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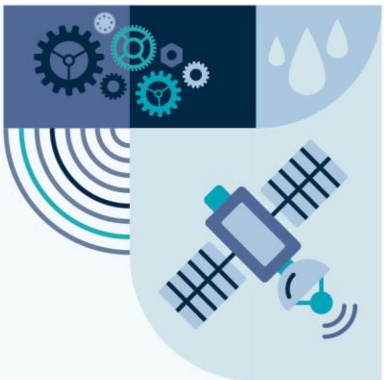

Employment Protection, Adjustment Costs, and Technology Adoption

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Employment Protection, Adjustment Costs, and Technology Adoption

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2026 Directorate-General for Research and Innovation

Abstract[1]

This paper examines how employment protection legislation shapes firm-level technology adoption across OECD countries using novel survey data. We document a negative association between employment protection legislation and the adoption of artificial intelligence and other restructuring-intensive technologies, while more modular digital technologies display weaker relationships with labor market institutions. The patterns are particularly pronounced among large incumbent firms, while younger and fast-growing firms exhibit higher adoption rates. To interpret these patterns, we develop a general equilibrium model with heterogeneous firms in which workforce restructuring costs raise the productivity threshold for technology adoption. The model predicts heterogeneous firm responses: some adopters expand employment, others contract, and highly productive incumbents may optimally refrain from adoption when restructuring costs rise with scale. The framework is extended to incorporate endogenous technology arrival and diffusion through both adoption by incumbent firms and entry of new firms implementing frontier technologies. The analysis highlights how labor market institutions can affect technology diffusion and, through this channel, influence incentives to develop and commercialize new technologies.

JEL codes: O33, J24, J38, L25, O32

Keywords: Employment protection legislation, technology adoption, artificial intelligence, labor market institutions, firm heterogeneity, restructuring costs, general equilibrium

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Executive summary

This paper studies how employment protection legislation (EPL) is related to firms' adoption of new technologies across OECD countries, using novel firm-level survey data. We document a negative association between employment protection legislation and the adoption of artificial intelligence and other restructuring-intensive technologies across countries, while adoption of more modular digital technologies such as cloud computing is much less affected. These patterns are particularly pronounced among large firms, suggesting that workforce scale and restructuring requirements play a central role in shaping adoption decisions.

To interpret these empirical regularities, the paper develops a general equilibrium model of heterogeneous firms that face fixed, retraining, and severance costs when adopting new technologies. EPL can raise these restructuring costs, increasing the productivity threshold required for adoption, while the model also captures positive effects on workforce stability and in-house training. As a result, adoption is not monotone in firm productivity: medium-productivity firms are most likely to adopt and expand employment, while highly productive firms may optimally refrain from adoption when workforce reductions become too costly. Empirical cross-tabulations from the survey closely mirror this predicted sorting of firms into adopters, expanders, downsizers, and high-productivity holdouts.

The framework is further extended to allow for multiple technological trajectories and endogenous technology arrival, linking downstream adoption incentives to upstream R&D investment. It also highlights an additional diffusion margin through firm entry, as new firms can adopt frontier technologies without facing legacy restructuring costs. When stricter EPL dampens adoption (especially by frontier firms) it may therefore reduce private incentives to develop restructuring-intensive technologies, creating a wedge between private and social returns to R&D. Quantitative exercises illustrate how these mechanisms vary across technological trajectories and institutional regimes.

Overall, the analysis suggests that labor market institutions shape not only the extent but also the composition of technology adoption. Institutional environments that provide worker security while preserving firms' ability to reorganize - such as flexicurity-type arrangements - may support broader diffusion of productivity-enhancing technologies and strengthen incentives for technological upgrading.

1. Introduction

The question of how Europe can regain technological leadership has moved to the center of the policy debate. Recent reports - most prominently those by Mario Draghi (2024) and Enrico Letta (2024) - warn that the European Union is falling behind the United States and other major economies in the development and diffusion of key technologies, including artificial intelligence (AI). In response, the European Commission has proposed a substantial expansion of its research and innovation programs and several new instruments gathered under the Competitiveness Compass (European Commission 2025a,b). While financial constraints and the availability of risk capital are widely cited as principal barriers to European innovation, other institutional features - such as labor market regulation - may also play an important role in shaping firms' ability and incentives to adopt new technologies.

Recent work emphasizes that Europe's difficulty in competing in complex, frontier technologies reflects fragmentation and institutional barriers that impede coordination and scaling (Balland et al. 2025). This paper focuses on the role of employment protection legislation (EPL) in influencing firm-level innovation and technology adoption. Although a large literature examines the relationship between employment protection legislation and innovation, the empirical evidence remains mixed, and comparatively little attention has been paid to the link between EPL and technology adoption as distinct from innovation. Technology adoption, however, is the key mechanism through which new ideas translate into productivity gains. Understanding how labor market institutions influence adoption is therefore critical for explaining Europe's productivity slowdown and its widening gap with the global technological frontier.

We study these issues using a new large-scale firm survey on "Startups, scaleups, and entrepreneurship" conducted in early 2025 (European Commission 2025c). The survey covers firms in all EU Member States and several non-EU economies (including Canada, Switzerland, the United Kingdom, and the United States) and collects detailed information on product, process, marketing, and management innovation, as well as adoption of a wide range of technologies: AI, cloud computing, robotics, digital security, Internet of Things, blockchain, biotech, nanotech, advanced materials, and clean technologies. Its broad coverage and simultaneous measurement of innovation and technology adoption make it well suited for cross-country analysis. We complement these data with OECD indicators of EPL, which display substantial variation across countries but change slowly over time. The data suggest a systematic negative association between employment protection legislation and the adoption of artificial intelligence and other advanced technologies. Countries with stricter employment protection tend to exhibit lower adoption rates than countries with more flexible labor market institutions, including the United States, the United Kingdom, and Canada. This pattern is consistent with recent survey-based evidence documenting substantial cross-country differences in AI adoption, including a persistent gap between Europe and the United States (Bick et al., 2026).

Throughout, the empirical evidence is interpreted as descriptive correlations rather than causal estimates. The role of the quantitative model is to provide an internally consistent mechanism - centered on workforce restructuring costs - that can rationalize the stylized facts and serve as a disciplined laboratory for counterfactual analysis. Accordingly, the policy implications are conditional on the model's structure and on interpreting employment protection legislation as a proxy for adjustment frictions faced by firms.

The model is a parsimonious general equilibrium framework with heterogeneous firms that incorporates several policy-relevant margins. Employment protection legislation raises the costs associated with adoption - most notably through severance obligations and fixed reorganization costs - while also shaping firms' reliance on retraining and workforce retention during the adoption process. The model abstracts from potential additional benefits of employment protection, such as greater predictability and the allocation of adjustment risks between firms and workers. The analysis predicts heterogeneous employment responses across firms: medium-productivity adopters expand employment, high-productivity adopters may downsize, and some highly productive firms optimally refrain from adoption when restructuring costs rise disproportionately with scale. The framework is further extended to incorporate endogenous innovation by allowing the arrival of new technologies to depend on R&D investment, with innovation rents determined by downstream adoption. Through this channel, stricter employment protection affects not only firms' adoption decisions but also private incentives to invest in innovation by reducing the expected returns from diffusion.

More broadly, the mechanism studied in this paper can be interpreted as one example of a wider class of institutional adjustment frictions that affect firms' ability to reorganize production when new technologies emerge. While the empirical analysis focuses on employment protection legislation, similar frictions may arise from insolvency regimes, collective bargaining structures, or other institutional features that influence the costs of workforce and organizational restructuring. From this perspective, employment protection legislation can be interpreted as one salient institutional determinant of the adjustment costs associated with technological change.

The baseline model focuses on technology adoption by heterogeneous incumbent firms facing restructuring costs associated with employment protection legislation. To capture additional channels of technological diffusion observed in the data, the framework is later extended to allow for multiple technological trajectories and for diffusion through firm entry and exit, highlighting the role of startups and scaleups in the spread of new technologies.

Our framework builds on existing models of employment protection, innovation, and technology adoption, but - to our knowledge - no previous paper combines (i) heterogeneous firms facing EPL-induced restructuring and retraining costs, (ii) a potentially non-monotone technology adoption pattern in productivity, and (iii) endogenous innovation arrival with innovation rents derived from licensing the new technology to adopters, all within a parsimonious quantitative framework linking employment protection, firm heterogeneity, and technology adoption.

The paper also highlights that labor market institutions may affect not only the overall rate of technology adoption but also the channels through which new technologies diffuse. When workforce restructuring is costly, adoption by incumbent firms may become less attractive, increasing the relative importance of entry and expansion by new firms implementing frontier technologies. This distinction between incumbent adoption and entry-based diffusion plays an important role in shaping both the speed of technological upgrading and the incentives to develop new technologies.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the Eurobarometer and OECD data used in the analysis. Section 4 documents the empirical evidence and organizes it around a set of stylized facts on firms' technology adoption that motivate the structure and key mechanisms of the model. Section 5 develops the baseline theoretical framework. Section 6 introduces model extensions that allow firms to choose among multiple technological trajectories and incorporate technology diffusion through firm entry and exit. Section 7 presents the quantitative implementation of the model. Section 8 introduces endogenous innovation and analyzes how labor market institutions affect the level and direction of R&D investment. Section 9 discusses the policy implications of the framework. Section 10 concludes and discusses broader implications for technological diffusion and productivity growth.

2. Related literature

This paper relates to four strands of literature: the productivity slowdown, the determinants of innovation, the drivers of technology adoption, and the labor market consequences of technological change.

2.1. Productivity slowdown and digital technologies

A large literature examines the causes of the secular slowdown in productivity growth in advanced economies. One view emphasizes that recent technological advances yield diminishing marginal returns and lack the transformative impact of earlier general-purpose technologies (Fernald 2015; Gordon 2016). Related work documents sharply rising research costs, suggesting that the production of new ideas has itself become increasingly difficult (Bloom et al. 2020).

An alternative perspective emphasizes diffusion rather than invention as the key bottleneck. Historical evidence shows that general-purpose technologies generate productivity gains only gradually, as firms undertake complementary investments in organizational restructuring, skills, and new business processes (Griliches 1957; Jovanovic and Rousseau 2005; Comin and Hobijn 2010). Recent contributions argue that digital technologies and artificial intelligence may exhibit particularly long adjustment lags, giving rise to a "productivity paradox" despite rapid technical progress (Brynjolfsson et al. 2021). A growing literature therefore emphasizes technology diffusion as a key driver of cross-country productivity differences. In particular, Comin and Mestieri (2018) show that slow and uneven diffusion of new technologies can account for persistent gaps in productivity levels across countries. At the microeconomic level, adoption decisions respond to relative costs, factor endowments, and institutional environments. Caselli and Coleman (2006) find that cross-country differences in the adoption of information and communication technologies reflect variation in economic incentives rather than differences in access to frontier technologies. Taken together, this literature points to technology adoption and diffusion - rather than innovation alone - as central margins for understanding productivity dynamics.

2.2. Institutions and innovation

In canonical endogenous growth models, firms invest in innovation to capture rents, while knowledge spillovers generate a wedge between private and social returns, motivating policy interventions such as intellectual property protection and R&D subsidies (Romer 1990; Aghion and Howitt 1992). Empirically, innovation outcomes depend not only on firm characteristics but also on the institutional environment, including product and labor market regulation. The effect of employment protection legislation on innovation is theoretically ambiguous. Stricter dismissal protection may discourage risky investment by raising adjustment and restructuring costs, but it may also foster firm-specific human capital accumulation and worker commitment (Belot et al. 2007). Empirical work suggests that EPL primarily affects the composition of technologies and production methods rather than the aggregate level of innovation, by reducing labor reallocation and biasing firms' technology choices (Bartelsman et al. 2016; Manera and Uccioli 2024; Cerpentier et al. 2024).

A growing literature further emphasizes that public policy and institutions influence not only the level of innovative activity, but also its direction, by altering relative returns across technological trajectories (Aghion et al. 2019).

Recent work highlights restructuring costs and "costs of failure" as a key channel through which institutions affect innovative activity. Haltiwanger et al. (2014) provide evidence that rigid labor market regulations impair firm-level reallocation and productivity growth, consistent with institutions raising the costs of adjustment for firms. Complementary evidence by Coatanlem and Coste (2025) documents substantial cross-country differences in restructuring costs - significantly higher in Western Europe than in the United States or Denmark - and argue that high costs of failure discourage risk-taking and innovation. This evidence suggests that labor market institutions may shape innovation incentives primarily through their impact on firms' ability to reorganize and adjust following unsuccessful or disruptive investments, rather than through direct effects on R&D inputs alone.

2.3. Technology adoption and diffusion

Innovation and adoption are distinct economic processes. While innovation creates new ideas, adoption involves integrating existing technologies into production and often requires substantial complementary investments in training, organizational restructuring, and supply-chain adjustments. Firms' absorptive capacity - shaped by prior knowledge and organizational capabilities - plays a central role in determining adoption outcomes (Cohen and Levinthal 1990; Hall and Khan 2003). Consistent with this perspective, recent survey-based evidence also documents substantial cross-country differences in AI adoption and highlights the role of firm characteristics and management practices in shaping these patterns (Bick et al., 2026).

A large literature shows that institutional distortions can generate substantial productivity losses by misallocating resources across heterogeneous firms (Restuccia and Rogerson 2008). While this work focuses primarily on static misallocation, the present paper highlights technology adoption as a dynamic margin through which labor market institutions shape productivity outcomes.

Compared to innovation, the relationship between labor market institutions and technology adoption has received relatively limited attention. Existing evidence focuses mainly on specific technologies. Traverso et al. (2022) document a negative association between EPL and robot adoption across advanced economies, attributing it to higher adjustment and dismissal costs. Theoretical work suggests that flexicurity - weak employment protection combined with strong income support - can encourage adoption by lowering restructuring barriers (Lommerud and Straume 2012). More recent contributions highlight organizational and social frictions in the adoption of artificial intelligence, including trust between workers and firms over job security and task reallocation, constraints related to data availability and quality, and concerns about workforce adjustment (Cubric 2020; Kim et al. 2025). However, systematic cross-country evidence on how labor market institutions shape the adoption of a broad set of emerging digital and AI-related technologies remains scarce.

2.4. Technology, employment, and institutions

A growing literature examines the labor market consequences of technological change. Models of skill-biased technical change and automation predict heterogeneous employment and wage effects across workers and firms (Katz and Murphy 1992; Autor et al. 2003). With the advent of artificial intelligence, attention has shifted toward task reallocation and the interaction between human and machine capabilities, generating both displacement and productivity effects (Acemoglu and Restrepo 2019).

Labor market institutions play a key role in mediating these outcomes. Firing costs and adjustment frictions affect firm dynamics, reallocation, and productivity (Hopenhayn and Rogerson 1993; Hopenhayn 2014). Empirical evidence suggests that worker perceptions of automation and its well-being consequences vary systematically with institutional protections (Mulas-Granados et al. 2019). Firm-level studies document heterogeneous employment responses to automation and digital technologies, with expansion in some firms and contraction in others, reflecting differences in productivity, scale, and organizational change (Brynjolfsson and Hitt 2000; Bessen 2018). Yet existing models of automation and firm heterogeneity typically abstract from labor market regulation as a direct determinant of technology choice.

Taken together, this literature suggests that labor market institutions may play a central role in shaping the diffusion and economic impact of new technologies, but existing evidence remains fragmented. Prior work has examined EPL's effects on innovation inputs, labor reallocation, or the adoption of specific technologies, yet we lack a unified framework that links EPL directly to firms' technology adoption decisions across a broad set of emerging digital and AI-related technologies. Moreover, the mechanisms through which EPL affects adoption - via restructuring costs, severance obligations, and workforce adjustment - have not been integrated into a quantitative general equilibrium model with heterogeneous firms.

This paper complements existing evidence that labor market institutions affect productivity, investment, and technology diffusion (Bassanini et al., 2009; Cingano et al., 2010; Andrews et al., 2015; Fedotenkov et al., 2024). It contributes by highlighting a specific mechanism: employment protection legislation can shape firms' adjustment costs when introducing new technologies, thereby influencing technological diffusion. It does so by combining new cross-country firm-level data on technology adoption with a parsimonious general equilibrium model of technology adoption under labor market frictions. The framework clarifies how employment protection legislation can constrain technology adoption, highlights heterogeneous firm responses, and provides a structured way to assess how labor market institutions shape technology diffusion, employment reallocation, and innovation incentives.

3. Data

This section describes the data sources and key variables used in the analysis, drawing on firm-level survey data from the European Commission's Flash Eurobarometer 559 and country-level indicators of employment protection and product market regulation from the OECD.

3.1. Flash Eurobarometer 559: Innovation and technology adoption

The primary data source is the Flash Eurobarometer 559 survey on "Startups, Scaleups and Entrepreneurship", conducted by Ipsos on behalf of the European Commission between February and April 2025. The survey covers firms in the 27 EU Member States and 11 non-EU economies, including Norway, Switzerland, the United Kingdom, Turkey, Canada, Japan, and the United States. Very small countries with limited firm samples (Montenegro, North Macedonia, Albania, and Serbia) are not included in the final sample. The dataset used in this paper consists of 14,656 firms spanning both SMEs and large enterprises, interviewed via telephone.

Table 1. Descriptive statistics of the Flash Eurobarometer 559

Variable	Mean	Obs.
Panel A. Technology adoption		
AI	0.210	14,656
Cloud computing	0.521	14,656
Robotics	0.103	14,656
Internet of things	0.241	14,656
Digital technologies for security	0.393	14,656
Blockchain	0.033	14,656
Biotechnology	0.043	14,656
Micro- and nanoelectronics	0.043	14,656
Advanced materials	0.079	14,656
Clean technologies	0.166	14,656
Panel B. Firm characteristics		
SME (1-249 employees)	0.934	14,656
Large firm (≥500 employees)	0.031	14,656
Startup	0.041	14,656
Scaleup	0.239	14,656
Registered before 2005	0.538	14,219
Registered between 2005 and 2019	0.382	14,219
Registered between 2020 and 2023	0.068	14,219
Registered 2024 or later	0.011	14,219

Notes: Means refer to the share of firms in the sample for which the corresponding indicator variable equals one. Descriptive statistics are computed for the analysis sample used in Section 4. Observations for which firm-level productivity cannot be computed are excluded. Sampling design follows the Eurobarometer methodology.

Source: European Commission (2025c).

