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AI's Economy and Its Political and Institutional Consequences[1]

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Abstract: We examine the political consequences of artificial intelligence's economic impact. Although AI may affect nonroutine jobs in particular, we show that current models about the vulnerability level of occupations and economic sectors differ widely in their forecasts. This may explain why public opinion is not settled about the effects of AI. While many fear AI may displace them from their jobs, a majority seems optimistic about its overall impact. Responses vary, however, by cohort and depending on survey framing. AI's current training and computing needs have magnified capital concentration and business investment in fixed assets, intensifying the technological sector's interest in regulatory capture. Taken together, AI's effects on labor and capital may strain democracy unless a set of policies we outline here are gradually implemented.

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1. Introduction

Artificial intelligence has been increasingly hailed as the ultimate technological frontier – a tool or set of tools capable of yielding explosive productivity gains and replacing all human labor in the next few years or decades. At the same time, however, it has triggered widely divergent assessments about its social and political consequences. While some celebrate it as a liberating instrument that will usher in a 24/7 leisure society, others predict that it will lead to a dramatically unequal society, with a split between a few ultra-rich and an impoverished multitude, and to a powerful state capable of controlling all the minutiae of its citizens' daily lives.

In this chapter, which examines the political and institutional consequences of the economic changes brought about by AI, we arrive at a more conservative, middle-of-the-road position. This is probably the case for two reasons. First, we rely on evidence gathered during the short period of time that has elapsed since the development and actual implementation of AI. Second, we find substantial variation in researchers' assessments of its impact. Nevertheless, going beyond our description (based on current research) of AI's short-term effects, we also provide a conceptual discussion of its (likely stronger) political and social repercussions over the medium and long run.

The chapter can be summarized around seven broad claims:

First, whereas the information technology revolution benefited highly skilled workers and polarized labor markets, AI may replace non-manual, non-routine tasks preferentially done by highly educated individuals. This prediction is, however, uncertain for at least two reasons. Current (and widely used) measures and indexes developed to estimate the exposure and vulnerability of labor tasks to AI are weakly correlated with each other, yielding rather contradictory forecasts about which occupations are more likely to be replaced in the future. In addition, the methods and procedures of AI, which researchers normally use to assess its progress, are different from its actual application to management and production processes.

Second, the effect of AI on employment, collective bargaining, and wages is likely to be conditional on the structure of labor institutions.

Third, public attitudes toward AI are in a state of flux. Even though a significant fraction of the public worries about the labor displacement effects of AI, a majority in advanced countries still view AI as a positive development. Reactions to AI, which are more negative among young cohorts, at least on labor-related issues, are strongly susceptible to the type of questions and treatments developed in the surveys and, in at least one study, highly affected by some personality traits of respondents.

Fourth, although most economic researchers and survey analysts have focused on the impact of AI on labor markets, AI's economic (and, therefore, political) effects seem to be as – or even more – consequential on capital. The use and training of foundation models and the computational demands that come with those processes have accelerated capital concentration and reduced capital mobility in the technological sector. Those effects have increased, in turn, the lobbying power of technological firms as well as their incentives to capture the regulator.

Fifth, while information technologies are associated with the political polarization of the last decades, we cannot discard the possibility that, if AI ends up replacing non-routine jobs, it could foster a process of political de-polarization. Yet, perhaps paradoxically, this effect may not stabilize electoral politics due to the negative impact of AI on the relative position of individuals and on younger cohorts entering the labor market.

Sixth, AI-driven economic changes may have negative consequences for democracy. The combination of labor substitution (and a concomitant reduction of wages) and growing capital concentration (particularly in the technological sector) may jeopardize the social consensus needed to accept democratic elections. Still, higher productivity and economic growth, if distributed fairly, could reduce social and political conflict, even to the point of neutralizing any potential de-democratizing effects of AI.

Finally, AI may affect not only the within-country distribution of economic gains and losses (triggering a corresponding electoral realignment). It could reverse recent economic trends toward cross-country economic convergence (related to globalization) and widen the technological gap between developed and developing economies.

The overall structure of the chapter is as follows. After presenting existing evidence on the changes triggered by AI on capital and labor markets, we outline its political consequences. Section 2 ("Labor Market") discusses three topics related to AI and labor: current evidence on the labor-augmenting and labor-substituting effects of AI; the nature and robustness of AI exposure indexes; and the potential mediating effects of labor unions and wage bargaining institutions on AI's economic impact. Section 3 ("AI and Public Opinion") explores the public's perceptions toward AI. Section 4 ("Capital Concentration and Market Power") describes the impact of AI on the nature and concentration of capital. Section 5 ("AI and Democracy") considers how an AI-induced transformation of the labor market and capital may shape democratic politics – both triggering an electoral realignment and destabilizing political institutions in general. Most of the research and discussion on AI's consequences has been done so far for advanced economies. However, the spread of AI should have important effects on the Global South, a topic we discuss in Section 6 ("Economic and Political Backsliding Across the World?"). The concluding section suggests future avenues of research for the social science community and offers some policy recommendations.

2 Labor Market

2.1 Substitution and Augmentation

The task model of production offers a convenient way to study how automation and AI affect work. According to this view, production is organized as a collection of routine and non-routine tasks that can be performed by capital or labor, with labor hired either domestically or offshore.[2] Firms assign each task to the cheapest feasible input, given technology and relative prices.

Over the last few decades, several waves of digitalization and computerization substituted machine-based procedures for routine tasks while raising the value of non-routine problem-solving and interpersonal work.[3] The structure of the labor market shifted accordingly. While the need for middle-skill clerical and production tasks fell, the demand for high-skill analytic activities and low-skill service work went up (Autor et al., 1998, 2002, 2003). Job polarization followed. Employment shrank in middle-wage occupations while jobs grew at the top and bottom of the wage distribution (Goos & Manning, 2007; Goos et al., 2009; Autor, 2013, Humlum, 2019; Jaimovich & Siu, 2019; Hoffmann et al., 2020), causing a shift in the US wage-structure (Acemoglu & Restrepo, 2022). Regions and workers more exposed to robots or other forms of automation, especially in manufacturing, experienced job losses and weaker wage growth. That resulted in broader local spillovers in the form of population decline and fewer high-skill job opportunities (Chiacchio et al., 2018; Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020; Sarto et al., 2025). Individual-level studies show higher separation risk and persistent earnings losses after automation shocks, with many displaced workers either accepting lower-paying jobs that still use their skills or leaving the labor force, particularly among older workers (Bessen et al., 2025; Lerch, 2021; Braxton & Taska, 2023).[4]

Technological change arguably contributed, too, to a shift in the capital and labor shares of national income. By 2022, the labor share of US national income was at its lowest since 1929. After peaking in 1946, it fell by 0.2 percentage points per decade until 1970. Coinciding with the entry of information and digital technologies, its decline accelerated to 1.6 percentage points loss per decade from 1971–1995 and by 1.8 percentage points per decade after 1996. Labor shares

[2] See Acemoglu & Autor (2011) and Autor (2013), and the review in Acemoglu & Restrepo (2019).

[3] Digitalization refers to the adoption of ICT (Kurer & Gallego, 2019) and computerization to job automation by computer-controlled equipment (Frey & Osborne, 2017, p. 254).

[4] The net effect of pre-AI automation on employment seemed to depend on how quickly new tasks and sectors expand and on the extent of reallocation within and across firms (Autor & Salomons, 2018; Acemoglu & Restrepo, 2019; Dauth et al., 2021; Koch et al., 2021).

fell across almost all industries since 1987. In the information industry, the labor share for 1987–2021 averaged 43 percent – the fourth lowest among 20 industries in the economy and higher than only real estate, utilities, and mining and oil (Karabarbounis, 2024). By contrast, in 2024 after-tax corporate profits were equivalent to 11.5% of GDP, almost twice their level in the 1980s.[5]

New developments in AI have the potential to extend automation from routine activities into complex cognitive and interactive tasks and, potentially, into full workflows with limited human oversight (Susskind & Susskind, 2022; Autor, 2024). These possibilities have sparked a wide debate about AI's long-run labor-market effects.

For some, AI will eventually substitute human labor, resulting in a steep decline in labor's income share, which, at some point, will approach zero (Restrepo, 2025). For others, AI will mainly augment human labor, raise workers' productivity, or enable them to perform more complex responsibilities. Here, AI is even foreseen as a tool to rebuild parts of the middle class by extending expert capabilities to more workers (Autor, 2024). For example, nurse practitioners – already performing tasks once limited to physicians thanks to digital records and improved communication systems – could see their clinical judgment strengthened as AI supports an expanding scope of practice. A third, more sanguine position, sees AI as a standard technology that reallocates tasks and shifts relative demands without fully displacing workers (Narayanan & Kapoor, 2025).

