, it increases in n in the sense of first-order stochastic dominance. The result follows from these three facts.

Observe that

$$\lim_{n\to\infty} \frac{g(\bar{\epsilon}) - \nu_g(b(s)-w)G(b(s)-w)^{n(s)} - \int_{b(s)-w}^{\bar{\epsilon}} h'(\epsilon)G(\epsilon)^{n-1}d\epsilon}{(1-G(b(s)-w)^{n(s)})/n} \to \infty$$

and therefore $\lim_{n\to\infty} w(b,r,s) \to y$. This follows from the fact that the numerator goes to $g(\bar{\epsilon})$, while the denominator goes to 0 due to the fact that $\lim_{n\to\infty} G(b(s)-w)^{n(s)} \to 0$.

Observe that

$$\frac{\partial w}{\partial n} = \frac{m(b(s)-w)}{1-m'(b(s)-w)} \left(\frac{1}{n(s)} + \frac{\ln G(b(s)-w)}{1-G(b(s)-w)^{n(s)}} + \right.$$
$$\left. n \frac{m(b(s)-w)}{1-G(b(s)-w)^{n(s)}} \int_{b(s)-w}^{\bar{\epsilon}} \nu_G(\epsilon) g(\epsilon) G(\epsilon)^{n-1} \big(1-(n-1)(\ln G(b(s)-w) - \ln G(\epsilon))\big) d\epsilon \right) > 0$$

Observe that the sum of the first two terms can be re-written as follows: $\frac{1-G^n}{n(s)} + G^n \log F$, When evaluated at $\bar{\epsilon}$, this is zero, while at $-\bar{\epsilon}$, it is equal to 1 since $G^n \log G$ goes to zero (by L'Hopital). The derivative of this with respect to ϵ is given by $n^2 G^{n-1} g \log G$, which is 0 at $-\bar{\epsilon}$ and strictly negative in $(-\bar{\epsilon}, \bar{\epsilon}]$ and therefore $\frac{1-G^n}{n(s)} + G^n \log G \geq 0$. This together with the fact that $\ln G(b(s)-w) - \ln G(\epsilon) \leq 0$ for all $\epsilon \geq b(s)-w$ proves the result. $\square$