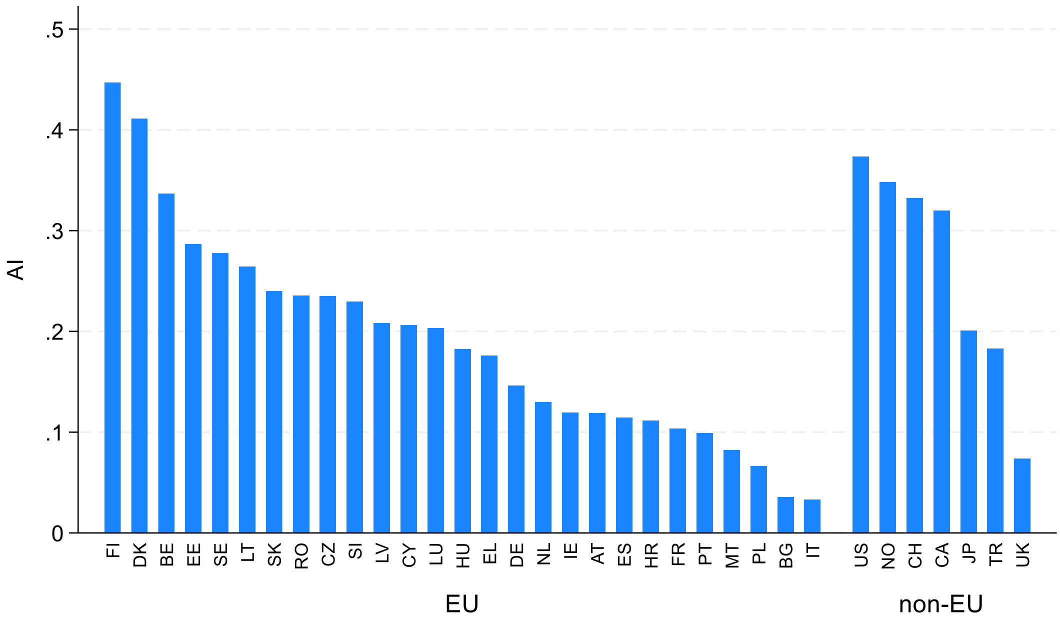
The survey provides rich and internationally comparable information on firms' innovation activities, adoption of advanced technologies, organizational characteristics, and business environment assessments. Table 1 summarizes the key variables used in the analysis (measured as binary variables; reported means therefore correspond to adoption rates or the share of firms with a given characteristic), including firm-level indicators of technology adoption and firm characteristics. A description of all variables included in the analysis is provided in Appendix A.[2]

[2] The Eurobarometer survey defines startups and scaleups based on firm age, innovation activity, and growth dynamics (European Commission, 2025c). Startups are young firms, founded in 2020 or later, that have introduced an innovation in the past 12 months and report plans to grow in turnover and/or employment. Scaleups are firms founded before 2020 that have achieved sustained growth since 2021, defined as at least 30% growth in turnover or employment; for micro firms (1-9 employees), the employment criterion corresponds to an increase of at least three employees.

Technology adoption variables

The survey records whether the firm has adopted any of ten advanced technologies. These include artificial intelligence (e.g., machine learning, large language models); cloud computing; robotics; Internet of Things; cybersecurity technologies; blockchain; biotechnology; micro- and nanoelectronics and photonics; advanced materials; clean and resource-efficient technologies. Cloud computing (52%) and cybersecurity (39%) are the most widely adopted technologies. Overall, 21% of firms report adopting AI technologies, with substantial cross-country variation and adoption rates generally higher in the United States than in most European economies (Figure 1).[3]

Figure 1. AI adoption rates in the EU and non-EU countries



Notes: The figure reports the share of firms that indicate having adopted artificial intelligence technologies, based on responses to Flash Eurobarometer 559 (Spring 2025). Bars represent country-level averages for EU Member States and selected non-EU economies. AI adoption is measured based on firms' self-reported use of artificial intelligence technologies. Adoption is measured by a binary indicator taking value 1 if the firm reports using any AI tool (e.g., machine learning or large language models) and 0 otherwise. Adoption rates are computed using the full Eurobarometer sample. Sampling design follows the Eurobarometer methodology.

Firm characteristics

The dataset provides detailed information on sector, ownership structure, firm age, size, exporting status, managerial assessments of skills availability, and whether the firm is a startup or scaleup. SMEs (fewer than 250 employees) account for the majority of respondents, with 4% classified as startups and 24% as scaleups.

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[3] Cross-country differences should be interpreted with caution, as they may reflect differences in reporting, firm composition, and the interpretation of AI across countries. In addition, a limitation of the Eurobarometer data is that it captures technology adoption only on the extensive margin - whether a firm reports having adopted a given technology - without information on the intensity of use, investment volumes, or the share of business processes affected. Complementary evidence from the European Investment Bank Investment Survey (EIB 2025) suggests that differences along the intensive margin may be economically important. In particular, while reported AI adoption rates are broadly comparable between the EU and the United States, US firms tend to deploy AI across a larger number of business processes, indicating more pervasive use.

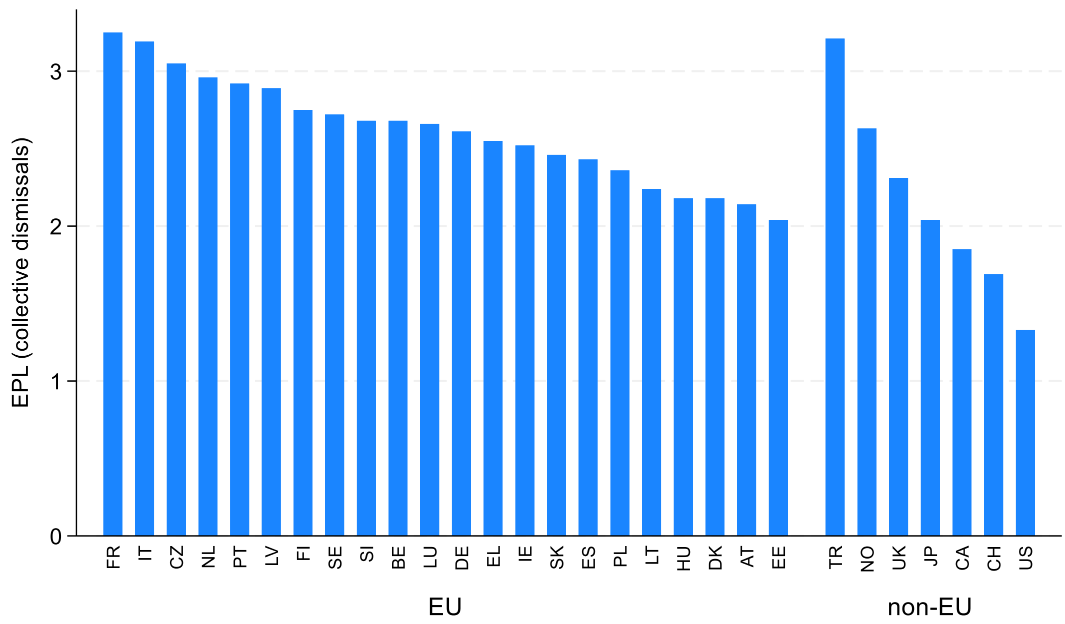
3.2. Employment protection legislation

Employment protection legislation is designed to provide workers with income security and bargaining power by limiting arbitrary dismissals and encouraging longer-term employment relationships. While employment protection legislation enhances worker security and may support firm-specific human capital formation, it can also affect firms' adjustment margins by raising the costs of workforce reallocation.

To capture cross-country variation in labor market regulation, we merge the firm-level survey with the OECD's Employment Protection Legislation (EPL) indicators. These de jure indicators measure the strictness of rules governing dismissals and the use of temporary contracts. They cover individual dismissals (regular contracts), collective dismissals (regular contracts), and temporary contracts.[4]

EPL scores range from 0 (least restrictive) to 6 (most restrictive), and are based on statutory laws, collective agreements, case law, and detailed documentation from national experts. Although the most recent available year is 2019, employment protection legislation is relatively stable over time, making these indicators a reasonable proxy for the institutional environment prevailing at the time of the 2025 survey.

Figure 2. EPL indicator for collective dismissals (regular contracts)



Notes: OECD EPL indicators (scale 0-6) measure statutory restrictions and procedural requirements for collective dismissals. Higher values indicate stricter employment protection. Data refer to 2019; EPL levels are stable over time.

The OECD sample covers 22 EU Member States and the 7 non-EU countries which are also included in the Eurobarometer survey (Canada, Japan, Norway, Switzerland, Turkey, the United Kingdom, and the United States). For this paper's focus on restructuring costs, EPL for collective dismissals is the most relevant and is depicted in Figure 2. Among EU countries, Czechia, France, and Italy have the

[4] De jure statutory provisions may differ from de facto enforcement, particularly in countries where dismissal rules and severance arrangements are partly determined through collective bargaining. To the extent that de jure EPL proxies for broader adjustment frictions faced by firms, the analysis interprets EPL as a summary indicator of institutional constraints rather than a precise measure of enforcement intensity.

strictest collective dismissal rules; Estonia and Austria are among the most flexible. The United States and Switzerland feature the lowest EPL levels.

3.3. Product market regulation

To capture institutional features outside the labor market, we also include the OECD's Product Market Regulation (PMR) indicators, which quantify regulatory barriers to competition in goods and services markets. The PMR indicators are widely used in studies of productivity, innovation, and technology diffusion. We focus on the Barriers to Trade and Investment (BTI) component, which measures restrictions on foreign entry, discrimination against foreign suppliers, and limitations on cross-border mergers and acquisitions. High BTI scores indicate more protectionist regimes. Lower BTI is typically associated with stronger competitive pressure, higher innovation intensity, and faster technology diffusion (with Sweden and the Netherlands exhibiting the lowest levels within the EU).

4. Stylized facts on technology adoption and labor market institutions

Rather than pursuing causal estimation of the effects of employment protection legislation, we organize the empirical evidence around a set of stylized facts on firm-level technology adoption. These facts discipline the structure of the model developed in the next sections and motivate its key mechanisms.

Stylized Fact 1: EPL is selectively associated with the adoption of advanced technologies

The relationship between employment protection legislation and technology adoption displays clear and systematic patterns across technologies. Table 2 reports regression-adjusted descriptive associations between employment protection legislation and firms' adoption of advanced technologies. The regression-adjusted specifications are used as a descriptive device to summarize cross-country patterns while accounting for observable firm characteristics and sector composition.[5] We do not interpret these coefficients causally. The estimates reveal substantial heterogeneity across technologies. Employment protection legislation is negatively associated with the adoption of artificial intelligence and digital security technologies - two restructuring-intensive technologies that typically require substantial workforce and task reorganization. By contrast, EPL is not significantly associated with the adoption of cloud computing, robotics, the Internet of Things, or biotechnology.[6]

This pattern suggests that employment protection legislation does not uniformly discourage technology adoption. Instead, stricter employment protection is selectively associated with lower adoption of technologies that are more likely to involve organizational restructuring, changes in task allocation, and adjustments in the composition of the workforce across occupations and skill groups.[7] Technologies that are more modular, capital-embedded, or incremental in nature appear substantially less sensitive to labor market regulation. Related work shows that AI-related and automation technologies are particularly sensitive to organizational and adjustment frictions (Acemoglu and Restrepo 2020). By contrast, evidence from the OECD indicates that more modular digital technologies tend to diffuse more uniformly across institutional environments (OECD 2024).

[5] Firm productivity is included to control for differences in firms' capabilities and absorptive capacity. Since technology adoption may itself affect productivity, this variable is used as a control and not interpreted causally.
[6] A comparable analysis for the innovation variables included in the Eurobarometer survey is included in Appendix D.
[7] These findings are consistent with the evidence reported in Nicoletti et al. (2020).

Table 2. Employment protection and the adoption of advanced technologies

	(1) AI	(2) Cloud computing	(3) Robotics	(4) IoT	(5) Digital security	(6) Blockchain	(7) Biotech	(8) Nanotech	(9) Advanced materials	(10) Clean tech	(11) Any of these technologies
EPL	-0.095***	-0.019	-0.007	0.006	-0.099***	0.003	-0.000	0.010	-0.031**	-0.020	-0.038*
	(0.029)	(0.028)	(0.012)	(0.031)	(0.025)	(0.008)	(0.012)	(0.011)	(0.014)	(0.028)	(0.022)
PMR	0.057	-0.058	-0.007	-0.072	0.121	0.011	-0.056***	-0.004	0.101***	0.130*	0.044
	(0.069)	(0.116)	(0.021)	(0.075)	(0.086)	(0.015)	(0.020)	(0.019)	(0.024)	(0.068)	(0.076)
Startup	0.171***	0.098***	0.043**	0.121***	0.093***	0.012	0.008	0.003	0.043**	0.123***	0.131***
	(0.038)	(0.028)	(0.021)	(0.032)	(0.026)	(0.009)	(0.013)	(0.013)	(0.019)	(0.024)	(0.027)
Scaleup	0.032***	0.025**	0.001	0.012	0.022*	0.007*	0.001	0.005	0.009	0.019**	0.032***
	(0.008)	(0.012)	(0.007)	(0.010)	(0.013)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.009)

Notes: Delta-method standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The EPL indicator refers to collective dismissals (regular contracts), and the PMR indicator to the medium level indicator on barriers to trade and investment. Startup and scaleup are dummy variables taking value 1 if the firm is a startup or scaleup, and 0 otherwise. Controls for firm productivity (details are included in Appendix B), perceived business environment in terms of availability of staff with the right skills, export status, sector, firm age, ownership, and firm size are included. The model also includes a dummy taking value 1 if the country is an innovation leader according to the European Innovation Scoreboard 2025 and 0 otherwise (European Commission 2025d). The total number of observations is 12,096 and 29 countries are included in the analysis. Reported coefficients from the multilevel mixed-effects probit regression model refer to average marginal effects. Further details about the quantitative procedure can be found in Appendix C.

Sensitivity checks confirm that these findings are robust. For both artificial intelligence and digital security technologies, the negative association with employment protection is strongest for the EPL component governing dismissals, while the OECD's EPL measure for temporary contracts is not significantly associated with adoption. For AI, the negative association is stronger for scaleups, whereas no comparable interaction emerges for digital security. Restricting the sample to EU countries leaves the estimated relationship negative and of similar magnitude.

Stylized Fact 2: Cross-country differences in AI adoption are concentrated among large firms

Figures 3 and 4 together illustrate how the cross-country association between employment protection legislation and AI adoption varies across firms. Figure 3 documents a clear negative cross-country association between EPL and aggregate AI adoption rates. Figure 4 then disaggregates adoption by firm size, comparing the European Union and the United States. While adoption rates among small and medium-sized firms are broadly similar across regions, large firms exhibit markedly higher AI adoption in the United States than in Europe. Taken together with the variation in employment protection across countries, this pattern indicates that cross-country differences in AI adoption are concentrated among large firms, suggesting that firm size mediates the relationship between labor market institutions and adoption.[8]

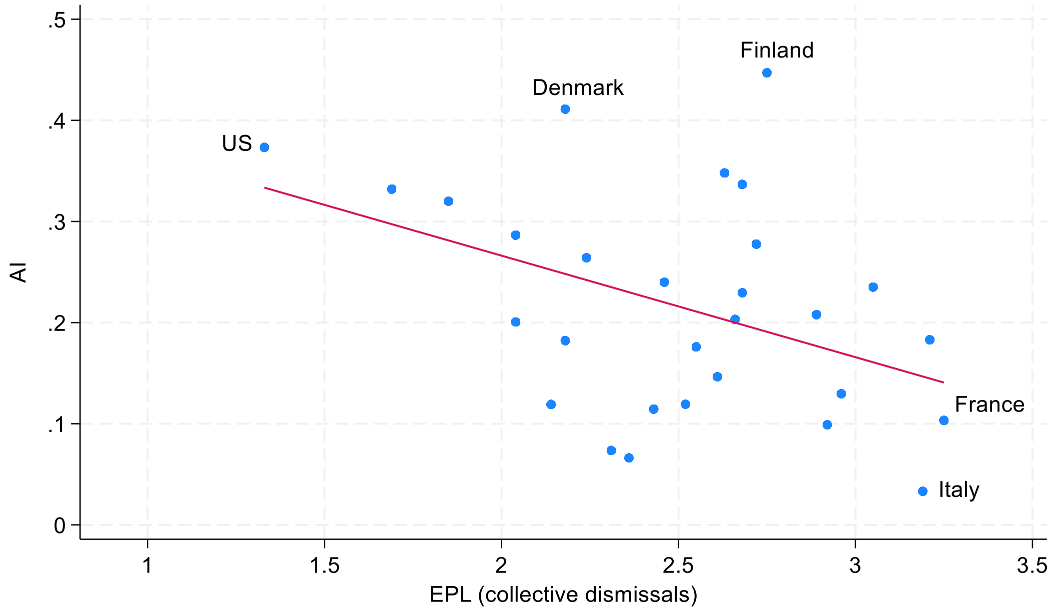
This size gradient points to an interaction between workforce scale and labor market institutions in shaping adoption decisions. For large firms, adopting AI typically entails substantial reorganization of production processes, task allocation, and occupational structures, increasing the relevance of dismissal costs and other adjustment frictions. Smaller firms, by contrast, may face lower absolute restructuring costs or may adopt AI in more limited, task-specific applications.[9]

A comparison with other technologies reinforces this interpretation. Figures 4 and 5 show that the firm-size gradient is considerably steeper for artificial intelligence than for cloud computing. While AI adoption rises sharply with firm size - particularly in the United States - the size differential for cloud computing is substantially weaker, consistent with its more modular and less restructuring-intensive nature. For completeness, Appendix Figure A.1 reports AI adoption rates across US regions. While there is meaningful variation across regions, dispersion within the United States is substantially smaller than the cross-country differences observed within the European Union, and the main EU-US contrast remains unchanged.

[8] Recent firm-level evidence indicates that AI adoption is concentrated among larger and more productive firms (Babina et al. 2024).

[9] An alternative interpretation is that differences between firm sizes may also reflect different positions along the technology diffusion curve. If one region is further along the diffusion process, the steeper segment of the S-curve may generate larger differences between early and late adopters. In contrast, regions at an earlier stage of diffusion may exhibit smaller gaps across firm sizes. These mechanisms are not mutually exclusive.