Either way, the substitution and augmentation effects of AI will likely be conditional on the pace of technological progress and on the specificity and availability of the required complementary skills. Rapid technological advances – either exceeding the capacity of education and training systems to adapt to them or rewarding very narrow technical skills – will tend to push production toward labor substitution and downward wage pressure. Slower or more predictable change, including skill demands that can be met through incremental retraining, will create more room for workers to adjust and for AI to act as a productivity aid, rather than a replacement tool. In addition, governance and workplace norms may slow or reshape the adoption of AI advances in high-stakes settings, even when the technical capability exists.

Current empirical work on the labor market consequences of AI takes two forms: studies measuring the potential exposure or vulnerability of current occupations to AI as a function of the latter's characteristics; and empirical research on realized outcomes.

Measuring Exposure to AI. Most recent measures tying AI capabilities to job requirements – whether through patents, benchmark tasks, or model-task mappings – tend to find higher levels of AI exposure among higher-education, higher-wage occupations (Webb, 2020; Felten et al., 2021). Using large-language-model task mappings, Manning et al. (2023) estimate that roughly

[5] Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/W273RE1A156NBEA. Accessed on February 14, 2026.

80 percent of workers have at least 10 percent of their tasks exposed, and that between one-fifth and one-third may face disruption to half or more of their tasks (Kinder et al., 2024). Macro projections similarly suggest that up to 8 percent of total hours could be automatable by generative AI by 2030 (Ellingrud et al., 2023).

The estimated exposure or vulnerability to AI seems to be uneven across skills, industries, regions, and age groups (Webb, 2020; Felten et al., 2021; Brynjolfsson et al., 2025; Huang, 2025) and, crucially, very dependent on how exposure is defined – whether at the occupation or task level, whether based on technical capability or observed deployment, and whether augmentation is counted as exposure.[6]

Figure 7.1 compares three popular measures of AI vulnerability (Brynjolfsson et al., 2019; Webb, 2020; Felten et al., 2021). We matched each measure to the Standard Occupational Classification (SOC) 2010 classification yielding triplets of AI-exposure measures for 775 harmonized occupations in the US. The main diagonal of Figure 7.1 shows the distribution of each measure, while the lower off-diagonal cells provide bivariate scatterplots. Their distribution differs and the scatterplots do not reveal clear patterns of covariation. This is confirmed by the low rank correlations (Kendall's τ) as well as low distance correlations (which also capture patterns of non-linear dependence; Székely et al., 2007). Both measures are reported in the upper off-diagonal cells. **Table A1** illustrates a larger number of widely used indicators since the early 2000s and shows how different measurement choices yield sharply different headline numbers (Arntz et al., 2017; Frey & Osborne, 2017; Webb, 2020; Felten et al., 2021; Manning et al., 2023).

[6] Importantly, however, these exposure measures represent technical upper bounds. They indicate where AI could substitute for or augment tasks if firms re-engineer workflows, not how much substitution is occurring now or how fast it will unfold (Brynjolfsson et al., 2021; McElheran et al., 2025).

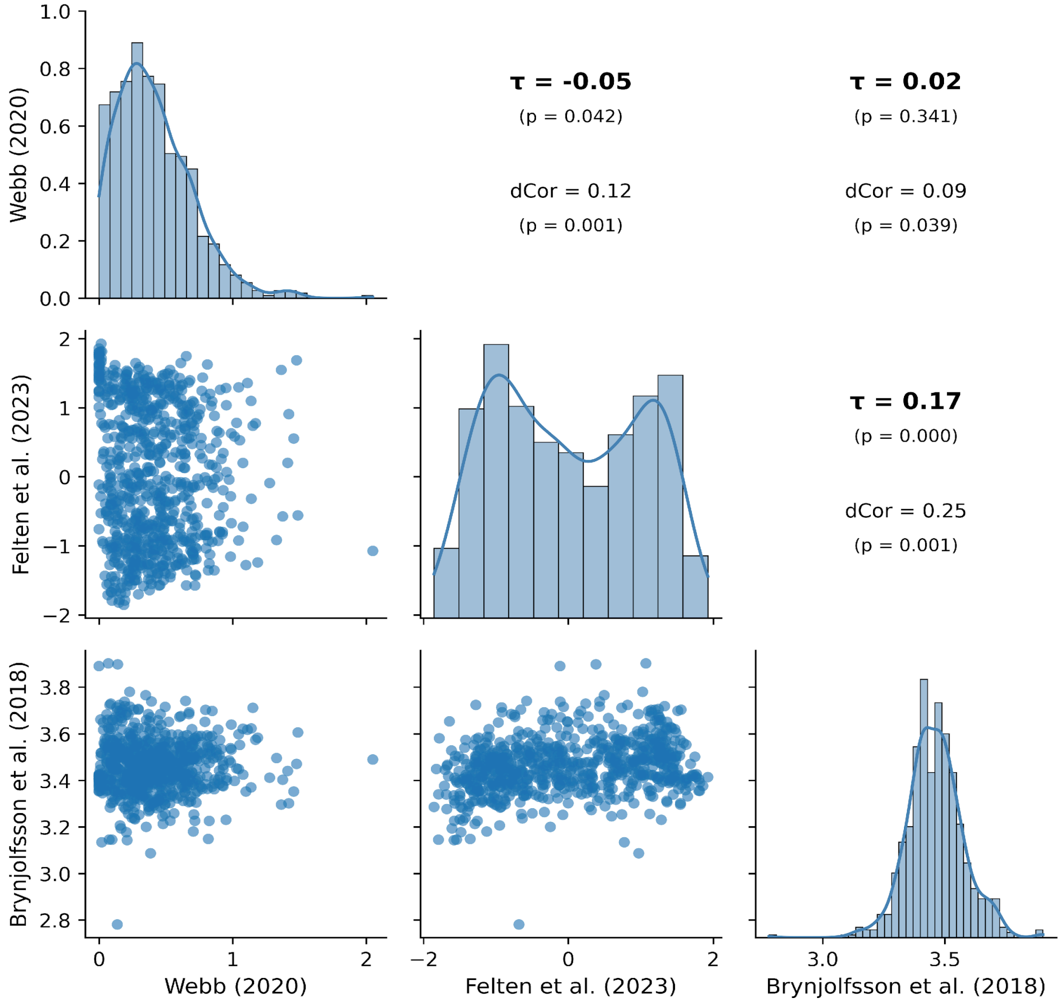

Figure 7.1 *Comparison of three popular AI exposure measures.*

We interpret these differences as a sign that each vulnerability index is capturing different aspects of the same underlying phenomenon (and measuring the latter by emphasizing different dimensions related to work). If this is the case, the predicted economic and political implications of these measures are heterogeneous and, as a matter of fact, substantially uncertain. We consider the economic effects here. We turn to the political consequences in subsection 5.1 ("The Electoral Arena").[7]

[7] This variability in AI exposure indexes has implications for empirical practice, too. If they indeed capture different aspects of the same phenomenon (as opposed to being noisy measures of an underlying latent variable), empirical analyses should use them in combination and not as "robustness tests" of each other. For a study that distinguishes between GenAI exposure (or the theoretical technical applicability of GenAI) and AI-substitution vulnerability (or the practical likelihood that employers replace workers with AI) and considers their joint effect on labor replacement, see Liu et al (2025).

***Table 7.2** Sector-specific exposure measures*

Sector	Felten		Brynjolfsson		Webb	
	Value	Rank	Value	Rank	Value	Rank
Finance and Insurance	0.861	1	3.540	1	0.376	7
Educational Services	0.839	2	3.488	6	0.310	10
Information	0.634	3	3.530	3	0.429	4
Public Administration	0.435	4	3.487	7	0.344	9
Prof., Scient., & Techn. Serv.	0.344	5	3.498	5	0.425	5
Wholesale Trade	0.094	6	3.513	4	0.374	8
Retail Trade	0.012	7	3.539	2	0.296	12
Other Services (except PA)	−0.138	8	3.460	9	0.301	11
Manufacturing	−0.372	9	3.477	8	0.471	2
Arts, Entertainment, & Rec.	−0.407	10	3.454	10	0.179	13
Construction	−0.743	11	3.439	12	0.438	3
Transportation & Warehousing	−0.799	12	3.450	11	0.405	6
Agriculture, Forestry, Fishing	−1.117	13	3.414	13	0.636	1

Table 7.2 To get a sense of the economy-wide implications of AI exposure, this table shows (private-sector) employment-weighted averages of occupational exposure to AI (and their rank order) for 13 major sectors of the economy. The values are calculated by matching different AI exposure measures to national employment estimates by occupation and the North American Industry Classification System (NAICS) 2-digit sector from the Bureau of Labor Statistics' Occupational Employment and Wage Statistics Survey[8] and then aggregating them to 13 major sectors.

While the indexes of both Brynjolfsson et al. and Felten et al. rank finance and insurance as highly likely exposed, Webb's AI measure ranks them only seventh and instead implies that agriculture and manufacturing are highly vulnerable. On the other hand, all three measures agree that the information sector and professional, scientific, and technical services are relatively highly exposed. It is also noteworthy that, according to the measure by Felten et al. (2021) and especially Brynjolfsson et al. (2018), retail and wholesale trade face sizable exposure, indicating that AI as a general-purpose technology (Bresnahan & Trajtenberg, 1995; Brynjolfsson et al., 2021) is likely to penetrate widely throughout all economic sectors.

[8] See U.S. Bureau of Labor Statistics, www.bls.gov/oes. We use May 2023 estimates.

As Narayanan & Kapoor (2025) emphasize, however, current indicators should be treated as guides rather than predictions, since they often conflate progress in methods with progress in applications and diffusion. Frontier benchmarks showing that models can pass professional exams or solve self-contained coding tasks do not reveal whether firms will trust these systems with high-stakes legal work, complex software development, or safety-critical operations. Likewise, existing uplift studies mainly document incremental productivity improvements, rather than large-scale automation of occupations. What remains uncertain, therefore, is not only how quickly new tasks will emerge, how broadly augmentation will diffuse, and how far institutions and policies will go in smoothing worker transitions, but also which empirical indicators best capture these processes and how far ahead they can be projected without overstating the scale of disruption.

Realized Effects of AI. Compared to digital technologies and computer-controlled equipment, AI has been deployed for a limited number of years. This logically affects both the number and robustness of any studies on its labor market effects. Overall, however, the evidence so far points to some productivity gains, substitution in routine and possibly many non-routine tasks, and rising demand for AI-complementary skills.

On the one hand, recent work finds AI to be restructuring employment patterns in two directions. First, areas more exposed to AI-related advances have seen weaker employment and wage growth among workers whose tasks are close substitutes for current systems (Huang, 2025). Still, this net displacement has been estimated to be smaller once new tasks and complementarities are considered, particularly in non-routine jobs (Kogan et al., 2023; Pizzinelli et al., 2023). Brynjolfsson, Chandar et al. (2025) find that AI's replacement impact may be operating mostly among young cohorts, arguably because they have not been able to develop yet the kinds of tacit knowledge and contacts gained while working that may make up for AI-led substitution. Examining 285 million job postings from 2018-2025, Liu et al (2025) find that occupations vulnerable to artificial intelligence experienced a fall in demand following the release of ChatGPT in the fall of 2022. By contrast, a recent analysis of job posting data in Germany, the Netherlands, the United Kingdom and the United States shows no evidence that AI is behind a fall in early-career hirings, instead attributing the latter to rising interest rates in the middle of 2022 (Burn-Murdoch & O'Connor, 2026a).

Second, current surveys indicate that AI-related skills are increasingly valued over prior job experience in many industries (Microsoft, 2024). Skill profiles with AI-related capabilities have enjoyed a wage premium of roughly 5–10 percent in many countries (Alekseeva et al., 2021) and even higher levels in some emerging markets (Copestake et al., 2023). Firm-level studies show that adopters reorganize toward more educated, STEM-intensive workforces, with fewer mid-level managers, higher revenue, and higher valuations (Babina et al., 2023, 2024). However, most early adopters do not immediately reduce headcount. An OECD survey reports that only about one-quarter of AI-using firms cut employment, with many redeploying workers to new tasks (Milanez, 2023).

On the other hand, AI also appears to augment human labor, although these effects vary widely with worker experience and type of task. Studies of human-AI teams in customer support show that access to a generative-AI assistant reduced resolution times by about 14 percent, with the largest gains for less experienced workers (Brynjolfsson et al., 2025). Experimental settings for writing tasks find higher-quality drafts produced more quickly and a narrowing of performance gaps between lower- and higher-skill workers (Noy & Zhang, 2023). In software development, programmers using tools such as GitHub Copilot complete coding tasks substantially faster than without them (Peng et al., 2023). However, there is also randomized controlled trial evidence suggesting slowdown effects for experienced developers (Becker et al., 2025).[9] In settings with highly trained specialists, such as expert radiologists, AI decision-support has so far had limited effects on accuracy because professionals choose not to rely on its recommendations (Agarwal et al., 2023; Yu et al., 2024).

We conclude this subsection by making two additional observations. First, we still know little about how AI-driven employment decisions interact with bargaining institutions, competition policy, and data governance. This makes it difficult to read long-run wage and employment trajectories from the behavior of early adopters alone (Narayanan & Kapoor, 2025).

Second, most of the discussion so far concerns software and digital services. As AI becomes embedded in physical equipment and robotics, "embodied AI" may result in the automation of manual and service work, with fundamental consequences in terms of substitution and augmentation across cognitive and physical tasks and, as we discuss in Section 5, for politics.

2.2 Labor Unions and Worker Mobilization

Besides shaping labor demand, technological change (and AI should be no exception here) may impact labor market institutions, that is, the strength of labor unions (trade unions in British English) as well as the level and reach of collective wage bargaining. This may affect, in turn, wages and working conditions (Farber et al., 2021; Jäger et al., 2025), inequality (Iversen, 1999; Hall & Soskice, 2001), and democratic politics (Leighley & Nagler, 2007; Ahlquist, 2017; Kerrissey & Schofer, 2013; Rosenfeld, 2019; Becher & Stegmueller, 2021; Hertel-Fernandez, 2025; Kaplan & Naidu, 2025; Yan, 2025).

Because it is too early to give anything close to a conclusive empirical answer about the consequences of an increased use of AI at work on workers' interests and in their ability to organize in unions, in the remainder of this subsection we discuss several models emphasizing the negative and positive effects that AI may have on wage bargaining and union labor membership sequentially. We conclude by pointing to research on the regulation of AI in collective bargaining agreements.

[9] Burn-Murdoch and O'Connor (2026b) report an upward inflection point in software productivity by the end of 2025, coinciding with the launch of ClaudeCode and OpenAI's Codex.

AI May Weaken Labor Unions

AI may weaken labor unions through two channels: skill-biased technological change; and labor substitution in imperfectly competitive labor markets.

AI's impact on labor market institutions likely depends on the type of skills and occupations that are more vulnerable to these new technologies. If AI rewards the more educated, existing theories of skill-biased technological change and unions' performance, developed in the 1980s and 1990s (e.g., Pontusson & Swenson, 1996; Iversen, 1999), will continue to apply in the age of AI. According to that view, a shift from Fordist to diversified quality production undermined centralized wage bargaining and solidaristic wage policy pursued by unions. By widening the productivity gap between workers in different sectors or firms, skilled workers who benefited from technological change found it harder to stomach the costs of wage compression, which benefited lower skilled workers. The distributive effects of technological change increased the incentives of technology winners to push for a shift from centralized (nationwide) to industry or even company-level wage bargaining between firms and unions.[10]

Standard task models, which capture the idea that automation may result in labor substitution, assume that all markets are perfectly competitive. Nonetheless, this unrealistic assumption, which brackets the possibility of collective bargaining over wages and working conditions, has been challenged in recent task-based models analyzing the impact of automation on labor unions. Based on a recent extension of the task framework that incorporates labor market search frictions, Leduc & Liu (2024) argue that automation can reduce union power during business cycle downturns. Examining how exogenously given wage rents shape firms' decision to automate, Acemoglu & Restrepo (2024) argue that automation will target high rent tasks. If unions are indeed concentrated in such tasks or more likely to target them for mobilization, firms may have incentives to use AI to pursue inefficient automation in part to weaken existing unions or keep them out of the company's labor force to begin with. Relatedly, Golden (1997) argues that firms that downsize their workforce due to technological change or business cycles sometimes want to target dismissals to union members and their workplace leaders. Moreover, employers may use AI to increase the segmentation of the workplace in global value chains, through outsourcing, subcontracting, temporary work, and less worker autonomy (Doellgast et al., 2025).

AI May Strengthen Labor Unions

Contrary to our previous discussion, the skill-mediated impact of AI may strengthen labor unions and collective wage bargaining. If it is highly educated individuals who turn out to be more exposed to AI (in line with the Felten and Webb indexes plotted in Figure 7.5 later in the chapter)

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[10] The breakdown of Sweden's centralized wage setting system at the time has been explained with reference to this framework (Pontusson & Swenson, 1996). For a formalization of this logic in the private sector, see Acemoglu et al. (2001).

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than less educated workers, support for union-led wage bargaining may increase and converge across all workers.

In addition to the mediating effect of AI on skills, a number of models examine the positive impact of AI on labor unions due to the specific nature of the capital investments AI entails. Building on the task framework and considering an open economy setting with imperfect competition, Becher & Stegmueller (2025) suggest that automation can strengthen (as well as weaken) worker mobilization and bargaining power. In a global economy, the threat to relocate production often gives the upper hand in collective bargaining to firms. However, investments in automation, such as AI-enabled robots, process automation, or data centers powering AI applications, can, under certain conditions, reduce firms' relocating threat. If the productivity gains from automation either depend on co-specific skills in non-automated tasks or rest on complementary services such as robot integrators, and/or if the cost of relocating and running the machines abroad are relatively high, workers' power at the bargaining table goes up. That increases, in turn, the gains from mobilizing workers. By contrast, if those conditions are not met, and AI replaces unionized labor, AI-driven automation will weaken unions.