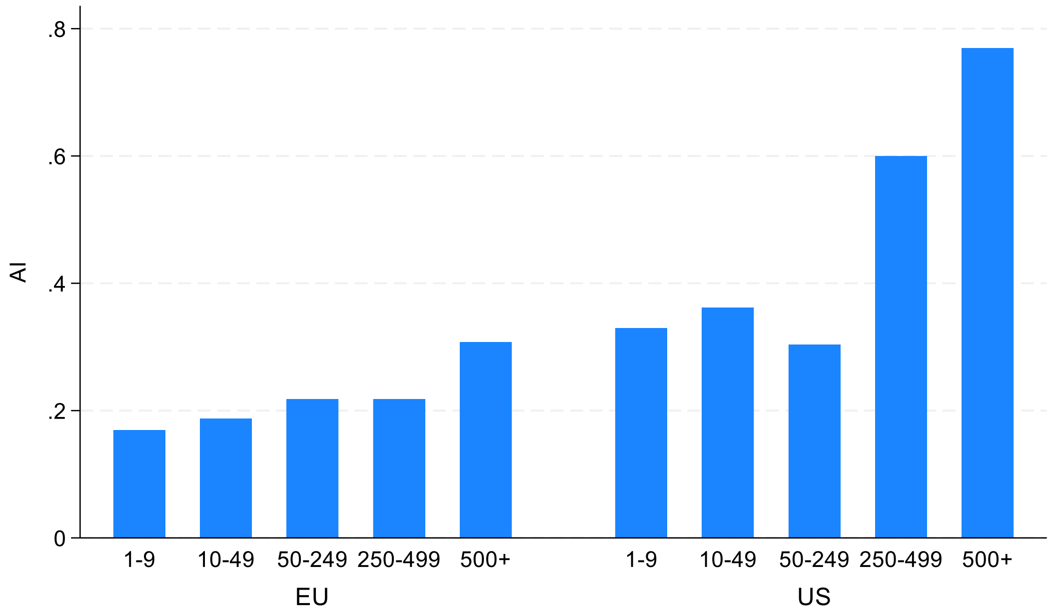
Figure 3. Correlation between AI adoption rates and EPL strictness



Notes: AI adoption rates are computed using the full Eurobarometer sample. Sampling design follows the Eurobarometer methodology.

Source: Own calculations from Flash Eurobarometer survey 559 and OECD EPL database.

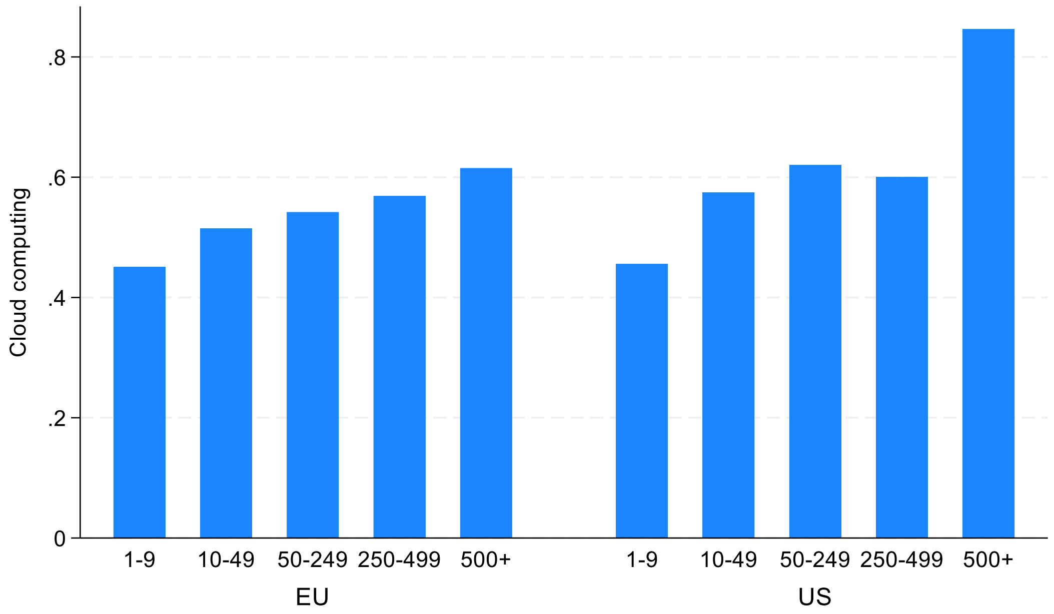
Figure 4. Artificial intelligence adoption by firm size in the European Union and the United States



Notes: AI adoption rates are computed using the full Eurobarometer sample. Sampling design follows the Eurobarometer methodology.

Source: Own calculations from Flash Eurobarometer survey 559.

Figure 5. Cloud computing adoption by firm size in the European Union and the United States



Notes: Cloud computing adoption rates are computed using the full Eurobarometer sample. Sampling design follows the Eurobarometer methodology.

Source: Own calculations from Flash Eurobarometer survey 559.

Stylized Fact 3: Startups and scaleups exhibit higher adoption rates for several technologies

Startups and scaleups exhibit higher adoption rates than incumbent firms, although this pattern does not hold uniformly across all technologies (Table 2). The advantage of younger and fast-growing firms is particularly pronounced for artificial intelligence and several other digital technologies. Adoption is systematically higher among startups across most technologies, whereas the effect is substantially smaller for scaleups. This pattern is consistent with the idea that younger firms face lower organizational and adjustment costs, while firms that have begun scaling may already experience increasing restructuring frictions.

Combined with the weaker adoption of artificial intelligence among incumbent firms in environments with stricter employment protection legislation, this pattern suggests that the diffusion of restructuring-intensive technologies may rely not only on adoption by incumbent firms but also on the entry and expansion of new firms.

The prominence of startups and scaleups therefore highlights the role of institutional environments that facilitate firm entry, growth, and reallocation for the diffusion of advanced technologies. Firms with fewer legacy organizational structures may find it easier to integrate new technologies from the outset, while incumbent firms may face higher adjustment costs when reorganizing existing production processes. This interpretation is consistent with a broader literature showing that firms with lower legacy costs and greater organizational flexibility - often younger and fast-growing firms - play a disproportionate role in the diffusion of new technologies (Haltiwanger et al. 2013; Brynjolfsson et al. 2021).

This observation motivates an extension of the theoretical framework developed below, in which technological diffusion can occur both through adoption by incumbent firms and through firm entry.

Taken together, these stylized facts point to systematic heterogeneity in adoption patterns across firms, technologies, and institutional environments. Finally, it must be emphasized that employment protection legislation does not operate in isolation. Across OECD countries, EPL is positively correlated with product market regulation, reflecting broader institutional environments in which labor and product market policies co-evolve. In such settings, restrictive product markets may allow firms to pass on costs or earn rents that sustain higher levels of employment protection. The descriptive patterns documented here should therefore be interpreted as reflecting the joint influence of labor market adjustment frictions and the broader regulatory environment in which firms operate, rather than the effect of EPL in isolation. Notably, although EPL and PMR are correlated at the country level, the adoption patterns documented above exhibit substantially stronger and more technology-specific associations with EPL than with PMR, suggesting that labor market adjustment frictions play a distinct role in shaping firms' adoption incentives.

A related concern is that employment protection legislation may proxy for broader institutional bundles (such as collective bargaining structures, insolvency regimes, or the generosity of social insurance) that also correlate with technology adoption. While the pronounced heterogeneity across technologies and firm types documented above is difficult to reconcile with a single generic omitted factor alone, the evidence should be interpreted as documenting robust correlations rather than isolating a causal effect of EPL. Taken together, these stylized facts highlight systematic heterogeneity in technology adoption across firms, technologies, and institutional environments. This motivates the use of a structural framework in the next section, in which labor market institutions - of which EPL is one salient dimension - are interpreted as proxies for adjustment and restructuring frictions, allowing their implications for adoption incentives to be examined in a controlled setting.

5. A general equilibrium model of technology adoption under employment protection

This section develops a static general equilibrium model of technology adoption in the presence of employment protection legislation. The model combines heterogeneous firms facing technology choices, à la Melitz (2003) and Atkeson and Kehoe (2007), with labor market institutions derived from Hopenhayn and Rogerson (1993) and Koeniger (2005). The framework is intentionally parsimonious but policy-rich, allowing us to isolate how labor regulation affects both the diffusion of new technologies and equilibrium employment.

Environment and production technology

The economy contains a continuum of firms indexed by productivity $z \in (0, \infty)$, drawn from a known distribution $F(z)$ with density $f(z)$. Each firm produces a homogeneous good using labor as the only variable input, and aggregate labor supply $\bar{L}$ is fixed and normalized to one.

Firms choose between an old technology O and a new technology N. Output under technology $j \in \{O, N\}$ is

(1) $$Y_j = T_j z l_j^{\alpha_j}, \qquad 0 < \alpha_j < 1,$$

where T_j denotes technology-specific efficiency and α_j captures labor intensity. We assume the old technology is more labor-intensive than the new one ($\alpha_O > \alpha_N$), while the new technology is more efficient ($T_N > T_O$). This formulation follows the directed technical change literature (Acemoglu 2002; León-Ledesma and Satchi 2019).[10]

Firms' static problem

Given a wage w_j, a firm operating technology j chooses labor l_j to maximize static profits:

(2) $$\pi_j(z, w_j) = \max_{l_j \geq 0} [T_j z l_j^{\alpha_j} - w_j l_j].$$

The first-order condition implies optimal labor demand

(3) $$l_j^*(z, w_j) = \left(\frac{\alpha_j T_j z}{w_j}\right)^{\frac{1}{1-\alpha_j}} = A_j w_j^{-c_j} z^{c_j},$$

where $c_j \equiv (1 - \alpha_j)^{-1}$ and $A_j \equiv (\alpha_j T_j)^{c_j}$. Equation 3 implies that employment is strictly increasing in firm productivity. More productive firms therefore operate at a larger scale and employ more workers. In the model, firm productivity thus maps directly into firm size: high-z firms correspond to large firms, while low-z firms correspond to smaller firms. This relationship is important for the restructuring mechanism studied in the paper,

[10] A large empirical literature documents a sustained decline in the labor share of income across advanced and emerging economies. Seminal contributions include Karabarbounis and Neiman (2014), who attribute the global fall in the labor share to the declining relative price of investment goods and the associated rise in capital-labor substitution, and Elsby et al. (2013), who emphasize offshoring and labor market institutions as additional drivers.

as both severance and retraining costs scale with the size of the workforce affected by technological adoption.[11] Substituting back yields equilibrium profits:

(4) $$\pi_j(z, w_j) = K_j w_j^{-a_j} z^{c_j},$$

with $a_j \equiv \alpha_j/(1-\alpha_j)$ and $K_j \equiv (1-\alpha_j)\alpha_j^{a_j} T_j^{c_j}$.

Right-to-manage Nash bargaining

Wages are set through right-to-manage Nash bargaining.[12] Workers have an outside option b and bargaining weight $\beta \in (0,1)$. The worker surplus equals

(5) $$WS_j(w_j) = (w_j - b) l_j^*(z, w_j).$$

The Nash function takes the form

(6) $$\max_{w_j} [\pi_j(z, w_j)]^{1-\beta} [WS_j(w_j)]^{\beta}$$

Using $\pi_j(z, w_j) \propto w_j^{-a_j}$ and $l_j^*(z, w_j) \propto w_j^{-c_j}$, the first-order condition yields a closed-form bargained wage:

(7) $$w_j^{NB} = b\left[1 + \beta\left(\frac{1}{\alpha_j} - 1\right)\right].$$

This wage depends only on technological parameters, not on firm productivity. Because more labor-saving technologies have lower α_j, the wage premium over b is higher for the new technology. The operational wage equals the maximum of the Nash-bargained wage and the statutory minimum wage $w_{\min}$, $w_j = \max\{w_j^{NB}, w_{\min}\}$. When $\beta = 0$, wages reduce to the outside option.

Technology adoption and restructuring costs

A firm with productivity z adopts the new technology if and only if

(8) $$\pi_N(z, w_N) - \pi_O(z, w_O) \geq R(z, w_O, w_N, EPL),$$

where $R(.)$ denotes restructuring costs, which depend on EPL.[13] A cutoff $z^*(w_O, w_N, EPL)$ satisfies

(9) $$\pi_N(z^*, w_N) - \pi_O(z^*, w_O) = R(z^*, w_O, w_N, EPL),$$

and firms adopt if $z \geq z^*$. The adoption rate is $\mu = 1 - F(z^*)$.

Firms incur a fixed restructuring cost

(10) $$R_{\text{fixed}} = \kappa\phi(EPL), \qquad \phi(EPL) = 1 + \eta_\phi EPL.$$

When $\eta_\phi = 0$, this reduces to a standard fixed adoption cost. When $\eta_\phi > 0$, EPL directly increases fixed restructuring expenses.

Switching technologies may require dismissing workers. Let

(11) $$D(z) = \max\{0, l_O^*(z, w_O) - l_N^*(z, w_N)\}$$

---

[11] This mapping between productivity and firm size provides a natural interpretation of the empirical patterns documented in Section 4, where technology adoption differences across institutional environments are particularly pronounced among large firms.

[12] While the model adopts a right-to-manage bargaining structure for tractability, the key mechanisms emphasized in the paper are not specific to this choice. Under efficient bargaining, wages and employment are jointly determined, but restructuring and severance costs continue to generate productivity- and scale-dependent adoption incentives similar to those highlighted here, including non-monotone adoption patterns driven by adjustment frictions.

[13] In practice, large firms are often observed to adopt frontier technologies more rapidly. One explanation is that innovation activity, typically concentrated in larger firms, builds absorptive capacity (Cohen and Levinthal, 1990). In addition, absorptive capacity may depend on the skill composition of the workforce, as firms employing more highly skilled workers face lower retraining and implementation costs when adopting new technologies. In this sense, the adjustment costs in the model can be interpreted as conditional on firm capabilities and workforce characteristics.

denote the number of dismissed workers (Acemoglu and Restrepo 2019). Severance costs equal

(12) $R_{\text{sev}} = \psi(EPL)w_O D(z), \qquad \psi(EPL) = S + \eta_\psi EPL.$

Function $\psi(EPL)$ governs how dismissal regulation translates into restructuring costs. The parameter $S \geq 0$ represents baseline severance obligations that apply even in the absence of employment protection, while $\eta_\psi > 0$ governs the marginal increase in severance costs associated with stricter EPL. This specification implies that severance costs are proportional to wages and to the scale of layoffs, and increase linearly with the strictness of employment protection legislation, capturing the idea that stricter EPL raises the marginal cost of workforce reductions without affecting firms that do not adjust employment. More generally, restructuring costs may rise more than proportionally with the scale of workforce adjustment. The key mechanism is that restructuring costs need not scale linearly with firm size. Large-scale workforce reorganization may entail disproportionate legal, managerial, and organizational disruption, making adoption particularly costly for highly productive incumbents with large workforces. This can be captured by replacing the linear severance term with $R_{\text{sev}} = \psi(EPL)w_O D(z)^\gamma$, with $\gamma > 1$. Such convexities strengthen the tendency for large firms to face disproportionately high adoption costs and reinforce the non-monotonic adoption patterns emphasized below.[14]

Following Acemoglu (1997), Canton et al. (2002), and Violante (2002), adoption entails loss of experience among retained workers. The number of retained workers is

(13) $L_r(z) = \min\{l_O^*(z, w_O), l_N^*(z, w_N)\}$

A fraction $1 - \rho$ (with $\rho \in [0,1]$) of experience is lost, requiring retraining:

(14) $R_{\text{train}} = \tau w_N (1 - \rho) L_r(z),$

where τ measures the retraining cost per retained worker as a fraction of the wage.

The total restructuring costs are thus given by

(15) $R(z, w_O, w_N, EPL) = R_{\text{fixed}} + R_{\text{sev}} + R_{\text{train}}$

We now characterize how restructuring costs and labor market institutions affect the adoption threshold z^*. Let $G(z, \theta)$ denote the indifference condition between technologies, with θ collecting the parameters of interest and $G(z^*, \theta) = 0$. For expositional clarity, we begin with the case in which $G(z, \theta)$ is monotone in productivity, yielding a unique adoption cutoff. Under the single-crossing property, comparative statics can be derived using the Implicit Function Theorem,

(16) $\frac{dz^*}{d\theta_k} = -\frac{G_{\theta_k}}{G_z}$

For example, regarding fixed restructuring cost (κ) it follows that

$$G_\kappa = -\phi \Rightarrow \frac{dz^*}{d\kappa} = -\frac{G_\kappa}{G_z} > 0$$

This says that higher fixed costs raise the cut-off z^* and reduce technology adoption.

Given wage levels w_O and w_N, aggregate labor demand is

(17) $L_D = \int_0^{z^*} l_O^*(z, w_O) dF(z) + \int_{z^*}^{\infty} l_N^*(z, w_N) dF(z).$

[14] In practice, severance payments are often capped and employment protection provisions may apply only above firm-size thresholds (cf. Boeri and Jimeno, 2005). The model abstracts from these nonlinearities and instead uses a smooth adjustment-cost function to approximate the empirically relevant feature that workforce restructuring costs rise with firm size over a broad range of firm sizes. Introducing caps or thresholds would alter the precise shape of these costs but would not eliminate the underlying scale dependence that drives the adoption patterns highlighted here. A related literature studies the optimal design of severance pay and employment protection from a welfare perspective (e.g., Boeri et al., 2017). While this work emphasizes the insurance and incentive roles of severance payments, our analysis takes employment protection as an exogenous institutional feature and focuses on how dismissal-related restructuring costs affect firms' technology adoption and innovation incentives.

Unemployment equals $U = \bar{L} - L_D \geq 0$. When the minimum wage binds, total employment is $L_D(w_{\min})$; otherwise, wages are set by Nash bargaining.[15] A mixed case arises when $w_O^{NB} < w_{\min} < w_N^{NB}$, in which the wage floor compresses the wage distribution.