Quantitative evidence on the impact of AI on unionization is still scarce. Prior research on twenty-one OECD countries from 1970 to 2019 finds that routine-biased technological change is associated with lower union density (Meyer, 2019). Using an instrumental variable strategy based on robot exposure in the same industries in other advanced economies, recent research finds that robotization reduces union density in Europe (Agnolin et al., 2025) and the US (Balcázar, 2023). After confirming that the overall effects of AI on unionization are negative, Becher & Stegmueller (2025) find significant heterogeneity of effects that is not explained by observable characteristics.

While AI is increasingly used in robotics and process automation, the data on robotization exposure used in these studies is not restricted to AI, and findings on robots may not travel to AI used in other areas, such as algorithmic management or services. Combining survey data on Western Europe (2012-2024) with an occupational measure of exposure to new digital technologies across six different categories, Agnolin & González-Rostani (2025) find that the level of unionization is correlated with the type of technology. While platform-based tools (e.g., for food delivery) are associated with lower unionization, others, such as exposure to machine learning or embedded systems, are associated with higher unionization.

Negotiating the Deployment of AI

Qualitative and quantitative work has started to explore how unions negotiate the use of AI at work, through collective bargaining with employers as well as broader social dialogue.

In what may be the most comprehensive case study to date, Doellgast et al. (2025) analyze efforts around the globe to encourage the use of AI to complement rather than substitute labor, to negotiate algorithmic management in a way that protects workers' rights and autonomy, and limit

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AI-enabled fragmentation of the workforce. It underscores that, besides the question of whether AI displaces or augments labor, another core issue is how AI is deployed for monitoring workers and making managerial decisions related to hiring, scheduling, or pay. In this respect, AI can be used mainly as a tool to discipline workers or to increase their autonomy. The study argues that constraints on employer exit, institutional support for worker voice, and strategies of inclusive labor solidarity foster bargains that encourage a more worker-friendly approach to AI adoption (also see De Stefano & Doellgast, 2023).[11]

3 AI and Public Opinion

How does the perceived or actual impact of AI on the workplace shape people's policy preferences and political behavior? For more than a decade, political economists and other social scientists have examined how technological shocks to labor markets based on information technology, computerization and, increasingly, AI are shaping (or not) democratic mass politics (for an excellent review, see Gallego & Kurer, 2022).

As with earlier technological changes, we should expect AI to result in winners and losers. While not meant to be an exhaustive review, this section highlights several directions of a still incipient research on AI-driven economic vulnerabilities and public opinion. Here as well as in the discussion in Section 5, it is important to keep in mind that current research in economics still is uncertain about the labor market risks and distributive effects of AI.

Several years into the AI boom, a majority of survey respondents in advanced economies say that recent digital technologies, including AI, have a positive impact on the economy. However, many also declare that robots and AI will displace more jobs than they create. And a sizable minority is concerned that their job may be displaced (e.g., Busemeyer et al., 2023; European Commission, 2024; Green et al., 2025). A recent survey asking respondents to evaluate AI-driven automation in 940 occupations shows that the American public supports automating 30% of occupations. That proportion doubles to 58% of occupations when AI is described as outperforming humans at lower cost (Friis and Riley, 2025).

Consistent with some evidence of AI's impact on the labor market (reviewed in Section 2), some studies show that the perceived labor market vulnerability to AI is higher among young people. For example, according to a Harvard Youth Poll from 2025, 44% of Americans aged 18 to 29 believe that AI will take away economic opportunities, 22% are unsure, less than 20% expect gains, and the rest expect no change (IOP, 2025). Surveys across the board also find AI anxiety among highly educated professionals in occupations with no or little exposure to previous waves of technological change.

[11] In the US, unions in the entertainment sector have negotiated collective bargaining agreements for screenwriters and actors that regulate specific uses of generative AI for filmmaking and video-game production. Agreements were only reached after months-long strikes. More broadly, issues of data privacy and worker autonomy are being contested and negotiated across countries and sectors.

Given that the adoption of AI at work is uneven, incomplete, and of course likely correlated with both observed and unobserved characteristics of workers, firms, location and so on, randomized experiments constitute an active strand of research. Overall, they capture that public attitudes regarding AI and policies designed to address labor market effects seem malleable to information, elite cues, and experience.

Researchers have explored different treatments and outcome variables. At the risk of oversimplifying, one can distinguish at least three approaches. One common experimental approach randomizes information about AI's potential labor market impacts. Zhang (2022) reports that, in a United States sample, information treatments about the general or occupation-specific AI risks raise the perceived threat of job displacement but have no effects on policy preferences regarding redistribution, immigration, or trade. However, other researchers find that providing information about AI risk increases support for social insurance and redistribution, at least if paired with rhetoric critical of tech elites (Jeffrey 2021), for regulation, with effects varying by information source (Mitts & Ravis, 2025) or AI knowledge (Heinrich & Witko, 2025), and for protectionist preferences such as trade restrictions (Gonzalez-Rostani 2024). In an intensive information design, workers across 98 occupations exposed to AI receive an occupation-specific video treatment about the capabilities of generative AI to perform key tasks in their occupation (Anelli et al., 2025). Fielded in Germany, Italy and the US, the study finds no average effects but argues that, based on different personality traits, respondents polarized in camps of pessimists and optimists.

A second type of experiment explores whether the experience of using AI at work shapes people's policy preferences. For example, Haslberger et al. (2025) randomize whether participants can use generative AI or not to complete work-related writing tasks in a UK sample of working-age adults, finding that experiential exposure to AI does not increase the perceived risk of job displacement and that it increases the belief that AI will be beneficial to them and society more broadly. Turning to policy preferences, the treatment reduces support for regulating AI but increases support for developing social measures to counter the effects of AI. In an earlier study focused on a sample of college-educated professionals in AI-exposed occupations, Noy & Zhang (2023) find increased concern about job displacement as well as heightened AI-optimism. Also employing an experiential treatment but focusing on management decisions rather than automation risk, related research randomizes whether platform workers interact with an algorithmic or a human boss (Margalit & Raviv, 2025). It finds that workers' personal experience with algorithmic decision-making affects workers' task satisfaction and effort, though not their policy preferences toward AI-based algorithms.

Finally, several experiments expose survey respondents to (hypothetical) scenarios about a firm's decisions to automate jobs and thus lay off workers. Studies focused on the manufacturing sector in different countries find that people are more sensitive to jobs lost to offshoring than to automation (Borwein et al., 2024; Kuo et al., 2024). Subsequent work distinguishes between whether the technology is domestic or foreign (Chaudoin & Mangini, 2025) and conducts conjoint experiments where subjects are either assigned to an AI or offshoring treatment and then complete a small number of rating tasks involving attributes such as positive and negative consumer prices and job gains or losses, intended to capture the heterogeneous effects of AI adoption (Magistro et al., 2025). Respondents are found to be as sensitive or more sensitive to price changes than employment shifts, more responsive to job losses than job gains, and to generally favor AI over offshoring. This relationship holds across the partisan divide in the United States. While Democrats are more supportive of AI, in general, the reaction to *changes* (e.g, job losses) is similar for Republicans and Democrats.

4 Capital Concentration and Market Power

While discussing the substitution effect of AI technologies, subsection 2.1 ("Substitution and Augmentation") already pointed to their potential impact on the income share of capital and labor. In this section, we turn to examine its repercussions on both the concentration of capital (in the AI industry as well as the economy in general) and its nature.

4.1 AI's Technological Requirements

Powered by the algorithmic revolution and cloud computing, the IT industry coalesced around a few, large platform-based companies, such as Amazon, Microsoft and Alphabet, by the turn of the twenty-first century (Kenney & Zysman, 2016; Rahman & Thelen, 2019). Starting in the 2010s, those companies pivoted away from traditional platform services to cloud computing and the supply of task-specific AI models that "could often be trained on a single server or a small cluster of servers" (Tan & Thelen 2025, p. 14). Critically, however, those models have been replaced, over the last few years, by the use of "foundation models," of which LLMs are the most well-known cases.

The development and use of foundation models entail a set of technological requirements that affect the market structure, capital concentration and type of capital in the AI industry.

The AI model of production (through foundation models) consists of two main processes: model pre-training and the direct provision of (mostly inference) services. Pre-training, necessary to generate foundation models, requires massive and growing computational resources. Although unit inference costs are low (and quickly falling), aggregate inference costs generally exceed training costs over a model's operational life.

Since 2020, the computational power used to train frontier AI models has multiplied by a factor of five every year. Power usage to train those models has grown by a factor of 2.4 per year (AI, 2025). The fact that the performance of foundation models increases with the amount of compute used in training the model (Kaplan et al., 2020) implies that the demand for compute power is set to accelerate in the near future. The cost of training frontier AI models has grown by a factor of two to three times per year for the past eight years, suggesting that the largest models may cost

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over a billion dollars by 2027 (AI, 2025). The significant costs imposed by the computational needs of foundation models are reinforced by a limited supply of both high-quality training data and human talent.