A distinctive feature of the model economy is that the mapping from productivity to adoption incentives is inherently non-linear. Although heterogeneous-firm models typically rely on a single-crossing property - implying in our context that higher-productivity firms always have stronger incentives to adopt - the restructuring costs induced by employment protection legislation can overturn this monotonicity. Because severance and retraining costs scale with firm size, highly productive firms may face disproportionately large adjustment costs when switching technologies. As a result, the net-benefit function may intersect more than once, generating an interior adoption region in which medium-productivity firms adopt while the least and most productive firms remain with the old technology.[16]

Under such an inverted U-shaped pattern between the firm's technology adoption decision and its productivity level, the aggregate labor demand function becomes:

(17') $$L_D = \int_{z \notin \mathcal{A}(w;\theta)} l_O^*(z, w_O) dF(z) + \int_{z \in \mathcal{A}(w;\theta)} l_N^*(z, w_N) dF(z).$$

where $\mathcal{A}(w;\theta)$ denotes the (potentially non-convex) set of adopters. Because $\mathcal{A}(w;\theta)$ may consist of multiple disjoint intervals - reflecting the non-monotonic adoption pattern - aggregate labor demand is no longer characterized by a single productivity cutoff but instead by integration over an adoption region.

When the single-crossing property does not hold, analytical comparative statics cannot be derived from the Implicit Function Theorem in a standard way. Instead, we characterize comparative statics numerically in the next section by computing the full adoption schedule for specific parameter configurations and examining how the set of adopters changes in response to parameter shifts. This approach allows us to capture non-monotonic adoption patterns - such as interior adoption regions in which intermediate-productivity firms adopt while both lower- and higher-productivity firms do not - that arise when restructuring costs or losses of firm-specific experience interact with productivity in a nonlinear way.

The model is designed to isolate one channel through which labor market institutions can affect technology diffusion: the costs of reorganizing employment and tasks when firms adopt new technologies. In doing so, it abstracts from other mechanisms emphasized in the literature through which employment protection legislation may influence innovation and firm behavior. For example, stronger employment protection may encourage investment in firm-specific human capital by fostering longer-term employment relationships and worker commitment, potentially supporting productivity and innovative activity (Belot et al., 2007).[17] Employment protection may also provide insurance against income risk and stabilize employment relationships, which can affect workers' incentives and firms' investment decisions in environments characterized by technological change (Pissarides, 2010). More broadly, employment protection may influence the quality of job matches and the stability of employment relationships, and the policy debate often emphasizes that labor market institutions should combine worker protection with productivity and competitiveness (European Commission, 2025e).

In the framework developed here, employment protection legislation is summarized by reduced-form cost shifters rather than modeled as a detailed legal process. The analysis should therefore be interpreted as identifying one mechanism through which labor market institutions may affect technology adoption, rather than as a comprehensive assessment of the overall economic effects of employment protection legislation.

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[15] The wage-setting assumption abstracts from firm-level wage dispersion. Allowing wages to vary with firm productivity would not eliminate the core mechanism, as restructuring costs would continue to scale with both employment levels and per-worker adjustment costs.

[16] In environments with very low employment protection, firms may also find it privately optimal to replace incumbent workers rather than retrain them following adoption. While the model abstracts from complete workforce replacement as a discrete choice, it captures the underlying trade-off between retraining costs and separation costs that governs firms' adjustment decisions.

[17] Belot et al. (2007) estimate a non-linear relationship between employment protection and GDP growth and report that the level of the EPL indicator maximizing growth is 0.37. Using their EPL measure for regular jobs (Table 2), most EU countries in their sample exhibit values above this level - including Germany (0.64), Sweden (0.66), Belgium (0.46) and the Netherlands (0.43) in 1995-1999 - implying that they lie on the downward-sloping segment of the estimated relationship.

6. Model extensions

The baseline model focuses on technology adoption by heterogeneous incumbent firms facing restructuring costs associated with employment protection legislation. This parsimonious setup isolates the central mechanism through which workforce adjustment costs affect firms' adoption decisions. In practice, however, firms may face multiple technological opportunities and technological diffusion may occur not only through adoption by incumbent firms but also through firm entry and exit.

This section introduces two extensions that capture these additional margins while preserving the tractability of the baseline framework. The first extension allows firms to choose among multiple technological trajectories that differ in their productivity effects and adjustment requirements. The second extension introduces firm entry and exit, allowing new technologies to diffuse through creative destruction as well as through adoption by incumbent firms.

6.1. Multiple technological trajectories

In the baseline framework firms choose between an incumbent technology O and a single new technology N. In practice, firms often face a menu of technological opportunities that differ in both their productivity effects and the organizational adjustments required for adoption. To capture this dimension, suppose firms can choose among a set of technologies $j \in \{O, 1, \dots, J\}$, where $j = 1, \dots, J$ represent alternative new technologies.

Adopting technology j requires paying an adjustment cost $R_j(z, EPL)$, which reflects severance payments, retraining costs, and fixed reorganization costs associated with workforce restructuring.

A firm with productivity z chooses the technology that maximizes profits

(18) $$j^*(z) \in \arg \max_{j \in \{O,1,\dots,J\}} \{\pi_j(z) - R_j(z, EPL)\},$$

where $R_O \equiv 0$.

Technologies may therefore differ not only in their productivity gains but also in the extent of workforce adjustment required for adoption. Technologies that deliver larger productivity improvements may require more extensive reorganization of production processes and occupational structures, making adoption more sensitive to labor market institutions that affect restructuring costs. Conversely, more modular technologies may involve smaller productivity gains but lower adjustment costs.

The formulation above implicitly treats alternative technologies as substitutes, in the sense that firms choose the technology that yields the highest net profits. In practice, however, firms may adopt multiple technologies simultaneously, particularly when digital technologies operate as complementary components of a broader technological portfolio. For example, artificial intelligence applications often rely on complementary investments in data infrastructure, cloud computing, or organizational software. Modeling such complementarities would require extending the framework to allow firms to adopt combinations of technologies rather than selecting a single alternative. While this would enrich the set of possible adoption patterns, the central mechanism emphasized in this paper - namely that technologies differ in the extent of workforce restructuring required for adoption and that labor-market institutions affect the relative profitability of these technologies - would continue to operate in a similar manner.

For tractability, the quantitative analysis in Section 7 and further evaluates different technological trajectories separately. Each trajectory corresponds to a particular configuration of productivity gains, labor intensity, and adjustment costs. This approach isolates how institutional environments affect adoption incentives for technologies with distinct restructuring requirements.

6.2. Firm turnover and technological diffusion

Technological diffusion may also occur through firm turnover. While incumbent firms must reorganize existing production structures in order to adopt new technologies, newly created firms can organize production around the frontier technology from the outset. This distinction creates an additional margin through which technologies can spread in the economy.

To capture this mechanism, the model can be extended to allow for endogenous firm entry and exit. In each period, a mass of potential entrants may pay an entry cost c_E in order to draw productivity z from distribution $F(z)$. Entrants then choose the technology that maximizes operating profits

(19) $$\max_{j \in \{O,1,\dots,J\}} \pi_j(z).$$

Unlike incumbent firms, entrants do not incur restructuring costs. This asymmetry reflects the absence of legacy workforces in newly created firms. Entrants can design production processes and organizational structures around frontier technologies from the outset, whereas incumbent firms must reorganize existing employment relationships.

Free entry implies that expected profits from entry equal the entry cost

(20) $$\int \max_{j\in\{O,1,\ldots,J\}} \{\pi_j(z), 0\} dF(z) = c_E.$$

Incumbent firms exit the market whenever continuation yields negative value.[18] Let $V(z)$ denote the value of operating a firm with productivity z. The exit condition is therefore

(21) $$V(z) = 0.$$

This extension introduces an additional channel through which technologies diffuse in the economy. Diffusion can occur through two distinct mechanisms. First, incumbent firms may adopt the new technology by reorganizing their workforce and production processes. Second, new firms may enter the market and adopt the frontier technology from the outset.

For simplicity, the extension is presented in partial equilibrium form. A full dynamic industry equilibrium would require tracking the distribution of firms over productivity and technologies and imposing a stationary equilibrium condition under which entry offsets exit. The key mechanism does not depend on these additional details: employment protection raises restructuring costs for incumbents, while entrants can adopt new technologies without bearing legacy adjustment costs.

Employment protection legislation affects these two channels asymmetrically. By raising the costs associated with workforce restructuring, stricter employment protection discourages technology adoption by incumbent firms. At the same time, entrants are not burdened by legacy adjustment costs and may therefore adopt new technologies immediately. As a result, institutional environments with higher restructuring costs may shift the diffusion of new technologies away from internal adoption toward diffusion through firm entry.

This mechanism provides a potential explanation for the prominent role of startups and scaleups in the diffusion of advanced technologies documented in Section 4. When restructuring costs make adoption more difficult for incumbent firms, technological upgrading may occur increasingly through the entry and expansion of new firms rather than through internal reorganization.

7. Quantitative implementation and results

7.1. Simulation setup

To implement the model quantitatively, we proceed as follows. We assume that firm-level productivity z follows a lognormal distribution, consistent with a vast empirical literature showing that productivity, sales, and TFP distributions across firms are well approximated by lognormal or Pareto-lognormal forms (see Syverson 2011 for a review). Specifically, we set $z \sim \exp(N(0, 0.5^2))$, and approximate the continuum of firms by drawing 10,000 values of z. To avoid implausible outliers, we truncate the distribution to the interval [0.3,3], which preserves the empirically relevant support while improving numerical stability.

For the old technology, we set the labor elasticity of output to $\alpha_O = 0.65$, consistent with standard estimates in the macro and firm-level literature,[19] and normalize technology-specific efficiency to $T_O = 1$. The bargaining weight $\beta = 0.5$, which is a common choice in the literature. We normalize the worker outside option to $b = 0.7$, corresponding to a fallback income equal to 70 percent of the old-technology wage in the calibrated economy.

The fixed adoption cost increases proportionally with EPL (via Equation 10), and we set the sensitivity of the fixed restructuring cost to employment protection to $\eta_\phi = 0.25$. Under this calibration, moving from a low- to a high-EPL environment with a two-point higher EPL index raises the fixed restructuring cost by 50%, holding other factors constant.

[18] In the baseline model firms do not exit endogenously because profits are non-negative for all productivity levels in equilibrium. Introducing endogenous exit would require an additional fixed operating cost, as in standard heterogeneous-firm models. Firms with sufficiently low productivity would then optimally exit the market. This extension would mainly affect the lower tail of the productivity distribution and does not alter the mechanism emphasized in the model, which focuses on how employment protection affects technology adoption through restructuring costs.

[19] With Nash bargaining, the production elasticity of labor need not coincide with the labor income share.

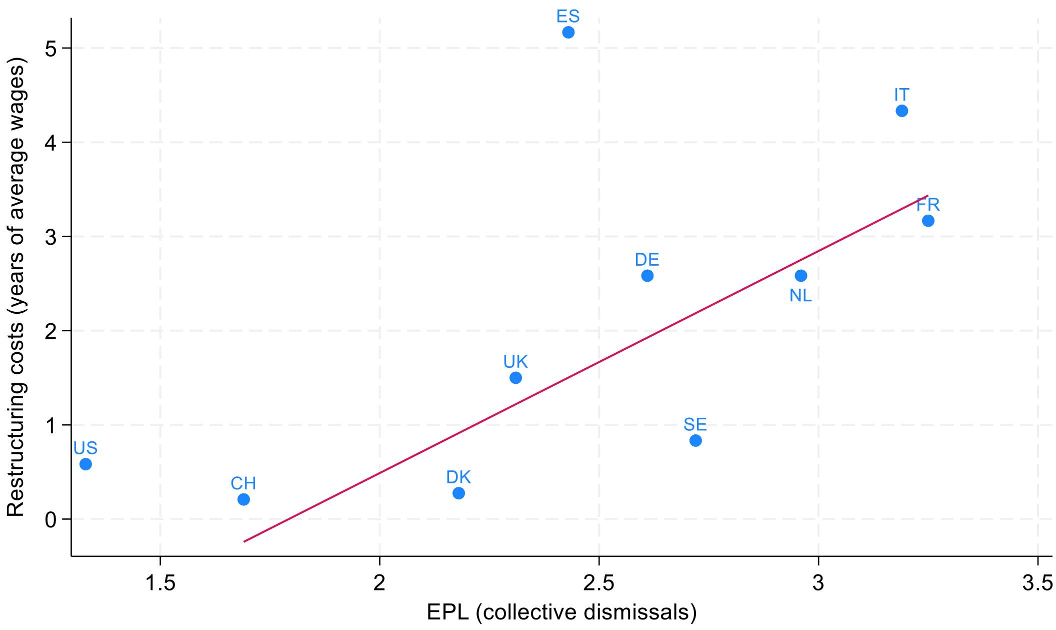
To discipline the severance cost associated with workforce restructuring, we draw on external evidence from Coatanlem and Coste (2025), who provide country-level estimates of the "cost of failure" for firms. Their measure aggregates severance pay, procedural costs, and income-support obligations following collective dismissals, expressed in months of average employee compensation. We use their estimates for ten advanced economies to map employment protection legislation (EPL) into per-worker restructuring costs.

Specifically, we parameterize severance costs per dismissed worker expressed in the wage under the old technology as

(12') $\frac{R_{\text{sev}}}{w_O D(z)} = \psi(EPL) = S + \eta_\psi EPL$

We estimate S and η_ψ by fitting a linear relationship between the Coatanlem-Coste cost-of-failure measure and the OECD EPL index. To avoid undue influence from extreme institutional configurations, we exclude Spain and the US from the fit. For Spain Coatanlem and Coste (2025) report unusually high severance obligations, while the United States combines minimal statutory protection with very low dismissal costs. Excluding these outliers yields a stable and economically plausible mapping for the included countries, as shown in Figure 6.

Figure 6. Cost of restructuring across selected OECD countries



Source: Own calculations based on Coatanlem and Coste (2025). Restructuring costs are expressed in units of annualized average wage earnings.

The resulting estimates are $S = -4.22$ and $\eta_\psi = 2.36$.[20] Evaluated at the OECD-average EPL level of 2.4, which is used in our baseline, this calibration implies severance and restructuring costs of approximately 1.44 years of average employee compensation per worker affected. This magnitude is closely aligned with institutional estimates for countries such as the United Kingdom and provides a realistic benchmark for advanced economies with intermediate levels of employment protection.

This calibration should be interpreted with appropriate caution. The underlying evidence on restructuring and severance costs is available for a limited number of countries, and the measurement of "costs of failure" necessarily aggregates heterogeneous components, including statutory severance pay, procedural requirements, litigation risk, and income-support obligations. Moreover, these costs may vary substantially across firms and sectors within countries in ways that are not captured by aggregate indicators. Accordingly, our approach does not aim to pin down precise country-specific restructuring costs. Rather, it provides an empirically grounded mapping from employment protection legislation into economically meaningful magnitudes that discipline the model's adjustment-cost channel. By tying severance costs directly to observed

[20] The negative intercept S should not be interpreted literally, as EPL values close to zero are outside the empirical support of the data.

institutional variation rather than targeting model outcomes, the calibration ensures that the employment-adjustment mechanism is disciplined by external evidence rather than fitted to match adoption patterns.

7.2. Technological trajectories and retraining costs

The model section abstracts from heterogeneity in the labor intensity of new technologies by treating adoption as labor-saving. In the quantitative implementation, we relax this assumption and consider three technological trajectories that differ in their productivity gains, labor elasticities, and retraining and restructuring needs.

We group the ten technologies covered in the survey into a small number of representative technological trajectories based on their adjustment and restructuring requirements. Restructuring-intensive technologies - such as artificial intelligence and digital security -require substantial task reallocation and retraining and display strong sensitivity to labor market institutions in the data. By contrast, modular digital and automation technologies - such as cloud computing, IoT, and robotics[21] - can often be adopted incrementally and show little sensitivity to employment protection. The model is implemented for these representative trajectories to capture heterogeneity across technologies without introducing a large number of technology-specific parameters.

Table 4. Technology trajectories and retraining costs

Trajectory	Parameterization	Description
AI-P	$T_N = 1.2$; $\alpha_N = 0.6$; $\tau = 0.3$; $\rho = 0.65$	**Process-augmenting AI**: AI technologies that raise productivity while largely complementing existing tasks. Adoption requires meaningful organizational adjustment and retraining but involves limited displacement of labor.
AI-T	$T_N = 1.5$; $\alpha_N = 0.5$; $\tau = 0.3$; $\rho = 0.65$	**Transformational AI**: Technologies that generate a large productivity gain and substantially alter task composition, reducing labor intensity. Adoption entails major workforce reorganization and is highly sensitive to employment protection.
MDT	$T_N = 1.04$; $\alpha_N = 0.65$; $\tau = 0.1$; $\rho = 0.9$	**Modular digital and automation technologies**: Incremental digital and automation technologies that can be adopted in a modular fashion. Productivity gains are modest and largely Hicks-neutral, with limited organizational disruption and weak sensitivity to EPL.

Table 4 summarizes the three technological trajectories used in the quantitative implementation. We distinguish between a process-augmenting AI trajectory (AI-P), a transformational AI trajectory (AI-T), and a modular digital technology trajectory (MDT). The trajectories differ in both the magnitude and factor bias of the productivity gain, as well as in the intensity of retraining and reorganization required upon adoption. These

[21] While industrial robots are often associated with labor-displacing automation, the empirical patterns in the data show that robotics adoption displays little sensitivity to employment protection legislation and behaves similarly to other modular digital technologies such as cloud computing and IoT. In practice, robot adoption typically occurs through incremental capital investment within existing production processes, as firms integrate robotic equipment into specific production lines rather than undertaking large-scale organizational restructuring. Consistent with this interpretation, empirical studies generally treat robot adoption as an investment decision in automation capital, even though its labor market effects may include displacement of certain tasks or occupations (e.g. Graetz and Michaels, 2018; Bonfiglioli et al., 2024; Benmelech and Zator, 2022). This classification is also consistent with the empirical evidence reported in Section 4, where robotics adoption shows little systematic association with employment protection legislation, in contrast to artificial intelligence and other more restructuring-intensive technologies. In the framework developed in Section 5, the key determinant of technology adoption is the extent of workforce and organizational restructuring required for implementation. Technologies such as robotics that can be integrated into existing production processes with relatively limited reorganization therefore generate lower adjustment costs for incumbent firms and are less sensitive to labor market institutions.

retraining needs operate through two channels. The parameter ρ governs the extent to which firm-specific experience is preserved following adoption: a fraction $1-\rho$ of accumulated experience with the old technology is lost when the new technology is introduced. The parameter τ captures the per-worker cost of retraining for retained workers, expressed as a fraction of the wage (cf. Equation 14).Under AI-P, productivity gains are moderate and largely task-augmenting, but adoption still entails non-negligible retraining needs and experience loss. AI-T combines a larger productivity improvement with a sharper reduction in labor intensity, thereby making adoption particularly sensitive to labor market institutions.[22] By contrast, MDTs involve limited disruption to existing production processes, with most firm-specific experience preserved and relatively low retraining costs. This classification allows the model to capture meaningful heterogeneity across technologies while keeping the number of technology-specific parameters limited.