4.2 Capital Concentration in the AI Industry

The combination of relatively low variable costs and high fixed costs generates large economies of scale in the AI industry. In addition, the latter enjoys substantial economies of scope because its current technologies can be deployed across many different economic sectors. Together, these economies of scale and scope foster the formation of a market with a shrinking number of firms and a tendency toward natural monopoly.

Microsoft, AWS and Google hold about three fourths of the combined generative AI software, model management platforms, and services market, which skyrocketed from a mere $191 million market in 2022 to $25.6 billion in 2024 (IoT-Analytics, 2025).[12] In the AI hardware market, and, specifically, data center GPUs, which grew sharply from $17 billion in 2022 to $125 billion in 2024, NVIDIA accounts for over 90 percent of sales (Fernandez, 2025). As of October 2025, for example, private LLM developers with a valuation of $1 billion or more summed up to around $1 trillion. The top four private LLM developers represented 90 percent of that valuation: OpenAI, xAI, Anthropic and Databricks had valuations of $500, $200, $183 and over $100 billion respectively.[13]

This trend toward market concentration has been reinforced by vertical integration (Korinek & Vipra, 2025). Upstream integration has consisted of large technology companies combining the design of chips and foundation models (for example, Google or Amazon designing their own AI accelerator chips, or NVIDIA offering foundation models), and establishing exclusive contracts between cloud computing services, data-rich companies and LLM developers. Downstream integration has proceeded through the integrated use of foundation models among cognitive workers and in commercial applications.

4.3 Capital Concentration across the Economy

Technological change, particularly through AI and automation, seems to be contributing also to an increasing concentration of capital and capabilities among larger firms across the overall economy. Firms with greater cash reserves and R&D capacity are more likely to demand AI-related labor, apparently experiencing higher productivity gains and innovation outcomes as a result. Alekseeva et al. (2021) document a growing demand for AI skills between 2010 and 2019, with associated wage premiums and a concentration of AI adoption in larger, more innovative firms. Larger firms are much more likely to adopt automation technologies, contributing to labor

[12] This market does not include the market for individual generative AI applications (such as ChatGPT).

[13] Data collected by the authors.

substitution and accounting for 20 to 30 percent of the labor productivity gap between large companies and the median firm (Acemoglu et al., 2022). AI investment leads to higher sales, employment, and market valuation, particularly in concentrated industries. AI-adopting firms shift toward more educated STEM and IT workforces and flatten organizational hierarchies by reducing middle management roles (Babina et al., 2024). These changes amplify the advantages of large firms. Automation has stronger adverse effects on employment and wages in small firms and among older and middle-educated workers (Bessen et al., 2020).

4.4 Shifting Type of Capital

The shift of large IT companies toward the development of AI models has arguably cemented their current market dominance. At the same time, it appears to be transforming the nature of their assets. Platform companies were "asset light" (Tan & Thelen, 2025). Their product model and market position rested on the exploitation of networks of contracts, data-intensive operations, and highly educated personnel. Today, the demand for large agglomerations of computational power to pre-train and run LLMs requires the construction of large data centers and the consumption of vast amounts of energy. As a result, technology companies are becoming massive owners of (immobile) physical infrastructure.

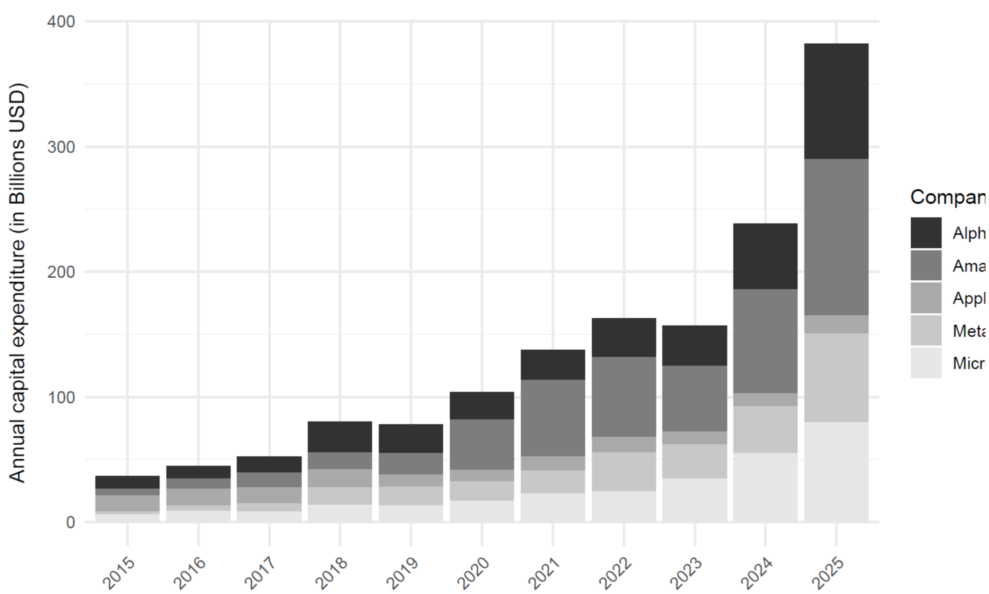

Figure 7.3. *Capital Expenditures of Top Five Technological Companies, 2015-2025*

Note: Data collected by authors. Main source: FinanceCharts.

As shown in Figure 7.3, capital expenditures by the five top companies grew from $36 billion in 2015 to around $150 billion in 2023. In the last two years, it has more than doubled to $400 billion. This represents over a third of all private fixed investment in information processing equipment and software.[14] Morgan Stanley projects $2.9 trillion in spending from 2025 to 2028 on chips, servers and data-center infrastructure.[15]

5 AI and Democracy

5.1 The Electoral Arena

The Electoral Consequences of the IT and Globalization Shocks

Automation and digital technologies, compounded by the lack of response from most mainstream parties, reshaped the electoral arena of postindustrial democracies in the last few decades in the following way (rendered here in a simplified manner for space reasons).

Rising wage inequality and rapid skill-biased employment change polarized voters' preferences. While highly educated voters continued to support the existing policy status, both white-collar voters and industrial workers with routine jobs and/or working in industries directly exposed to automation and foreign competition grew increasingly alienated from existing parties and their policy platforms.

That rising political alienation, combined with the limited response of mainstream parties – particularly left-wing parties that had traditionally represented low-income voters – to these economic transformations, triggered a broader process of electoral dealignment. In Western Europe, abstention grew from one out of five people in 1980 to one in three thirty years later, becoming highly and negatively correlated with income and age. Trust toward institutions and politicians plummeted.

Exploiting voters' dissatisfaction, a number of "populist" candidates jumped into the electoral arena, successfully inducing a partial process of electoral realignment (Boix 2019). Higher exposure to robotization raised support for populist candidates in Europe (Anelli et al. 2019, 2021, Caselli et al. 2021, Milner 2021) and the United States (Frey et al. 2018, Gonzalez-Rostani 2025). Likewise, exposure to technological change increased support for illiberal preferences – such as trade protectionism and anti-immigration positions – commonly espoused by populists (Gonzalez-Rostani 2024, Chaudoin & Mangini 2025). In response to this populist rise, some left-wing parties have recently pivoted toward more expansive tax-and-spend platforms, in some cases partially embracing elements of the populist agenda, alongside more direct redistributive policies.

[14] U.S. Bureau of Economic Analysis, Private fixed investment in information processing equipment and software [A679RC1Q027SBEA], retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/A679RC1Q027SBEA.
[15] Wall Street Journal, July 31, 2025, https://tinyurl.com/wsj-aispend

The Electoral Consequences of the AI Shock

The AI shock could eventually transform the current electoral market too. As with the political effects of globalization and the digital shock, the behavior and potential electoral realignment of voters will be a function of, first, changing economic conditions and, second, the response of political incumbents (and political entrepreneurs) to those changes.

Looking at the AI vulnerability index(es) we presented in Section 2 provides us with an entry point to measure the economic (and therefore potential electoral) impact of AI.