7.3. Calibration strategy

The quantitative implementation disciplines the fixed restructuring cost parameter κ using adoption behavior at the lower end of the productivity distribution. Intuitively, κ governs the presence of firms for which adoption is privately unprofitable even absent large employment responses, capturing administrative, organizational, and coordination costs that must be incurred upon adoption. We therefore choose κ so that the model reproduces the observed share of low-productivity firms that remain on the old technology.

This calibration is carried out separately for restructuring-intensive AI technologies and for modular digital technologies. For the AI trajectory, we use adoption rates of artificial intelligence and digital security technologies to discipline κ. For the MDT trajectory, we calibrate κ using observed adoption rates for cloud computing, robotics and IoT technologies.[23]

This procedure yields markedly different fixed restructuring costs across technological trajectories. For the AI trajectory, we obtain $\kappa = 0.04$, reflecting substantial fixed organizational and coordination costs associated with the adoption of restructuring-intensive technologies. By contrast, for the modular digital technology trajectory, the calibrated value is $\kappa = 0.004$, an order of magnitude smaller. This difference captures the fact that modular digital technologies can typically be adopted incrementally, with limited upfront organizational reconfiguration. Importantly, these values are disciplined by adoption behavior at the lower end of the productivity distribution rather than by the overall adoption profile. As a result, the calibration isolates differences in fixed adoption barriers across technologies while leaving the shape of adoption across productivity and the response to employment protection legislation to be determined endogenously by the model.

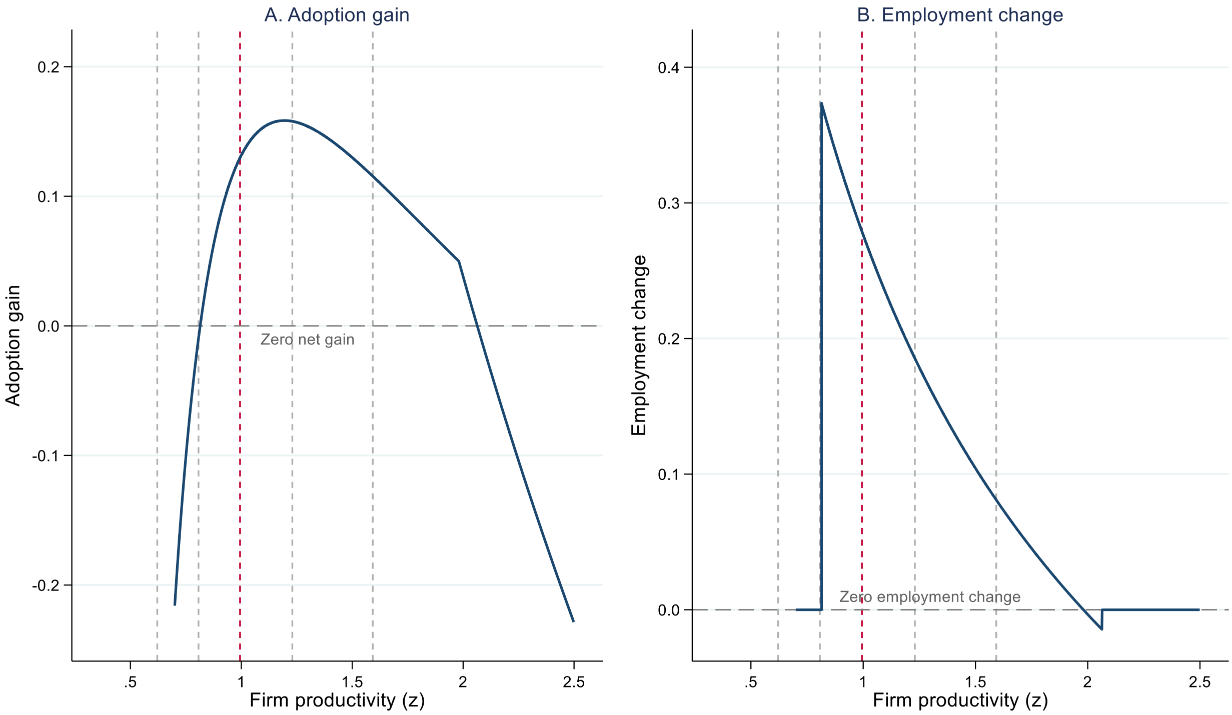
7.4. Adoption patterns

Figure 7 illustrates the adoption and employment implications of the process-augmenting AI (AI-P) trajectory. Panel A shows that adoption is confined to an intermediate range of productivity levels, reflecting the interaction between productivity gains and the costs of restructuring. Severance costs associated with employment protection legislation play a central role in shaping this pattern. For highly productive firms, adoption typically involves the dismissal of redundant workers as tasks are reorganized. When severance costs are high, these firms may optimally refrain from adopting despite large potential productivity gains. The emergence of these high-productivity holdouts bears some resemblance to the Schumpeterian replacement effect, in the sense that leading firms may optimally refrain from adopting new technologies. However, the underlying mechanism is distinct. In our framework, adoption is deterred not by cannibalization of existing rents, but by the interaction between labor-saving technologies and employment protection, which makes workforce restructuring particularly costly for large, highly productive firms.

[22] The distinction between process-augmenting and transformational AI technologies is consistent with recent macroeconomic evidence on artificial intelligence and aligns with OECD findings emphasizing that the macroeconomic impact of AI depends critically on whether it operates through task augmentation or more transformative changes in production structures (Filippucci et al., 2025).

[23] More precisely, for the AI-P and AI-T trajectories we define an adoption indicator that takes value one if a firm adopts at least one of artificial intelligence or digital security technologies, and zero otherwise. For the MDT trajectory, the adoption indicator takes value one if the firm adopts at least one of cloud computing, robotics, or Internet of Things technologies, and zero otherwise. Because firms may adopt multiple technologies simultaneously, we exclude robotics from the definition of AI-P and AI-T and include it only under MDT in order to keep the technological trajectories conceptually and empirically distinct.

Figure 7. Adoption and employment dynamics in AI-P trajectory



Notes: The adoption gain is calculated as $(\pi_N - \pi_O - R)/\pi_O$. Employment changes are normalized by labor demand under the old technology to ensure comparability across firms. The vertical red line denotes median productivity.

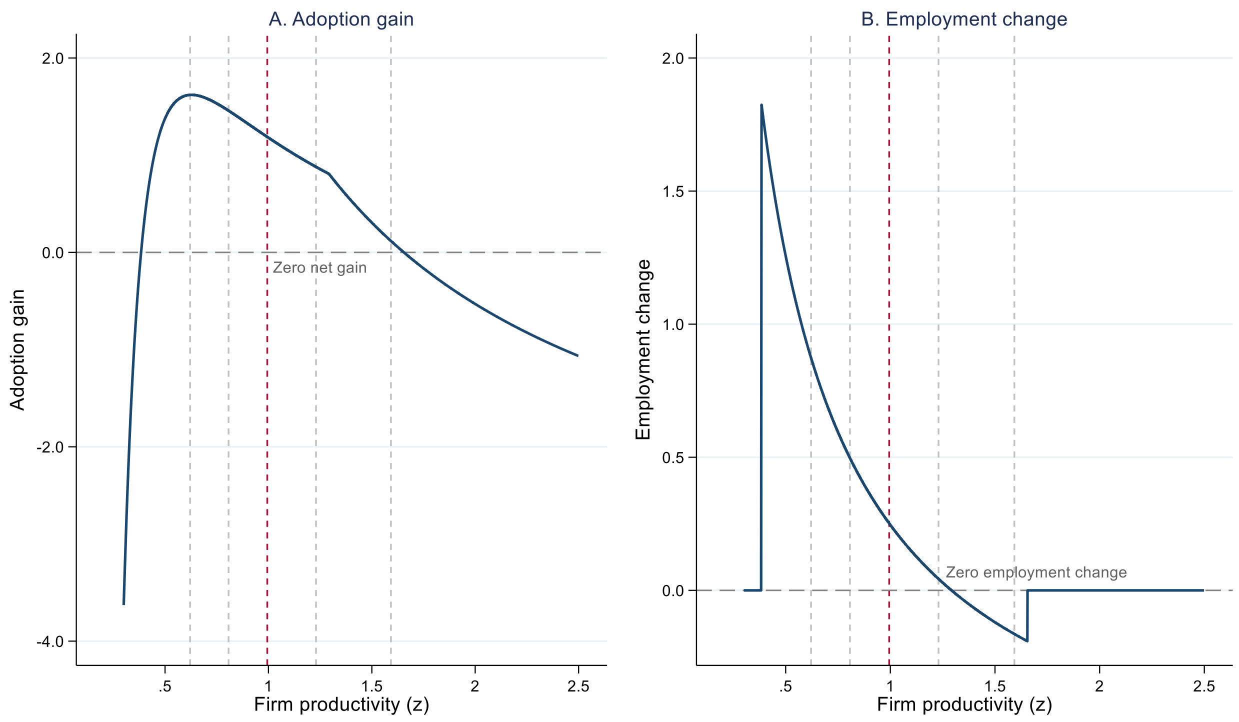
By contrast, among firms with intermediate productivity, adoption does not require workforce reductions and is instead associated with employment expansion, as shown in Panel B in Figure 7. For these firms, adoption entails fixed adoption costs and retraining costs for retained workers, as well as partial loss of firm-specific experience, but does not trigger severance obligations. As a result, productivity gains translate into higher employment and output. This distinction highlights that employment protection legislation selectively discourages adoption precisely where adoption would otherwise be most impactful - at the technological frontier - while leaving adoption by expanding firms largely unaffected. Together, these figures underscore that technology adoption is neither monotone in productivity nor associated with uniform employment responses, and that severance costs are the key mechanism driving heterogeneity across firms.

To assess the sensitivity of this mechanism to the calibration of severance costs based on Coatanlem and Coste (2025), we consider alternative parameterizations that differ substantially from the baseline but broadly reflect institutional environments with relatively low restructuring costs, such as Denmark, Sweden, Switzerland, and the United States. For example, setting $S = 0.06$ and $\eta_\psi = 0.2$ continues to produce an inverted-U adoption profile. Under this calibration, the implied cost of restructuring is approximately 0.54 years of average wages, comparable to estimates of around 0.58 years of average wages for the United States. This indicates that the emergence of a non-monotone adoption pattern is not driven by a knife-edge calibration of severance costs, although the quantitative details of firm sorting and employment responses may vary across parameter choices.

The results for the transformational AI (AI-T) trajectory, in Figure 8, amplify these mechanisms. Relative to AI-P, AI-T delivers a larger productivity gain but is substantially more labor-saving, implying more pronounced workforce reorganization upon adoption. As a consequence, severance costs play an even more central role in shaping adoption decisions. For highly productive firms, adoption of AI-T requires the dismissal of a sizable share of incumbent workers as production becomes less labor-intensive. In environments with strict employment protection, the resulting severance obligations sharply reduce the net surplus from adoption, leading many frontier firms to optimally refrain from adopting despite the large potential productivity gains.

Conditional on adoption, employment responses under AI-T are correspondingly more polarized. Firms with intermediate productivity may still expand employment if productivity gains outweigh retraining needs and fixed adoption costs, but downsizing among high-productivity adopters is both more frequent and more pronounced than under AI-P. This stronger employment contraction magnifies severance costs, reinforcing the deterrent effect of employment protection at the top of the productivity distribution. Retraining costs and the loss of firm-specific experience for retained workers further contribute to adoption frictions, but severance costs remain the dominant channel distinguishing AI-T from less disruptive technologies. Overall, the AI-T results highlight that employment protection legislation can be particularly consequential for the diffusion of highly transformative, labor-saving technologies.

Figure 8. Adoption and employment dynamics in AI-T trajectory



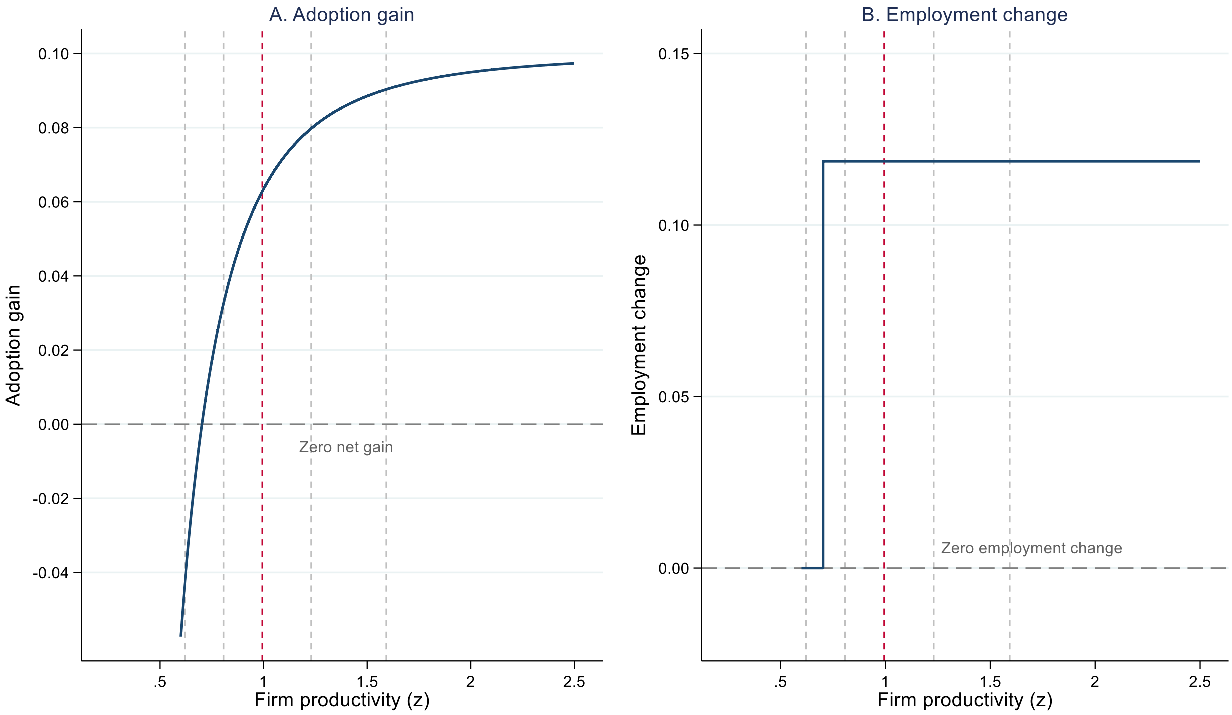
Notes: The adoption gain is calculated as $(\pi_N - \pi_O - R)/\pi_O$. Employment changes are normalized by labor demand under the old technology to ensure comparability across firms. The vertical red line denotes median productivity.

Figure 9 presents the adoption and employment implications of the modular digital technology (MDT) trajectory. In contrast to the AI trajectories, Panel A shows that adoption of MDTs is widespread and largely monotone in productivity. Because MDTs can typically be adopted incrementally and are associated with modest, Hicks-neutral productivity gains, adoption does not require substantial workforce reorganization. As a result, severance costs play a limited role in shaping adoption decisions, and employment protection legislation has only a weak effect on diffusion.

Conditional on adoption, Panel B shows relatively muted employment responses. Employment among adopting firms is moderately increasing, reflecting the fact that MDT adoption does not necessitate large-scale task reallocation or worker displacement. Adoption involves limited retraining needs and minimal loss of firm-specific experience, and does not trigger severance obligations. Consequently, the deterrent effect of employment protection on adoption is largely absent for MDTs. Together, these figures underscore that the impact of labor market institutions on technology diffusion depends critically on the nature of the technology, with modular digital technologies largely insulated from the restructuring costs that shape the adoption of more transformative AI-based technologies.[24]

[24] Appendix G presents a set of auxiliary figures illustrating labor demand and the individual components of restructuring costs across the three technological trajectories, providing additional insight into the underlying mechanisms.

Figure 9. Adoption and employment dynamics in MDT trajectory



Notes: The adoption gain is calculated as $(\pi_N - \pi_O - R)/\pi_O$. Employment changes are normalized by labor demand under the old technology to ensure comparability across firms. The vertical red line denotes median productivity.

7.5. Firm types

The interaction between firm-level productivity, workforce restructuring needs, and the cost of adoption implied by employment protection legislation yields a rich taxonomy of technology-adoption behaviors. Guided by the structure of the technology adoption model and its empirical implementation, we classify firms into seven mutually exclusive types based on (i) the sign of the adoption surplus, (ii) their position in the productivity distribution, and (iii) post-adoption employment dynamics:

- Zombies: Firms with negative adoption surplus located at the bottom of the productivity distribution. These firms neither adopt nor restructure and remain locked into low-productivity technologies.
- Marginal non-adopters: Low- to medium-productivity firms with negative adoption surplus. These firms are close to the adoption margin but do not adopt due to restructuring costs.
- Low-productivity adopters: Firms with positive adoption surplus at low to medium productivity levels. Adoption is profitable for these firms, but scale and employment responses are limited.
- Expanding adopters: Medium- to high-productivity firms that adopt the new technology and expand employment. These firms correspond to the standard adoption margin emphasized in canonical models of technology diffusion, in which adoption raises productivity and labor demand.
- Frontier stars: Very high-productivity firms that adopt and expand employment. These firms combine frontier productivity with favorable adjustment costs and represent the growth engine of the economy.
- Downsizing adopters: High-productivity firms that adopt the new technology but reduce employment following adoption, consistent with adoption of labor-saving technologies that entail substantial reorganization.
- Very high-productivity holdouts: Firms at the top of the productivity distribution with negative adoption surplus. Despite their high productivity, these firms optimally refrain from adoption because EPL-related restructuring costs dominate adoption gains.

Together, these seven firm types highlight how EPL and restructuring frictions shape both the extensive margin (the adoption decision) and the intensive margin (employment adjustment) of technological upgrading.

To assess the empirical relevance of the model, we compare the distribution of firm types generated by the model with those observed in the data. Firm types in the model are constructed using the same criteria as in the data, based on adoption status, productivity rank, and employment adjustment. This ensures a direct and transparent comparison between model predictions and observed firm-level outcomes.