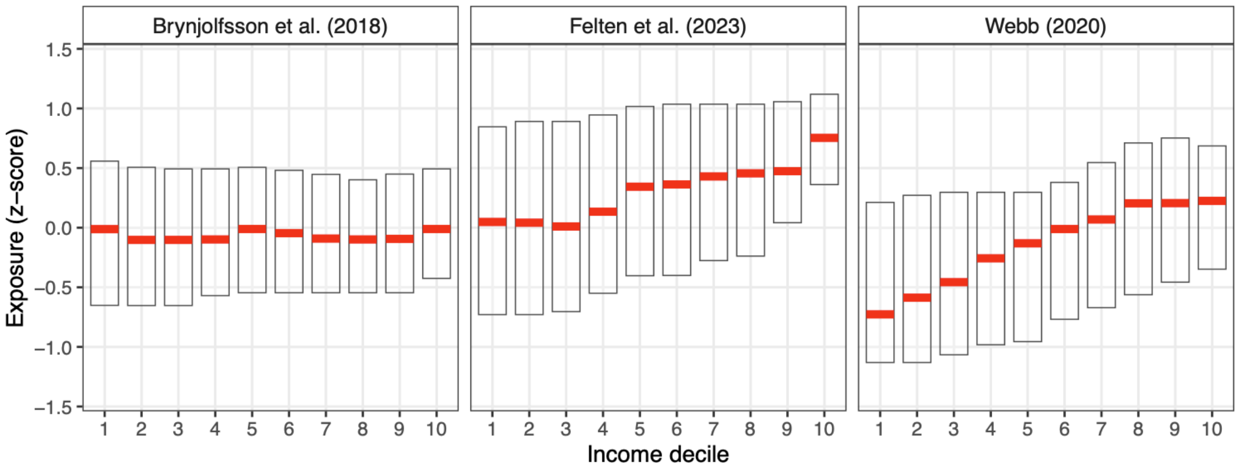

Figure 7.4. *AI exposure by Income Decile in the US*

Figure 7.4 plots the median AI exposure level according to three popular measures by income decile in the United States. To that effect, we use the 2023 American Community Survey 5-year file (a 5-in-100 national random sample of the population), match Census occupations to z-standardized AI exposure, and divide the sample into (weighted) deciles of respondents' pre-tax wage and salary income.[16] The plot shows box plots by decile for each measure.[17] The Brynjolfsson exposure index hardly varies across the income distribution (we estimate its correlation with income as -0.01). The Felten index implies that high-income deciles are more vulnerable than the average (correlation with income: 0.23). The Webb index also indicates a correlation of income with AI vulnerability (estimated as 0.2) but shows that low-income deciles are less vulnerable than the mean.

As discussed earlier, digitalization and computerization eroded the position of occupations characterized by routine tasks and hollowed out middle social strata, raising wage inequality and

[16] The reference period for wage income is the previous twelve months. Income values are expressed in 2023 US dollars. The analysis sample consists of 3,850,246 matched cases.
[17] To make the plot visually cleaner, it shows only the medians and inter-quartile range box.

allegedly polarizing politics. The Brynjolfsson et al. vulnerability index does not predict any relative change across the voters with respect to where they were after the digital and globalization shocks.

By contrast, the Felten and Webb indexes, which seem to forecast a wave of non-routine-jobs substitution, entail a reversal of the recent trend toward more inequality. Mechanically, less wage inequality could have two effects: first, some depolarization in elections; second, a political realignment of capital owners and low-skill, manual occupations against high-skilled, AI-vulnerable employees.

Even if that economically equalizing and electorally depolarizing scenario takes place, a fall in the demand for high-skilled jobs could still exacerbate political tensions. Lower wages among highly educated individuals could trigger more redistributive conflict, ignited by a drop in relative status and frustrated social expectations among educated voters. In addition, if AI turns out to affect new entrants in the labor market more than older cohorts, intergenerational conflict may become central in elections.

So far we have pointed to AI's short- and medium-term electoral effects. In the long run, full automation (replacing non-manual jobs with embodied AI) and its correlated steep returns to capital could overrun those initial de-polarization effects. It would also foster the emergence of a strong electoral cleavage between capital and labor (Boix, 2024).

At the end of the day, the electoral consequences of AI-driven economic change will be mediated by the strategic decisions of parties. Figure 7.5 plots the correlation between the three AI exposure indexes and district partisanship in the US. The vertical axis uses district-level exposure calculated by matching employment-weighted industry-level exposure to industry-level employment shares in each district of the 118th Congress, while the horizontal axis employs Cook's Partisan Voting Index, which captures the two-party vote margin compared to the national average. The beta coefficients noted in each panel show the linear relationship between the two.[18]

[18] The coefficients are calculated from a robust (median) regression. Note that the vertical axes are clipped at four standard deviations for presentational purposes. The beta coefficients are based on all districts.

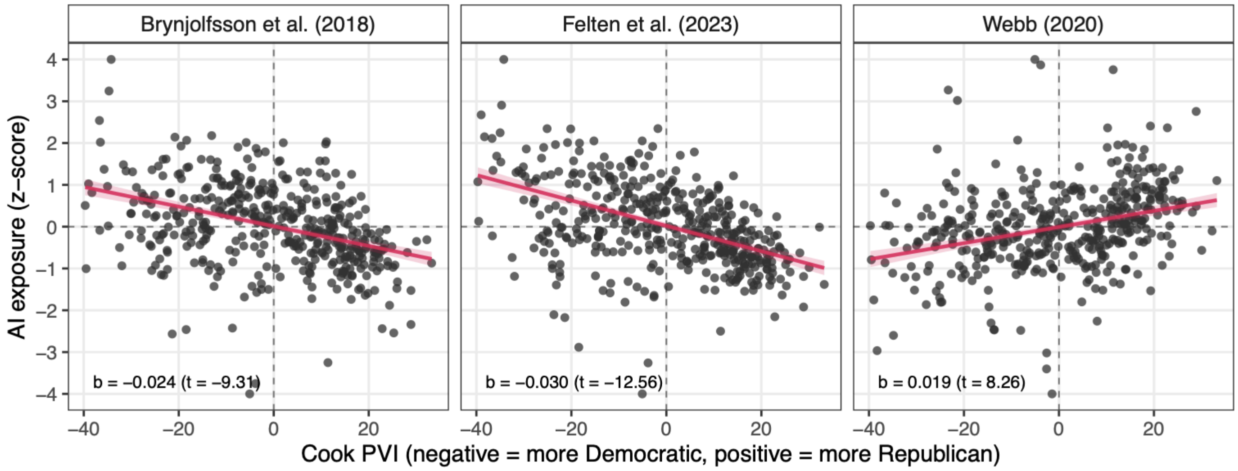

Figure 7.5. *District-level AI exposure and Partisan Vote in the US*

The level of AI vulnerability by partisan support varies considerably across indexes. According to the Brynjolfsson and Felten measures, Democratic-leaning districts are more vulnerable to AI than Republican-leaning ones. In the Webb index, Republicans are (moderately) more exposed to AI. In light of the first two indexes, Republicans may have a lower electoral incentive to oppose and regulate AI. This could explain the relative preponderance of pro-AGI effective accelerationism in the current federal government – something reinforced by its current strong connections with technology companies.[19]

5.2 Impact on Democratic Institutions

To understand the potential effects of AI on democratic institutions, consider a simple set-up in which voters vote for the candidate that offers a policy platform that maximizes their welfare. Each candidate's policy platform specifies a level of redistribution across voters through a combination of taxes, transfers and regulatory measures – where the latter refer to the legal rules governing capital, labor and goods markets (such as migration policies or tariffs that determine the supply of labor or goods).

Voters differ in their income, which is a function of their respective occupations (in turn, defined as a bundle of tasks). Voters' preferred level of redistribution is negatively related to their income. At the same time, because the marginal utility of income declines as individual income

[19] Besides concerns about the employment and income effects of AI, public opinion is increasingly worried about the location of data centers and their impact on energy prices. As of November 2025, 41% of Americans favored a ban on the construction of data centers near where they live. About 36% opposed it. Support for a ban was marginally higher among Democrats. See Yokley, E. (2025, December 1). Support for AI data center bans is growing. *Morning Consult Pro*. https://pro.morningconsult.com/analysis/ai-data-center-energy-prices-november-2025. Accessed on February 9, 2026.

increases, the intensity with which voters may oppose redistributive policies falls as they become richer.

Because politicians are policy-oriented (and there is some uncertainty about the position of the median voter), they offer distinctive platforms that do not converge fully around the preferences of the median voter. In fact, their policy promises vary with the distribution of voters' preferences. As the latter become more polarized, redistribution platforms tend to diverge from each other (Beramendi et al., 2026).

Crucially, as political preferences become more (less) intense and/or extreme, voters are more (less) likely to tolerate undemocratic behavior that reduces the probability that the parties they oppose win elections (Graham & Svolik, 2020). Hence, as politics becomes more (less) polarized, incumbent politicians may have more (fewer) incentives to act anti-democratically. For a high level of polarization, democratic backsliding could even result in a breakdown of democracy (Beramendi et al., 2026).

In this set-up, the political impact of AI will depend to a large extent on whether it will intensify or attenuate economic inequality among voters.

Pro-democratic Effects of AI

AI's economic effects may consolidate democratic institutions through, at least, two mechanisms. In the first place, if AI equalizes the distribution of wages, particularly by displacing non-routine jobs, partisan competition may become more centripetal and therefore less susceptible to anti-democratic candidates. In the second place, even if wage dispersion increases or does not change, higher income growth (due to the productivity gains of AI) may attenuate the polarizing effects of inequality. With marginal utility of income converging to zero for very high income levels, those individuals benefiting directly from AI (and future embodied AI) may be willing to tolerate higher levels of redistribution (for example, through robot taxes).

AI and Democratic Backsliding

Conversely, AI may trigger a process of de-democratization for two reasons. It could intensify political polarization. And it could foster the rise of powerful technological companies with strong incentives to capture regulatory agencies and bypass the democratic process. We discuss the latter mechanism in subsection 5.3.

Political polarization may be the result of, at least, two main transformations. If embodied AI replaces manual occupations, employment and wages among low-educated workers will fall and income inequality will rise. Moreover, by accelerating capital-labor substitution, AI could compound the inequality effect generated by information and digital technologies in the last decades. At the end of 2025, the stock wealth of US households equaled close to three times their annual disposable income, or two and six times as much as in the early 2000s and 1980s respectively. The top income decile holds around 70% of all financial assets (Federal Reserve

Bank of St. Louis). As pointed out before, to the extent that those effects override any of AI's potential equalizing effects on the wage distribution, there should be higher polarization, now between capital-holders and the rest of the population, and a leftward shift in the candidates' position.[20]

At this point, it is unclear which forces will prevail for two reasons. First, AI's effects are still uncertain. Second, inequality and growth balance against each other in the model we lay out before. Beramendi et al. (2026) find, after examining the universe of all democratic spells from 1900 to 2017, that inequality has not trumped the pro-democracy effects of income in highly developed countries. Still, one could think of a scenario in which rising inequality could cancel out the "democratizing" effects of income growth. As we discuss in the conclusion, many of these outcomes may be, to a great extent, endogenous to politics. Policymakers could establish mechanisms to address the sources of inequality, such as investing in the generation of new skills among voters. They could also employ the wealth of today's advanced countries to compensate the losers of economic change.

5.3 Regulatory Capture

AI companies' market dominance and heavy investment in fixed assets, which make them more vulnerable to taxation, are likely to increase their opposition to regulatory measures to sustain market competition and break their dominant position.

Growing market dominance, which is a function of barriers to entry in the industry, makes businesses more concerned about policy. Any change in their input and output prices (potentially induced by government decisions) affects them more than if markets were highly competitive and new entrants could dissipate the benefits of pre-existing firms (Frieden 1991). Market dominance also has a direct effect on the collective action capacity and political clout of any industry. As the number of companies declines, the cost of lobbying governments falls. All else equal, market dominance reinforces the so-called structural power of capital over governments – the power that comes from the capacity to punish the latter with less investment if policy conditions are not favorable to potential investors.

The specificity of capital also affects the dependence of businesses with respect to governments. Owners of highly specific assets, that is, assets with value that drops substantially when put to an alternative use, have a strong incentive to shape policy because they can escape from governmental regulations only at a high cost (Boix, 2003, 2024). (This policy capture may include relying on public institutions to bail them out in the case of a systemic crash following current levels of investment.) In other words, firms substitute lobbying and capturing policymakers for the loss in the structural power that characterizes mobile capital.[21]

[20] Since the holders of assets are older than average, political conflict would also turn around intergenerational distributive issues.

[21] On current debates and strategies to regulate data centers, see Brennen & Mohammed (2025).

The market dominance of platform companies likely accounts for their strong current lobbying activity before American and European regulators.[22] The growing specificity of their current fixed capital investments likely encourages them to develop even stronger and more direct ties with policymakers (Tan & Thelen, 2025). In fact, it may explain why several large technology companies, shelving the liberal-leaning agenda they used to promote in the 2010s, are cultivating direct links with the current US administration.

6 Economic/Political Backsliding Across the World?

So far we have examined the potential impact of AI at the individual and sectoral level, mainly in the context of developed economies, which are capital-abundant and have a labor force of skilled and semi-skilled workers. Consider now the case of the Global South, fundamentally abundant in low-skilled labor.

Globalization benefited developing economies, making them deeply embedded in global value chains, and fostering a process of economic convergence with the North, particularly for East Asia and Eastern European and Latin American regions close to postindustrial countries. AI may reverse those trends. Still, because gen-AI is very recent—and cross-country evidence on adoption and realized effects is thin—claims about international spillovers are necessarily more speculative than what we can say about earlier automation and about domestic effects where the technology is directly deployed.

On the one hand, AI-driven changes in production, sourcing, and coordination can have positive or neutral effects in the Global South. East and South Asian economies are developing technological hubs or technology-intensive service platforms. AI may foster new economic opportunities, including expanded remote and freelance services (Baldwin & Forslid, 2023). On the other hand, AI may have a negative impact on developing economies. Access to AI tools that could augment work is likely to be uneven due to important supply constraints: reliable connectivity and electricity, data infrastructure, and AI-relevant skills vary widely, shaping whether AI complements workers or substitutes for them (Cazzaniga et al., 2024; Gmyrek et al., 2023). Perhaps more importantly, AI may reduce the costs of capital relative to labor, accelerating production reshoring to the North.

For now, the clearest evidence on cross-border transmission comes from a pre–gen-AI and easier-to-measure technology: industrial robots. Automation costs have fallen sharply in the last decades. Robot prices declined by roughly 80 percent between 1995 and 2017 (Construction Physics, 2024), making foreign capital far more likely to replace labor.

The offshoring boom of the early 2000s slowed down as automation made low wages less decisive for many tasks (Antràs, 2020; Faber et al., 2023). Growing research associates

[22] See Halpin & Nownes (2021) for the United States and Gorwa et al. (2024) for the European Union.

automation with less offshoring and more reshoring across firms and countries (De Backer et al., 2018; Krenz et al,. 2021; Pinheiro et al., 2023; Bonfiglioli et al., 2024;, Hidalgo & Micco, 2024). Those developments may affect economies specialized in labor-intensive manufacturing in particular (Rodrik, 2018; Stemmler, 2023). Studies linking U.S. robotization to outcomes in partner countries find losses centered in export-oriented, routine manufacturing sectors, with stronger impacts in emerging economies than in richer ones (Carbonero et al., 2020; Faber, 2020; Kugler et al., 2020; Díaz Pavez & Martínez-Zarzoso, 2024). Distributional costs often fall on workers with weaker outside options, including many women, older workers, and low-educated production workers (Faber, 2020; Kugler et al., 2020).

Nonetheless, trade effects are not one-directional. Productivity gains in advanced economies can also increase demand for some imported inputs, including commodities, such as mining inputs, contributing to greater reliance on resource-based imports from the Global South (Stemmler, 2023).

The World Bank estimates that roughly 1.8 billion jobs in developing countries – about two-thirds of their workforce – are potentially automatable (Frey & Rahbari, 2016). If anything, AI could extend this logic beyond manufacturing. Firms could increasingly use AI to deliver services that were previously offshored – from customer support and back-office processing to parts of software development, accounting, translation, and other higher-skill professional services. If that substitution scales, developing economies could face external AI shocks even in sectors where they once held a clear advantage in tradable services, and even where local AI adoption has started to take place.

While direct evidence on AI is still scarce, existing work on pre-generative AI automation suggests that technological change in the Global North can have substantial political spillovers in the Global South. Boix et al. (2025), who study exposure to foreign robot adoption across Mexican commuting zones, find that areas more exposed to foreign robots shift leftward politically – contrasting with evidence from advanced economies, where similar shocks often fuel right-wing populism. The authors attribute this difference to the structure of political coalitions in labor-abundant economies. Low-skill workers historically benefited from globalization, but foreign automation and reshoring threaten these gains, weakening pro-market coalitions and increasing support for redistribution and protection. The same exposure is also associated with higher levels of organized crime, consistent with broader evidence that adverse labor-market shocks can increase violence when formal employment opportunities contract (Dube & Vargas, 2013; Dix-Carneiro et al., 2018; Dell et al., 2019).

AI's long-run impact on political institutions may be even more dramatic. If it results in high levels of automation and reshoring, industrializing countries may be unable to escape from a middle-income trap. In the limit, they may even experience negative growth rates and a shrinking middle class and, as result, democratic backsliding or, in those places without free elections, the strengthening of authoritarian institutions (Boix, 2024).

Low fertility rates and aging in the advanced world account for part of recent South-North migratory flows. If at some point AI and robotics substitute for some migrant labor in care, agriculture, and other services, they will dampen Global South out-migration, increasing labor-absorption pressures at home.

7 Conclusions

In this chapter, we have examined the political economy of AI-driven transformation in labor markets, capital, and the production process in general.

In line with reports such as Narayanan & Kapoor (2025), we tend to view AI as a "normal" (general-purpose) technology, at least at this point in time and in regard to labor markets. First, the introduction of AI appears to have been gradual and circumscribed to a fraction of the multiple tasks that generally compose any occupation. By replacing specific tasks, AI is arguably allowing its direct users to expand their attention to the other components of their specific occupation. Second, the effects of AI appear to be conditional on its complementary with the skills of its users and mediated by the institutional environment in which it is diffused. Perhaps for these reasons, the public holds ambiguous views about the social and economic consequences of AI, making elite discourse central to its reception and regulation.

AI may be having a more substantial (but, so far, less researched) impact on capital. The economics of foundation models have reinforced market concentration in the technological sector and triggered massive investments in fixed assets. This, in turn, has boosted the lobbying capacity of technological firms and intensified their appetite for regulatory capture.