Table 5 compares the distribution of firm types observed in the data with the corresponding distributions generated by the model under the process-augmenting AI (AI-P) and transformational AI (AI-T) trajectories. The table shows that the model captures several salient features of the data, while also highlighting how different AI trajectories reshape the composition of adopters in economically intuitive ways.

Under the AI-P trajectory, the model generates a sizable mass of non-adopters at the lower end of the productivity distribution as well as a non-negligible group of highly productive holdouts. At the same time, a substantial share of adopting firms expand employment following adoption, reflecting moderate productivity gains that allow firms to reorganize without incurring severance costs. This configuration closely mirrors the empirical patterns, in which adoption is concentrated among intermediate-productivity firms.

The AI-T trajectory yields a markedly different composition. Adoption shifts toward lower- and intermediate-productivity firms, while the share of highly productive holdouts increases sharply. Among adopting firms, downsizing becomes substantially more prevalent, reflecting the strongly labor-saving nature of transformational AI and the associated severance costs. These features mirror the model's core mechanism: when adoption entails large workforce reductions, employment protection legislation disproportionately deters adoption among frontier firms, even when productivity gains are large.

Differences between the model and the data - such as the presence of stable adopters and productive holdouts not explicitly modeled - reflect the parsimonious nature of the framework rather than a failure of the mechanism. Overall, the table illustrates how variation in the nature of AI technologies can generate distinct adoption and employment patterns while remaining consistent with the broad empirical distribution of firm types.

We interpret the process-augmenting AI trajectory (AI-P) as broadly representative of current AI deployments, which tend to complement existing tasks and generate moderate productivity gains. The transformational AI trajectory (AI-T) should be viewed as a potential future technological path, characterized by larger productivity gains and more extensive task reallocation, whose realization remains uncertain.

Table 5. Comparison of model-predicted and observed firm types in technology adoption, AI trajectory

		Model economy	
Firm type	Data	AI-P	AI-T
Zombies	0.163	0.167	0.022
Marginal non-adopters	0.178	0.174	0
Low-productive adopters	0.208	0.160	0.478
Expanding adopters	0.088	0.333	0.204
Frontier stars	0.045	0.090	0
Downsizing adopters	0.016	0.014	0.148
Highly productive holdouts	0.077	0.063	0.147
Other:			
Stable adopters	0.045		
Productive holdouts	0.181		

Notes: Firm types are defined in Appendix E based on technology adoption, productivity quantiles, and employment dynamics.

Table 6. Comparison of model-predicted and observed firm types in technology adoption, MDT trajectory

		Model economy
Firm type	Data	MDT
Zombies	0.114	0.167
Marginal non-adopters	0.124	0.071
Low-productive adopters	0.310	0.262
Expanding adopters	0.131	0.333
Frontier stars	0.069	0.167
Downsizing adopters	0.025	0
Highly productive holdouts	0.047	0
Other:		
Stable adopters	0.066	
Productive holdouts	0.114	

Notes: Firm types are defined in Appendix E based on technology adoption, productivity quantiles, and employment dynamics.

Table 6 compares the distribution of firm types observed in the data with those generated by the model under the modular digital technology (MDT) trajectory. In the model economy, all firms that adopt MDT expand employment. This reflects the modest, Hicks-neutral productivity gains associated with MDT adoption, combined with limited retraining needs and negligible loss of firm-specific experience, which imply that adoption does not require workforce reductions or severance payments. Employment protection legislation therefore plays little role in shaping adoption decisions or employment outcomes.

Consistent with this mechanism, the model generates no downsizing adopters and no highly productive holdouts under the MDT trajectory. Frontier firms adopt rather than optimally refraining from adoption, and adoption is monotone in productivity. The absence of downsizing contrasts sharply with the AI trajectories, where adoption by highly productive firms often entails labor shedding and associated severance costs, leading to frontier non-adoption.

Overall, the MDT results reinforce the central insight that the interaction between labor market institutions and technology adoption depends critically on whether adoption entails workforce restructuring. When technologies are modular and primarily require retraining rather than worker displacement, employment protection legislation has little effect on diffusion or employment dynamics.

7.6. Technology sorting across firms

To illustrate the mechanism underlying the model, Figure 10 plots the net adoption gains associated with the three technological trajectories considered in the quantitative analysis: transformational artificial intelligence (AI-T), process-augmenting AI (AI-P), and modular digital technologies (MDT). The figure shows how these adoption gains vary with firm productivity for both incumbent firms and entrants.

In the entrant simulations, severance costs and retraining costs associated with incumbent workforce reorganization are set to zero, reflecting the absence of legacy organizational structures in newly created firms. Unlike incumbents, entrants do not need to dismiss workers or retrain retained employees when implementing a new technology. However, technology adoption is not frictionless for entrants. New firms must still incur setup and implementation costs related to installation, organizational design, and operational integration. To capture this, we assume that entrants face a positive technology-specific setup cost, parameterized as a fraction of the fixed adoption cost borne by incumbents. Specifically, we set $\eta_\phi = 0$, implying that the fixed adoption cost reduces to κ in the entrant simulations (cf. Equation 10). This yields a parsimonious distinction between the two margins of diffusion: incumbents face restructuring-intensive adoption, whereas entrants face adoption from scratch.

The horizontal axis represents firm productivity z, while the vertical axis reports the net gain from adopting a given technology relative to remaining with the baseline technology. The dashed horizontal line marks the zero-net-gain threshold: firms adopt a technology only if the associated adoption gain is positive. The vertical dashed lines indicate productivity levels at which the privately preferred technological trajectory changes.

The left panel shows adoption incentives for incumbent firms, which face restructuring costs when adopting new technologies. These costs increase with firm size because larger firms must reorganize a greater number of workers and production processes when implementing restructuring-intensive technologies. As a result, adoption gains decline with productivity for restructuring-intensive technologies. In particular, the adoption gain associated with transformational AI (AI-T) is high for relatively low-productivity firms but decreases sharply as productivity rises. Process-augmenting AI (AI-P) generates smaller restructuring costs and therefore exhibits a more moderate decline. Modular digital technologies (MDT), which involve limited organizational restructuring, display relatively flat adoption gains across the productivity distribution.

The right panel shows the corresponding adoption incentives for entrant firms. Because entrants can adopt technologies without facing legacy organizational structures or workforce adjustment costs, restructuring costs are substantially lower for this group of firms. As a result, adoption gains are generally higher for entrants than for incumbents, particularly for restructuring-intensive technologies such as AI-T. This highlights an important diffusion channel emphasized in the empirical analysis: new firms can implement frontier technologies without incurring the adjustment costs faced by incumbents.

Taken together, the figure illustrates how the model generates technology sorting across firms. Different technological trajectories become optimal at different productivity levels. Firms with relatively low productivity tend to favor technologies that deliver large potential productivity gains despite substantial restructuring requirements. Firms with intermediate productivity levels tend to adopt process-augmenting technologies that combine meaningful productivity improvements with more moderate adjustment costs. By contrast, highly productive firms may prefer technologies that can be implemented with limited organizational disruption, even when the associated productivity gains are smaller.

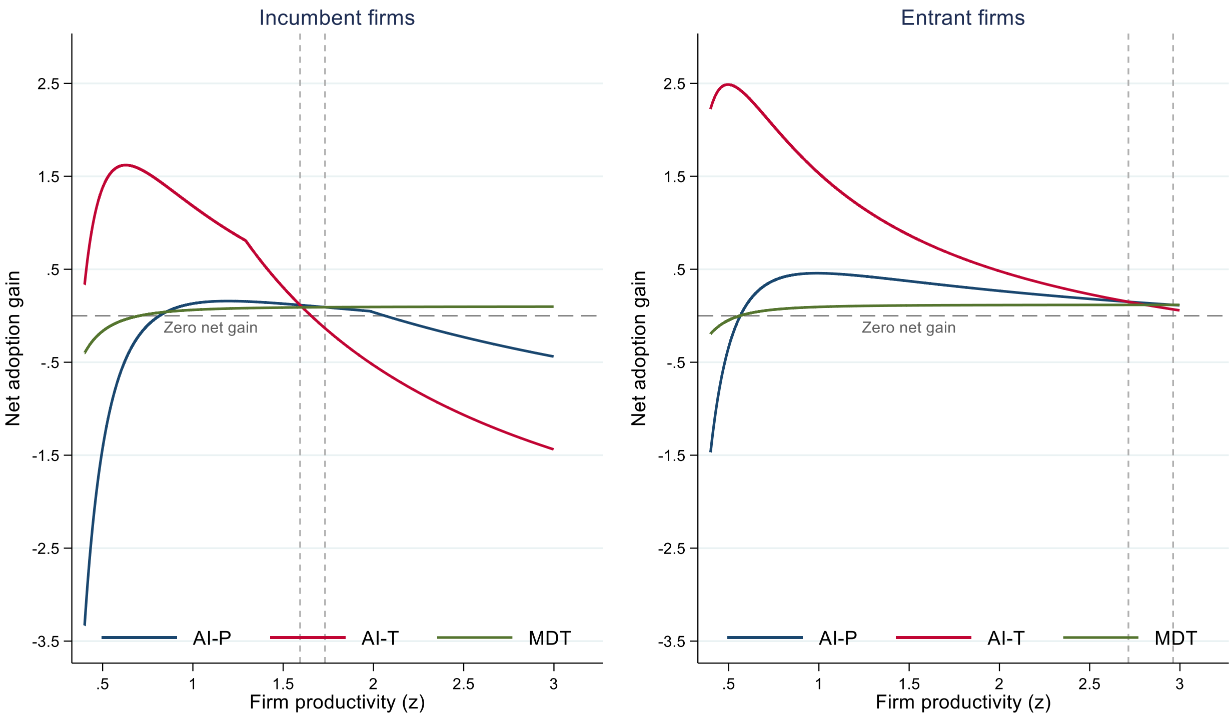
This sorting mechanism provides a natural explanation for the heterogeneous adoption patterns documented in the data. Technologies that require extensive reorganization of tasks and workforce structures - such as artificial intelligence - display stronger sensitivity to labor market institutions because restructuring costs play a central role in firms' adoption decisions. More modular technologies, which can be integrated into existing production processes with limited disruption, exhibit weaker relationships with employment protection legislation.

More broadly, the figure highlights that labor market institutions influence not only the overall level of technology adoption, but also the composition of technologies that diffuse across firms. When restructuring costs are high, technologies that require large organizational adjustments become less attractive for incumbent firms, shifting adoption toward either more modular technologies or toward diffusion through entry by new firms.

The quantitative implementation so far has treated the set of available technologies as given and focused on firms' adoption decisions in the presence of restructuring and retraining costs.[25] We now extend the framework by endogenizing technological change. In the next section, we introduce an innovation sector that can invest in the development of distinct technological trajectories drawn from a menu of technologies. The expected returns to innovation depend on downstream adoption incentives, which in turn are shaped by labor market institutions. This extension allows us to study how employment protection legislation influences not only the diffusion of existing technologies but also the direction of technological change.

[25] An overview of the complete numerical implementation is provided in Appendix F.

Figure 10. Technology adoption gains across firm productivity: incumbents and entrants



8. Labor market institutions and innovation incentives

This section extends the baseline framework by endogenizing the arrival of new technologies through an innovation sector. The purpose of this extension is conceptual rather than quantitative. It illustrates how labor market institutions that affect downstream technology adoption can, in turn, shape innovation incentives through their impact on expected diffusion rents. The analysis is not intended to provide a calibrated assessment of innovation policy or to quantify the causal effect of employment protection on R&D investment.

We consider a technology supplier who chooses R&D investment. Successful innovation leads to a "next-generation technology" characterized by T_N and α_N, which is licensed to production firms that then decide whether to adopt. Because adoption is less attractive under stricter EPL, the expected rents from innovation decline, reducing the optimal R&D effort. This mechanism links employment protection not only to the diffusion of existing technologies but also to the pace at which new technologies are created.

Endogenous technical change operates through the arrival of new technologies. Assume there is a representative innovator (or sector) that chooses R&D investment I, facing an arrival probability

(18) $$p(I) = 1 - e^{-\nu I}, \qquad \nu > 0,\ p'(I) > 0,\ p''(I) < 0,$$

Prior to a successful innovation, firms operate exclusively with the old technology. Upon successful innovation, the new technology becomes available alongside the existing one. The innovator extracts rents by licensing the technology to production firms, which optimally choose whether to adopt the new technology as described in the adoption problem above.

The innovator solves:

(22) $$\max_{I \geq 0} p(I) V^{\text{innov}}(T_N, \alpha_N, P_L, w, EPL) - I,$$

where V^{innov} is the revenue from selling the new technology $(T_N,\ \alpha_N)$ to adopting firms through a license fee P_L and I is (as mentioned) the total R&D investment.[26]

[26] For tractability, we assume that the innovator is risk-neutral and chooses R&D investment to maximize expected profits. This abstracts from additional wedges due to risk aversion or financial frictions in innovation, which would depress private R&D incentives.

Introducing a per-firm license fee P_L for the new technology simply adds to the fixed component of the adoption cost. The adoption decision becomes

(8') $$\pi_N(z, w_N) - \pi_O(z, w_O) \geq R(z, w_O, w_N, EPL) + P_L$$

so that a higher license fee uniformly reduces the net surplus from adoption and (weakly) shrinks the set of adopting firms. While under single crossing this manifests as an increase in the adoption cutoff, in our setting with potentially non-monotonic adoption it corresponds to a contraction of the entire adoption region.

The license fee reduces the innovator's market size. Formally, the adoption set is now

(23) $$\mathcal{A}(P_L; T_N, \alpha_N, w, EPL) = \{z: \pi_N(z, w_N) - \pi_O(z, w_O) \geq R(z, w_O, w_N, EPL) + P_L\},$$

and the adoption share is the measure of that set.

The first-order condition yields

(24) $$\nu e^{-\nu I^*} V^{\text{innov}} = 1,$$

so that innovation effort is given by

(25) $$I^* = \begin{cases} 0, & if\ \nu V^{\text{innov}} \leq 1 \\ \frac{1}{\nu}\ln(\nu V^{\text{innov}}), & if\ \nu V^{\text{innov}} > 1 \end{cases},$$

Hence, any parameter (such as EPL) that reduces V^{innov} lowers equilibrium R&D investment and, in the limit, can shut down innovation entirely.

Innovation menus

We now relax the assumption that firms face a unique innovation opportunity and instead allow the innovation sector to choose among a menu of technological trajectories. This menu corresponds to the three technology classes introduced in the quantitative analysis which differ in their productivity gains, factor bias, and retraining and restructuring requirements. In particular, the menu includes process-augmenting AI technologies that deliver moderate productivity gains with limited labor displacement (AI-P), transformational AI technologies that generate larger productivity improvements but require substantial reorganization and workforce adjustment (AI-T), and modular digital technologies that raise efficiency incrementally while largely preserving existing production structures (MDT).

Technological progress in this environment is therefore multidimensional rather than a uniform improvement in efficiency. Innovations may increase output while simultaneously altering the elasticity of production with respect to labor and the extent to which firm-specific experience can be preserved. The innovation sector allocates research effort across these trajectories in response to expected profits from downstream adoption, which depend on factor costs, retraining and severance obligations, and labor market institutions. Technologies that are cheaper to adopt or more profitable given the prevailing institutional environment are therefore more likely to be developed and diffused. As a result, labor market institutions shape not only the rate of technological progress but also its direction, with endogenous growth arising from equilibrium selection over this heterogeneous set of technological trajectories. While the innovation extension is deliberately stylized, it underscores that policies affecting technology adoption may also influence the direction and intensity of innovation through their effect on diffusion incentives.

Entry, diffusion, and creative destruction

Innovation incentives depend on the extent to which new technologies diffuse throughout the economy. In the framework developed above, diffusion can occur through two distinct margins. First, incumbent firms may adopt new technologies by reorganizing their workforce and production processes. Second, newly created firms may enter the market and adopt frontier technologies from the outset.

This distinction is important because the costs associated with technology adoption differ across these margins. Incumbent firms face restructuring costs when adopting new technologies, including severance payments and retraining costs associated with workforce reorganization. By contrast, new firms do not face legacy employment structures and can organize production around the frontier technology immediately. As a result, the diffusion of new technologies may occur both through adoption by incumbent firms and through entry of new firms.

Innovators earn rents from the diffusion of their technology. Let the total market size for a new technology be denoted by

(26) $$M = M_I + M_E,$$

where M_I denotes adoption by incumbent firms and M_E adoption through entry of new firms. The value of a successful innovation is proportional to the number of adopting firms:

(27) $$V^{\text{innov}} = P_L(M_I + M_E),$$

where P_L captures the rent earned per adopting firm through licensing.

Labor market institutions can influence these two margins differently. By raising the costs of workforce restructuring, stricter employment protection may discourage adoption by incumbent firms and reduce the diffusion of new technologies through this channel. At the same time, entrants are not burdened by legacy adjustment costs and may therefore adopt frontier technologies immediately. As a result, institutional environments that raise restructuring costs may alter the composition of technology diffusion, shifting adoption away from incumbent firms toward new entrants.

The entry margin can be interpreted as a simplified representation of Schumpeterian creative destruction. When new technologies emerge, newly created firms may adopt them immediately, while incumbent firms face adjustment costs associated with reorganizing existing production structures. In such environments, technological upgrading may occur partly through the entry and expansion of new firms rather than through internal adoption by incumbents. Although the model does not explicitly analyze endogenous incumbent exit following innovation, the mechanism captures an important channel through which creative destruction can operate in practice: new firms implementing frontier technologies may gradually replace less adaptable incumbents.

9. Social planner and policy implications

We now introduce a social planner[27] who chooses R&D investment and its allocation across technological trajectories, taking labor market institutions as given. The planner internalizes the effects of innovation on downstream adoption, aggregate productivity, and employment outcomes, including unemployment, but takes employment protection and retraining regimes as exogenously given. This benchmark allows us to isolate how market incentives distort the level and direction of innovation in the presence of employment protection. We then compare market and planner allocations across alternative institutional environments, including high employment protection and flexicurity regimes.

9.1. The social planner's R&D problem

The model allows us to distinguish between the private and social returns to R&D investment. The private return accruing to innovators is determined by expected licensing profits, which depend on the adoption decisions of downstream firms and the resulting license revenues. By contrast, the social return reflects the broader productivity gains generated by technology adoption across production firms, as well as the induced effects on aggregate output and employment. Because innovators do not internalize these economy-wide benefits, private incentives to invest in R&D generally fall short of the socially optimal level.