The disruptive effects of AI in the labor market and the growing role played by tech capitalists could exacerbate the political tensions that have recently characterized advanced democracies. At the same time, however, an AI-generated positive productivity shock may attenuate electoral conflict. Overall, these effects will be conditional on political responses. For example, stepping up AI-related training of the labor force could smooth the transition to a new production paradigm.

As stressed throughout this chapter, we still know little about the economic and political consequences of AI. This is undoubtedly due to the short period elapsed since the practical application of AI models to economic tasks. But part of it seems due to important disagreements on how to measure its effects and to the difficulty of translating what we know in terms of AI methods to their actual application in specific tasks and occupations. Hence, a critical line of research should consist of understanding the ways in which jobs are exposed to AI—and of reconciling the different vulnerability or exposure to AI measures that have been developed so far.

Future research on the political and social effects of AI should probably avoid any deterministic understanding of its impact. First, the extent to which AI will reshape society will depend on the speed of adoption (gradual, fast and massive, or even in the form of a technological singularity) as well as on our capacity for adjustment (Milner 2025). Second, its regulatory environment, and therefore its impact, will be a function of the discursive framing of political entrepreneurs and legal decisions made by policy-makers. Finally, its political effects will vary with the policy mechanisms developed to compensate the losers of change and to share the benefits of these new technologies.

When designing a policy tool kit in response to AI's disruptive effects, we need to consider two diverging future scenarios. In the first one, AI intensifies (or even reverses) the skilled-biased nature of current technological changes. In the second one, AI (mainly embodied AI) substitutes for most or all labor. Particularly in the second scenario, capital would represent a disproportionate share of national income.

The urgency and reach of the three main policy interventions we outline below will depend on which of the two scenarios we end up facing and on the extent of the disruption generated by AI. First, investing in education (including vocational training) should make the workforce easier to match to AI-complementary jobs. If the process of capital-labor substitution generates some persistent unemployment or permanently falling wages, countries could set a "universal basic capital" (UBC) system, giving everyone some fixed capital at birth. To incentivize prudential behavior, free disposition over its returns would happen at adult age. UBCs resemble the idea of a universal basic income (UBI) but give economic agency to their holders. UBCs could be funded through a tax on robots and structured as pension funds operate today. One may think of this policy as a system to maintain markets while constructing a society of capital holders. An alternative (or complementary) intervention could consist of creating a sovereign fund, funded through taxes or through the returns to shares in capital-intensive companies, that would sustain social spending.

Second, democratic institutions should invest in creating a legal framework that blocks the formation of a closed elite. That would require the combination of an active antitrust policy and of measures to reinforce political participation, reduce unequal electoral funding, publicize (ownership and marketing) relations between media and large firms, strengthen local level governance schemes, and so on.

Finally, although the economic and political repercussions of AI-driven automation for the Global South remain uncertain, they warrant closer political scrutiny. Policymakers may want to give some consideration to interventions that mitigate AI's potential negative effects on growth (through reshoring) there. In a world of stagnating or even declining population, advanced economies (or at least those clusters experiencing AI-productivity shocks) may wish to be open to immigration—both as a mechanism to equalize life chances across the world and to sustain welfare states in the North.

Appendix

Table A1. *Overview of Task and Automation Exposure Objective Measures*

Reference	Measure	What it captures
(Autor et al., 2003)	Task Groups	Canonical split of jobs into routine vs non-routine analytical, interactive, or manual. Relied on O*NET task data to classify occupational activities into three categories: Routine tasks — rule-based activities that can be easily automated (e.g., record-keeping, assembly). Non-routine cognitive tasks — analytical or problem-solving work requiring adaptability and judgment. Non-routine manual tasks — physical tasks demanding dexterity or situational flexibility that are difficult to automate. This classification forms the foundation of the task-based framework for understanding how technology reshapes labor demand.
(Goos et al., 2014)	RTI	An occupation-level index built from five DOT task variables (following Autor–Levy–Murnane). Tasks are grouped into Routine, Abstract, and Manual, and RTI is computed as $RTI = ln(Routine) - ln(Abstract) - ln(Manual)$. Industry- and country-level RTI for Europe by mapping occupational task content (O*NET/DOT to ISCO) and aggregating to industries; used to explain polarization and the role of offshoring.
(Frey & Osborne, 2017)	Computerization probability	Occupation-level automatability from expert-labeled training set and a classifier using O*NET features; yields the probability a job is susceptible to computerization.
(Arntz et al., 2017)	Task-based automation risk	Worker-level automation probabilities using PIAAC task surveys; accounts for within-occupation task heterogeneity and task bundling when estimating risk.
(Graetz & Michaels, 2018)	Robot intensity	Industry-level stock/flow of industrial robots with data from International Federation of Robotics (IFR) in particular “multipurpose manipulating industrial robots.” The stock was normalized by hours worked across countries; proxy for exposure to robot adoption in production.
(Brynjolfsson et al., 2019)	SML	Suitability for Machine Learning scores: task-level ratings on 23 criteria (e.g., data availability, definable objectives), aggregated to occupations to flag ML-amenable tasks. These ratings were applied to the textual descriptions of all O*NET occupations via CrowdFlower, a crowdsourcing platform. The resulting index provides a forward-looking estimate of which tasks are most likely to be automated through machine learning or AI in the near future.
(Felten et al., 2019)	AIOE	Uses data from the Electronic Frontier Foundation’s AI Progress Measurement project. It links nine AI application areas (e.g., image recognition, language modeling) to 52 O*NET ability scales through

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Reference	Measure	What it captures
		crowd-sourced relevance scores from Amazon MTurk. Each occupation's AI exposure is computed as a weighted sum of these application-ability scores, with weights reflecting the importance and prevalence of each ability in that occupation.
(Acemoglu & Restrepo, 2020)	Robot exposure	Commuting-zone exposure to robots: IFR industry robot penetration weighted by local 1990 industry employment shares; links robot diffusion to local labor outcomes.
(Webb, 2020)	AI patent exposure	Textual overlap between job task descriptions (O*NET) and AI patent text to measure direct exposure of occupations to AI technologies (also constructed for software/robots).
(Anelli et al., 2021)	Vulnerability to automation	Individual-level exposure combining (i) predicted occupation probabilities based on pre-treatment characteristics (age, gender, education), (ii) occupation automatability/robot relevance, and (iii) country–year robot adoption to gauge personal vulnerability.
(Manning et al., 2023)	LLM exposure (GPT-4)	Task- and occupation-level exposure based on alignment between O*NET tasks and LLM capabilities, using expert judgments and GPT-4 assessments; higher values indicate greater potential task impact.
(Pizzinelli et al., 2023)	AI exposure & complementarity	Extension of exposure metrics that separates exposure from complementarity by incorporating work context and skills; distinguishes high-exposure jobs where AI is more likely to complement vs. substitute labor.
(Kogan et al., 2023)	Labor-Saving vs Labor-Augmenting Exposure (Patent–Task)	Text similarity between patents and occupation tasks to build time-varying exposure measures that distinguish substitution (labor-saving) from augmentation (labor-augmenting) at worker/occupation levels. Patents whose language closely matches routine tasks are treated as labor-saving (automation); matches to non-routine, skill-intensive tasks are treated as labor-augmenting (complementary).
(Eisfeldt et al., 2023)	Generative AI workforce exposure	Firm-level exposure derived by mapping generative-AI-susceptible occupational tasks to each firm's workforce mix; used to study market valuation effects of GenAI.
(Agnolin & González-Rostani, 2025)	Monitoring, Augmentation	1) Map ISCO occupations to six families of workplace technologies using the TechXposure patent-text embedding method (machine learning, embedded systems, remote monitoring, smart mobility, intelligent logistics, food-ordering), then scale each occupation's score by the respondent's country-year Enterprise Resource Planning systems (ERP) adoption rate from Eurostat to capture diffusion, producing individual-level exposure. 2) Build an LLM-based index at the industry-occupation level that rates augmentation, monitoring, and replacement on 1-10 scales with paired certainty scores and binary exposure flags.
(Prytkova et al., 2025)	Emerging Technologies & Patents	Measured by matching patent text to standardized industry (NACE Rev.2, 3-digit) and occupation (ISCO-08, 4-digit) descriptions using sentence-transformer embeddings (all-mpnet-base-v2) and cosine

Reference	Measure	What it captures
		similarity. These similarities are then aggregated within 40 technology clusters obtained by k‑means on patent embeddings, weighted by patent citations, and transformed with an inverse‑hyperbolic‑sine to reduce skew, yielding technology‑specific exposure scores for each industry and occupation.
(Tomlinson et al., 2025)	AI applicability	Score built from real-world usage of a generative-AI assistant, by classifying Bing Copilot conversations into work activities (e.g., gathering information, writing, advising) and recording how often and how successfully AI performs each. They then map those activities to the activity mix of occupations, weighted by measured task success and breadth of impact, to produce a per-occupation score capturing how much current gen-AI can be productively applied to that job.

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