To formalize this wedge, we introduce a benevolent social planner who evaluates welfare conditional on the prevailing institutional environment, including employment protection legislation. The planner does not choose labor market institutions, but instead takes them as given. Within these constraints, the planner selects the level of R&D investment and its allocation across technological trajectories so as to maximize aggregate welfare. Comparing the planner's allocation with the market outcome allows us to characterize how employment protection distorts both the level and the direction of innovation by reducing downstream adoption and, in turn, weakening private incentives to invest in R&D relative to the social gains.

The social planner's problem over R&D is given by:

(28) $$\max_{I^S} p(I^S)W_1 + \left(1 - p(I^S)\right)W_0 - I^S$$

W_0 stands for social welfare when the new technology has not arrived (only old tech available), and W_1 represents social welfare when the new technology has arrived and firms decide whether to adopt or not.

The FOC for the socially optimal R&D level I^S is:

[27] Examples of social planners in endogenous growth models include Lucas (1988) and Canton and Uhlig (1999), where the planner internalizes knowledge externalities when choosing innovation or investment paths.

(29) $p'(I^S)\Delta W = 1$

where $\Delta W \equiv W_1 - W_0$. The model delivers a wedge between private and social returns to R&D. Because the innovator internalizes only licensing revenues, whereas the planner values the full impact of innovation on aggregate output and employment outcomes, equilibrium R&D investment is generally below the socially optimal level.

Social welfare depends on aggregate output and unemployment

(30) $W(I^S) = p(I^S)\{Y_1 - R_1 - \xi U_1\} + (1 - p(I^S))(Y_0 - \xi U_0) - I^S$

where Y_0 is aggregate output if only the old technology is available, Y_1 is aggregate output in the equilibrium where the new technology is available and firms optimally decide whether to adopt or not, R_1 is the economy's total cost of restructuring, U_0 is unemployment in the old-technology-only equilibrium, U_1 is unemployment in the equilibrium when the new technology is available (and firms choose adoption), and ξ measures the planner's concern for unemployment. As a result, the socially optimal level of R&D investment may differ from the level that maximizes aggregate output alone, reflecting a trade-off between productivity gains and unemployment outcomes. This framework provides a natural rationale for policy interventions - such as R&D subsidies, adoption incentives, or labor market policies - that jointly address underinvestment in innovation and the employment consequences of technological change.

9.2. Market versus social planner allocation of R&D

To compare private and socially optimal R&D investment numerically, we impose additional quantitative assumptions. First, we set the per-adopter license fee to $P_L = 0.04$ under the AI-P and AI-T trajectories and to $P_L = 0.007$ under MDT, capturing the idea that modular digital technologies generate smaller appropriable rents - for example because they are more standardized and supplied in more competitive markets. For tractability, we model license payments as part of the fixed adoption cost. Under this assumption, changing P_L affects innovators' expected licensing revenues but leaves firms' adoption thresholds unchanged, so that the set of adopters is determined by technology and adjustment costs rather than by pricing.

Second, we parameterize the innovation technology through the arrival rate using trajectory-specific values: $\nu = 0.008$ for AI-P, $\nu = 0.005$ for AI-T, and $\nu = 0.1$ for MDT, consistent with faster incremental innovation in modular technologies than in frontier AI. Finally, we set the planner's unemployment weight to $\xi = 0.7$, matching the worker outside option in the wage-setting block; under this calibration, the welfare cost of unemployment is expressed in units comparable to forgone earnings embodied in the outside option.

Table 7 compares private and socially optimal R&D investment across technological trajectories. In all three cases, private R&D falls well short of the social optimum, reflecting innovators' failure to internalize the aggregate productivity and employment effects generated by downstream adoption. The magnitude of this wedge varies systematically with the nature of the technology. For both AI-based trajectories, private R&D investment is similar despite substantial differences in productivity gains and employment effects, indicating that private licensing profits do not fully reflect the social value of more transformative technologies. This divergence is particularly pronounced for transformational AI (AI-T), which delivers the largest net welfare gains but is also associated with higher equilibrium unemployment due to its labor-saving character and restructuring costs. By contrast, modular digital technologies (MDT) generate more modest productivity improvements but diffuse widely with minimal employment disruption. Although private R&D investment is low for MDT, its relatively high R&D multiplier reflects the efficiency with which even small increases in R&D translate into net output gains.[28] Overall, the table illustrates a directional distortion in innovation incentives. While process-augmenting AI (AI-P) generates the highest expected profits for the innovation sector, a social planner would allocate R&D toward transformational AI (AI-T), which delivers substantially larger net welfare gains despite requiring greater organizational restructuring.

[28] The implied R&D multipliers fall within the empirical range discussed by Jones and Summers (2020).

Table 7. Market and social planner solution under different technology trajectories

	Technology trajectory		
	AI-P	AI-T	MDT
Private R&D (I/Y_1)	0.5%	0.6%	0.1%
Exp. profits innovation sector	30.1	27.6	25.6
Socially optimal R&D (I^S/Y_1)	2.2%	2.4%	2.6%
R&D multiplier	5.0	7.1	5.8
Unemployment rate ($U_1/\bar{L}$)	4.2%	6.8%	0.4%
Net welfare gain	13.0%	22.4%	16.5%

Notes: Expected profits of the innovation sector are calculated as $pV^{\text{innov}} - I$. The R&D multiplier is defined conditional on the availability of the new technology as $(Y_1 - R_1 - Y_0)/I^S$. Net welfare gains are defined conditional on the availability of the new technology as $(Y_1 - R_1 - \xi U_1 - (Y_0 - \xi U_0) - I^S)/Y_0$. Differences in innovation arrival rates affect the frequency of such events but not the welfare impact.

9.3. Institutional environments as exogenous regimes

We next examine how market and social planner allocations of R&D vary across institutional environments. Rather than treating labor market institutions as policy instruments chosen within the model, we interpret employment protection and flexicurity as exogenous regimes that shape firms' adoption incentives and the expected returns to innovation. In particular, we compare a high-employment-protection environment - characterized by elevated severance and restructuring costs - with a flexicurity regime.

The flexicurity regime considered here is motivated by labor market systems that combine relatively low ex ante dismissal barriers with strong ex post income support and active labor market policies. Denmark is often cited as a leading example of such an institutional configuration. While the model does not attempt to replicate any specific country, the flexicurity scenario is intended to capture the qualitative features of systems in which worker security is provided primarily through unemployment insurance and retraining rather than through strict employment protection.

Specifically, a central feature of flexicurity in the model is its effect on ex ante adoption costs. Under high employment protection, dismissal regulations and procedural requirements raise the fixed costs firms expect to incur when reorganizing production, even before adoption takes place. These ex ante costs discourage investment in restructuring-intensive technologies by reducing the expected surplus from adoption. Flexicurity mitigates this channel by lowering the sensitivity of fixed adoption costs to employment protection, while preserving worker protection ex post through income support and retraining.

By holding the structure of the innovation problem fixed and varying only the institutional environment, this exercise isolates how labor market regimes affect the level and direction of R&D through their impact on downstream adoption.

Table 8 shows that labor market institutions systematically shape R&D incentives across technological trajectories. Private R&D investment is for restructuring-intensive AI technologies lower under high employment protection than under flexicurity, reflecting weaker downstream adoption incentives. In contrast, socially optimal R&D varies little across institutional regimes. Differences in R&D multipliers are driven primarily by technology characteristics rather than institutional design. High EPL is associated with higher post-adoption unemployment under AI trajectories, while flexicurity mitigates these employment costs and yields higher net welfare gains without materially affecting outcomes for modular digital technologies.

An additional implication concerns the ranking of technologies. Under high employment protection, modular digital technologies generate the highest private profits for the innovation sector, whereas under flexicurity process-augmenting AI becomes privately most attractive. By contrast, transformational AI delivers the largest net welfare gains under both institutional regimes. This divergence highlights how labor market institutions can redirect private innovation toward technologies with lower adjustment costs but smaller social payoffs.[29]

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[29] The cross-scenario differences in innovation-sector profitability relate closely to the debate on the directionality of R&D. A growing literature emphasizes that public policy and institutions influence not only the level of innovative effort but also its composition by altering relative returns across technological trajectories

Table 8. R&D investment under alternative labor market regimes

	High EPL			Flexicurity		
	AI-P	AI-T	MDT	AI-P	AI-T	MDT
Private R&D / Y_1	0.5%	0.5%	0.1%	0.6%	0.6%	0.1%
Exp. profits innovation sector	22.0	18.9	24.5	41.5	21.3	27.5
Socially optimal R&D / Y_1	2.2%	2.5%	2.5%	2.3%	2.5%	2.6%
R&D multiplier	4.8	6.9	5.8	5.3	7.1	5.8
Unemployment rate ($U_1/\bar{L}$)	4.5%	5.6%	0.4%	3.7%	5.5%	0.3%
Net welfare gain	12.2%	21.6%	16.4%	14.1%	22.6%	16.6%

Notes: Expected profits of the innovation sector are calculated as $pV^{\text{innov}} - I$. The R&D multiplier is defined conditional on the availability of the new technology as $(Y_1 - R_1 - Y_0)/I^S$. Net welfare gains are defined conditional on the availability of the new technology as $(Y_1 - R_1 - \xi U_1 - (Y_0 - \xi U_0) - I^S)/Y_0$. Differences in innovation arrival rates affect the frequency of such events but not the welfare impact.

9.4. Interpretation and policy implications

The policy implications below follow from counterfactual comparisons within the model and should be interpreted as conditional on the restructuring-cost channel emphasized here.

The analysis yields three central insights into how labor market institutions shape innovation incentives and the effectiveness of innovation policy. First, employment protection legislation affects innovation primarily through its impact on adoption incentives, rather than through a direct effect on R&D technology. By raising expected restructuring and severance costs, EPL weakens downstream adoption, particularly for restructuring-intensive technologies. These adoption frictions feed back into the innovation sector by reducing expected licensing revenues, generating a wedge between private and social returns to R&D that is both large and highly technology-specific.

Second, this wedge has a directional component. Private R&D is systematically biased away from technologies with large social payoffs but high adjustment requirements - most notably transformational AI - and toward technologies that are easier to adopt but deliver smaller productivity gains. As a result, labor market institutions shape not only the level of innovative activity but also the technological trajectories along which innovation occurs. This mechanism operates even when total R&D investment responds weakly to institutional change, highlighting the importance of composition effects that are not captured by aggregate innovation measures alone.

Third, the comparison between high EPL and flexicurity regimes illustrates that institutional design matters as much as institutional stringency. Flexicurity mitigates innovation distortions not by eliminating worker protection, but by shifting it from ex ante constraints on firms toward ex post insurance for workers. By reducing the sensitivity of fixed adoption costs to employment protection, flexicurity raises adoption incentives for restructuring-intensive technologies and increases private returns to R&D. At the same time, stronger income support and retraining preserve worker welfare and limit unemployment costs.

From a policy perspective, these results suggest that innovation policy and labor market institutions are complements rather than substitutes. R&D subsidies or mission-oriented innovation programs may be less effective in environments where employment protection strongly discourages adoption of the targeted technologies. Conversely, reforms that reduce ex ante restructuring frictions while preserving ex post security for workers can increase private R&D incentives, thereby enhancing the effectiveness of innovation policy.

(Acemoglu 2002; Aghion et al. 2019). In this perspective, labor market institutions act as a source of implicit directionality, tilting innovation incentives toward technologies that are more compatible with existing regulatory constraints. Our results show that stricter employment protection disproportionately reduces the profitability of restructuring-intensive, labor-saving innovations, thereby favoring more labor-augmenting or incremental technologies even in the absence of explicit technology mandates. This mechanism complements arguments that innovation policy operates through broad institutional environments and relative price signals rather than solely through targeted subsidies or mission-oriented programs (Acemoglu et al. 2012; Mazzucato 2018).

Importantly, these gains do not require policymakers to choose specific technologies ex ante; instead, they arise from improving the institutional environment in which firms evaluate adoption and innovation decisions.

An important qualification is that employment protection legislation does not operate solely through the level of dismissal costs, but also through the predictability and allocation of adjustment risks between firms and workers. From this perspective, employment protection can be interpreted as an insurance mechanism that smooths income risk for workers in the presence of incomplete markets. The analysis does not imply that the optimal level of regulation is zero. Rather, it highlights that the design of labor market institutions - particularly the balance between ex ante dismissal constraints and ex post insurance - matters for how adjustment costs affect technology adoption and innovation incentives.

More broadly, the analysis highlights a central tension facing advanced economies confronted with transformative technological change. Technologies with the largest long-run productivity gains often require substantial reorganization of production processes and labor. The model suggests that when labor market institutions make such reorganization prohibitively costly ex ante, innovation may be steered toward safer but less transformative technological paths. Addressing this tension requires policies that recognize the joint determination of innovation, technology adoption, and labor market adjustment, rather than treating these domains in isolation.

A useful way to interpret these results is through a transatlantic comparison. Relative to the United States, European economies combine stronger employment protection with more limited adoption of restructuring-intensive technologies, most notably advanced AI. In the model, this institutional configuration weakens downstream adoption incentives and, in turn, depresses private returns to innovation in precisely those technologies with the largest potential productivity gains. By contrast, the US institutional environment - characterized by lower ex ante restructuring frictions - supports broader diffusion of transformative technologies, even in the absence of explicit innovation targeting. Importantly, the model suggests that this gap does not reflect differences in innovative capacity per se, but rather institutional environments that shape how firms evaluate adoption and innovation decisions.

10. Conclusions

This paper studies how labor market institutions shape the diffusion of advanced technologies. Using new multi-country firm-level survey data, we document that employment protection legislation is weakly related to most innovation activities but is associated with lower adoption of restructuring-intensive technologies, most notably artificial intelligence. Product market regulation plays a comparatively limited role. These patterns suggest that labor market institutions influence productivity growth primarily through technology adoption rather than through innovation alone.

To interpret these findings, we develop a general equilibrium model in which heterogeneous firms choose whether to adopt a new technology in the presence of EPL-induced restructuring costs. In the model, employment protection legislation increases the effective cost of adjusting employment and tasks when firms adopt new technologies. This mechanism generates non-monotone adoption incentives: while medium-productivity firms adopt and expand employment, very high-productivity firms may optimally refrain from adoption when restructuring costs scale with workforce size. Extending the framework to endogenous innovation shows that adoption frictions feed back into upstream R&D incentives by limiting diffusion and reducing the expected returns to innovation.

A central implication of the framework is that the employment effects of technology adoption are inherently heterogeneous. Firms sort into distinct behavioral types, including expanding adopters, downsizing adopters, and highly productive holdouts that forego adoption despite strong fundamentals. As a result, the same technology - particularly AI - can generate employment gains in some firms and employment losses in others, depending on productivity and institutional constraints. The presence of high-productivity holdouts is especially consequential, as it implies that strict employment protection may selectively deter adoption among firms best positioned to scale new technologies.

The framework developed in the paper provides a coherent interpretation of the stylized facts documented in the empirical analysis. First, the model predicts that technologies requiring more extensive organizational restructuring are more sensitive to labor market institutions, helping explain why employment protection legislation is negatively associated with the adoption of artificial intelligence and digital security technologies but not with more modular digital technologies. Second, because restructuring costs scale with firm size, the model generates heterogeneous adoption incentives across firms, with larger and more productive incumbents facing higher adjustment costs when reorganizing their workforce. Third, the model highlights an additional diffusion margin through firm entry, as new firms can adopt frontier technologies without facing legacy restructuring costs, consistent with the prominent role of startups and scaleups in technology diffusion documented in the data.

Taken together, the empirical patterns and the model highlight how labor market institutions influence the channels through which new technologies diffuse in the economy. When workforce restructuring becomes more costly, adoption by incumbent firms (particularly large and highly productive firms) may become less attractive, shifting part of the diffusion process toward entry and expansion by new firms implementing frontier technologies. While this entry margin can partially offset slower adoption among incumbents, it is unlikely to fully substitute for adoption by large firms, which typically account for a substantial share of investment, employment, and productivity growth. In economies where startups face barriers to scaling, slower adoption among incumbents may therefore translate into weaker aggregate diffusion of transformative technologies.

These findings carry important implications for policy. When adoption is constrained by labor market institutions, policies aimed solely at stimulating innovation or R&D may have more limited effects on productivity growth. Conversely, institutional arrangements that facilitate workforce adjustment - for example by combining flexibility in firm reorganization with income support and retraining - can help strengthen the link between innovation, diffusion, and productivity growth. More broadly, the results highlight that technology policy and labor market policy are complements rather than substitutes in shaping the pace of technological change.

To conclude, the results highlight that technological diffusion depends not only on technological opportunities, but also on the institutional environment in which firms operate. The analysis does not take a normative stance on the level of employment protection legislation, but instead focuses on how EPL can shape technology adoption and diffusion. The relationship between EPL, technological change, economic performance, and labor market outcomes is inherently complex and calls for an open debate and a careful assessment of the impacts of different policy options. This paper aims to contribute to this debate by investigating how labor market institutions affect firms’ adjustment costs associated with the introduction of new technologies.

References

Acemoglu, D. (1997). Training and innovation in an imperfect labour market. Review of Economic Studies, 64(3), 445–464.

Acemoglu, D. (2002). Directed technical change. Review of Economic Studies, 69(4), 781–809.

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. American Economic Review, 102(1), 131–166.

Acemoglu, D., & Restrepo, P. (2019). Artificial intelligence, automation, and work. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The Economics of Artificial Intelligence: An Agenda. University of Chicago Press.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244.

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. Econometrica, 60(2), 323–351.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., & Li, H. (2019). Missing growth from creative destruction. American Economic Review, 109(8), 2795–2822.

Andrews, D., Criscuolo, C., & Gal, P. (2015). Frontier firms, technology diffusion and public policy: Micro evidence from OECD countries. OECD Productivity Working Papers 2015-02, OECD Publishing, Paris.

Atkeson, A., & Kehoe, P. J. (2007). Modeling the transition to a new economy: Lessons from two technological revolutions. American Economic Review, 97(1), 64–88.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics, 118(4), 1279–1333.

Babina, T., Fedyk, A., He, A., Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745.

Balland, P.A., Di Girolamo, V., Benoit, F., Ravet, J., & Hobza, A. (2025). Divided we fall behind: Why a fragmented EU cannot compete in complex technologies. R&I Paper Series 2025/04, Directorate-General for Research and Innovation, European Commission, Brussels.

Bartelsman, E., Gautier, P., & De Wind, J. (2016). Employment protection, technology choice, and worker allocation. International Economic Review, 57(3), 787–826.

Bassanini, A., Nunziata, L., & Venn, D. (2009). Job protection legislation and productivity growth in OECD countries. Economic Policy, 24(58), 349–402.

Belot, M., Boone, J., & Van Ours, J. (2007). Welfare-improving employment protection. Economica, 74(295), 381–396.

Benmelech, E., & Zator, M. (2022). Robots and firm investment. NBER Working Paper No. 29676.

Bessen, J. E. (2018). AI and jobs: The role of demand. NBER Working Paper No. 24235.

Bick, A., Blandin, A., Deming, D. J., Fuchs-Schündeln, N., & Jessen, J. (2026). Mind the gap: AI adoption in Europe and the US. Brookings Papers on Economic Activity, BPEA Conference Draft, March 26-27, 2026.

Bloom, N., Jones, C. I., Van Reenen, J., & Webb, M. (2020). Are ideas getting harder to find? American Economic Review, 110(4), 1104–1144.

Boeri, T., Garibaldi, P., & Moen, E. R. (2017). Inside severance pay. Journal of Public Economics, 145, 211–225.

Boeri, T., & Jimeno, J. F. (2005). The effects of employment protection: Learning from variable enforcement. European Economic Review, 49(8), 2057–2077.

Bonfiglioli, A., Crinò, R., Fadinger, H., & Gancia, G. (2024). Robot imports and firm-level outcomes. Economic Journal, 134 (November), 3428–3444.

Brynjolfsson, E., & Hitt, L. (2000). Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives, 14(4), 23–48.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. American Economic Journal: Macroeconomics, 13(1), 333–372.

Canton, E., de Groot, H., & Nahuis, R. (2002). Vested interests, population ageing and technology adoption. European Journal of Political Economy, 18(4), 631-652.

Canton, E., & Uhlig, H. (1999). Growth and the cycle: Creative destruction versus entrenchment. Journal of Economics, 69(3), 239–266.

Caselli, F., & Coleman, W. J. (2006). The world technology frontier. American Economic Review, 96(3), 499–522.

Cerpentier, M., Schulze, A., Vanacker, T., & Zahra, S.A. (2024). Employment protection laws and the commercialization of new products: A cross-country study. Research Policy, 53(7), 105039.

Cingano, F., Leonardi, M., Messina, J., & Pica, G. (2010). The effects of employment protection legislation and financial market imperfections on investment: Evidence from a firm-level panel of EU countries. Economic Policy, 25(61), 117–163.

Coatanlem, Y., & Coste, O. (2025). Cost of failure, disruptive innovation and targeted flexicurity: More evidence supporting targeted reforms. Working Paper. Institute for European Policymaking, Bocconi University.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1), 128–152.

Comin, D., & Hobijn, B. (2010). An exploration of technology diffusion. American Economic Review, 100(5), 2031–2059.

Comin, D., & Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? American Economic Journal: Macroeconomics, 10(3), 137–178.

Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. Technology in Society, 62, 101257.

Draghi, M. (2024). The Future of European Competitiveness; Part A – A Competitiveness Strategy for Europe. European Commission, Brussels.

Elsby, M., Hobijn, B., & Şahin, A. (2013). The decline of the U.S. labor share. Brookings Papers on Economic Activity, Fall 2013, 1–52.

European Commission (2025a). A Competitiveness Compass for the EU. COM(2025) 30 final, Brussels.

European Commission (2025b). The EU Startup and Scaleup Strategy; Choose Europe to Start and Scale. COM(2025) 270 final, Brussels.

European Commission (2025c). Startups, Scaleups and Entrepreneurship. Flash Eurobarometer 559, Brussels.

European Commission (2025d). European Innovation Scoreboard 2025. Brussels.

European Commission (2025e), Labour Market and Wage Developments in Europe 2025. Brussels.

European Investment Bank (2025). EIB Investment Survey 2025. Luxembourg.

Fedotenkov, I., Kvedaras, V., & Sanchez-Martinez, M. (2024). Employment protection and labour productivity growth in the EU: Skill-specific effects during and after the Great Recession. Empirica, 51, 209–262.

Fernald, J. G. (2015). Productivity and potential output before, during, and after the Great Recession. NBER Macroeconomics Annual, 29, 1–51.

Filippucci, F., Gal, P., Laengle, K., & Schief, M. (2025). Macroeconomic productivity gains from Artificial Intelligence in G7 economies. OECD Artificial Intelligence Papers 41, OECD Publishing, Paris.

Gordon, R. J. (2016). The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War. Princeton University Press.

Graetz, G., & Michaels, G. (2018). Robots at work. Review of Economics and Statistics, 100(5), 753–768.

Griffith, R., & Macartney, G. (2014). Employment protection legislation, multinational firms, and innovation. Review of Economics and Statistics, 96(1), 135–150.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. Econometrica, 25(4), 501–522.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. Review of Economics and Statistics, 95(2), 347–361.

Haltiwanger, J., Scarpetta, S., & Schweiger, H. (2014). Cross country differences in job reallocation: The role of industry, firm size, and regulations. Labour Economics, 26, 11–25.

Hall, B. H., & Khan, B. (2003). Adoption of new technology. NBER Working Paper No. 9730.

Hopenhayn, H. (2014). Firms, misallocation, and aggregate productivity: A review. Annual Review of Economics, 6(1), 735–770.

Hopenhayn, H., & Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. Journal of Political Economy, 101(5), 915–938.

Jones, B. F., & Summers, L. H. (2022). A calculation of the social returns to innovation. In A. Goolsbee & B. F. Jones (Eds.), Innovation and Public Policy, University of Chicago Press.

Jovanovic, B., & Rousseau, P. L. (2005). General purpose technologies. In P. Aghion & S. Durlauf (Eds.), Handbook of Economic Growth, Vol. 1B. Elsevier.

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. Quarterly Journal of Economics, 129(1), 61–103.

Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors. Quarterly Journal of Economics, 107(1), 35–78.

Kim, J., Schweitzer, S., Riedl, C., De Cremer, D. (2025). People reduce workers' compensation for using Artificial Intelligence (AI). D'Amore-McKim School of Business, Northeastern University.

Koeniger, W. (2005). Dismissal costs and innovation. Economics Letters, 88(1), 79–84.

León-Ledesma, M. A., Satchi, M. (2019). Appropriate technology and balanced growth. Review of Economic Studies, 86(2), 807–835.

Letta, E. (2024). Much More Than a Market - Speed, Security, Solidarity; Empowering the Single Market to deliver a sustainable future and prosperity for all EU citizens. Brussels.

Lommerud, K. E., & Straume, O. R. (2012). Employment protection versus flexicurity: On technology adoption in unionised firms. Scandinavian Journal of Economics, 114(1), 177–199.

Lucas, R. E., Jr. (1988). On the mechanics of economic development. Journal of Monetary Economics, 22(1), 3–42.

Manera, A., & Uccioli, M. (2024). Employment protection and the direction of technology adoption. MIT Working Paper.

Mazzucato, M. (2018). The Entrepreneurial State. Penguin Books.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica, 71(6), 1695–1725.

Mulas-Granados, C., Varghese, R., Boranova, V., deChalendar, A., & Wallenstein, J. (2019). Automation, skills and the future of work: What do workers think? IMF Working Paper WP/19/288.

Nicoletti, G., & Scarpetta, S. (2005). Product market reforms and employment in OECD countries. OECD Economics Department Working Paper No. 472, OECD Publishing, Paris.

Nicoletti, G., von Rueden, C., & Andrews, D. (2020). Digital technology diffusion: A matter of capabilities, incentives or both? European Economic Review, 128, 103513.

Organisation for Economic Co-operation and Development (2024). OECD Digital Economy Outlook 2024 (Volume 1): Embracing the Technology Frontier. OECD Publishing, Paris.

Pissarides, C. A. (2010). Why do firms offer 'employment protection'? Economica, 77(308), 613–636.

Restuccia, D., & Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. Review of Economic Dynamics, 11(4), 707–720.

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5), S71–S102.

Syverson, C. (2011). What determines productivity? Journal of Economic Literature, 49(2), 326–365.

Traverso, S., Vatiero, M., & Zaninotto, E. (2022). Robots and labor regulation: A cross-country/cross-industry analysis. Economics of Innovation and New Technology, 10.1080/10438599.2022.2063122.

Violante, G. L. (2002). Technological acceleration, skill transferability, and the rise in residual wage inequality. Quarterly Journal of Economics, 117(1), 297–338.

Appendix

Contents:

A. Summary of the Eurobarometer data

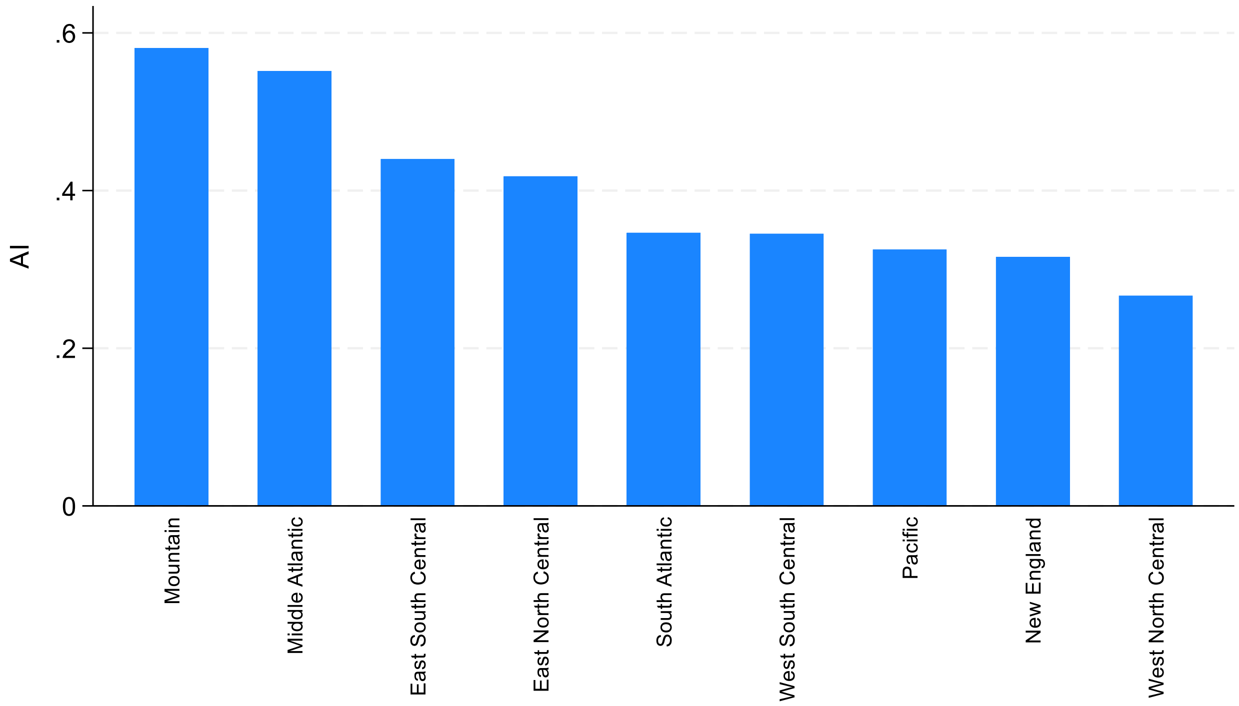
Table A.1. Descriptive statistics of the Flash Eurobarometer 559

Variable	Mean	Obs.
Panel A. Innovation		
Product innovation	0.267	14,656
Process innovation	0.202	14,656
Management innovation	0.175	14,656
Marketing innovation	0.212	14,656
Patented innovation	0.053	14,656
Panel B. Technology adoption		
AI	0.210	14,656
Cloud computing	0.521	14,656
Robotics	0.103	14,656
Internet of things	0.241	14,656
Digital technologies for security	0.393	14,656
Blockchain	0.033	14,656
Biotechnology	0.043	14,656
Micro- and nanoelectronics	0.043	14,656
Advanced materials	0.079	14,656
Clean technologies	0.166	14,656
Panel C. Firm characteristics		
Startup	0.041	14,656
Scaleup	0.239	14,656
1-9 employees	0.402	14,656
10-49 employees	0.356	14,656
50-249 employees	0.177	14,656
250-499 employees	0.035	14,656
500 employees or more	0.031	14,656
Registered before 2005	0.538	14,219
Registered between 2005 and 2019	0.382	14,219
Registered between 2020 and 2023	0.068	14,219
Registered 2024 or later	0.011	14,219
Mining and quarrying	0.004	14,656
Manufacturing	0.121	14,656
Electricity	0.010	14,656

Water supply	0.015	14,656
Construction	0.162	14,656
Wholesale and retail trade	0.206	14,656
Transportation and storage	0.058	14,656
Accommodation and food service activities	0.063	14,656
Information and communication	0.041	14,656
Financial and insurance activities	0.027	14,656
Real estate activities	0.015	14,656
Professional services	0.088	14,656
Administrative and support service activities	0.066	14,656
Education	0.043	14,656
Human health and social work activities	0.057	14,656
Arts	0.025	14,656
Solely owned by one person	0.358	14,656
Owned by more than one person	0.426	14,656
Part of a national or international enterprise group	0.086	14,656
Co-owned by a public entity	0.046	14,656
Co-owned by venture capital firm	0.010	14,656
Co-owned by business angel	0.009	14,656
Predominantly family owned	0.182	14,656
Jointly owned by its members (e.g. cooperative mutual society)	0.043	14,656
Fully or partially owned by a foreign non-EU entity	0.012	14,656
How would you rate your business environment in terms of: Availability of staff with the right skills (fraction “very good” or “fairly good”)	0.543	14,145
your enterprise only operates in (OUR COUNTRY)	0.674	14,656
Other EU countries/EU countries	0.281	14,656
Other European countries outside of the EU (incl. e.g. UK and Russia)	0.118	14,656
North America	0.074	14,656
Latin America and the Caribbean	0.042	14,656
China	0.041	14,656
Rest of Asia and the Pacific	0.061	14,656
Middle East and Africa	0.057	14,656

Source: European Commission (2025c).

Figure A.1. Technology adoption across US Census regions



Notes: The figure reports the share of firms that indicate having adopted artificial intelligence technologies, based on responses to Flash Eurobarometer 559 (Spring 2025). Bars represent averages for US Census regions. Adoption is measured by a binary indicator taking value 1 if the firm reports using any AI tool (e.g., machine learning or large language models) and 0 otherwise. Adoption rates are computed using the full Eurobarometer sample. Sampling design follows the Eurobarometer methodology.

Figure A.1 reports technology adoption rates by US Census division. Regions correspond to the standard nine Census divisions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific). Adoption rates are computed from firm-level survey data. For some Census divisions, the number of observations is limited, and adoption rates should therefore be interpreted with caution. Notwithstanding this limitation, the dispersion in adoption rates across US regions appears smaller than the corresponding variation observed across European countries.

B. Productivity classes in the Eurobarometer survey

We measure firm productivity as the logarithm of the ratio of the midpoint of turnover to the midpoint of the number of employees, as defined in the underlying tables. We discretize the continuous productivity distribution into six classes using quantile-based bins. Class 1 represents the bottom part of the distribution (lowest productivity firms) and Class 6 the top tail (frontier firms).[30] This level of discretization balances empirical realism - allowing meaningful productivity heterogeneity - with computational tractability. Productivity quantiles are calculated separately for each sector to accommodate cross-sectoral heterogeneity in production technologies. This approach ensures that firms are ranked relative to others facing similar technological conditions, avoiding distortions that arise when pooling sectors with differing production functions.

Table B.1. Assignment of midpoints for employment

Employment category (number of employees)	Midpoint
1-9	5
10-49	30
50-249	150
250-499	375
500+	600

Table B.2. Assignment of midpoints for turnover

Turnover category (in Euro)	Midpoint
<100k	50k
100k-500k	300k
500k-1 million	750k
1-2 million	1.5 million
2-5 million	3.5 million
5-10 million	7.5 million
10-50 million	30 million
>50 million	75 million

Table B.3. Productivity with 6 quantiles

Productivity quantile	Description
1	Very low productivity firms
2	Low productivity firms
3	Lower-middle productivity firms
4	Upper-middle productivity firms
5	High productivity firms
6	Very high productivity firms

[30] The number of firms differs across productivity classes, reflecting the skewed distribution of firm productivity. In particular, a large mass of firms is concentrated at low productivity levels, consistent with standard empirical evidence on firm heterogeneity.

C. Quantitative method to establish the correlation between EPL and technology adoption

To characterize the correlation between employment protection legislation and technology adoption while accounting for observable firm and country characteristics, we estimate multilevel probit specifications of the following form:

$$\Pr(T_{ic} = 1 | EPL_c, PMR_c, X_{ic}, \delta_s, \varepsilon_c) = \Phi(\lambda_1 EPL_c + \lambda_2 PMR + X_{ic}'\zeta + \delta_s + \varepsilon_c),$$

where T_{ic} is an indicator equal to one if firm i in country c reports adoption of a given technology, EPL_c is the employment protection index for country c, PMR_c is the product market regulation index for country c, X_{ic} is a vector of firm-level controls (startup, scaleup, productivity, sector, size class, age cohort, ownership type, export status, perceptions of skill availability), δ_s are sector fixed effects, ε_c is a country-level random intercept capturing unobserved national factors, $\Phi(.)$ denotes the standard normal cumulative distribution function, and λ and ζ are regression coefficients.

The multilevel structure accommodates the hierarchical nature of the data - firms nested within countries - and allows the effects of country-level institutions such as EPL to be identified separately from firm-level heterogeneity. Country-specific random intercepts $\varepsilon_c \sim N(0, \sigma_\varepsilon^2)$ absorb unobserved institutional, cultural, and regulatory features correlated with adoption decisions but not directly observed in the survey. Standard errors are clustered at the country level to account for residual within-country correlation.

Results are presented in Table 2 in the main text. The coefficient of interest is λ_1. Identification comes from cross-country variation in EPL, conditional on a rich set of firm-level covariates and sectoral fixed effects. Since EPL is measured at the national level and varies little over time, we treat it as predetermined for the purpose of this cross-sectional analysis. The random-intercept structure mitigates concerns that unobserved country characteristics correlated with EPL drive the results. Under this specification, a negative λ_1 indicates that stricter employment protection legislation is associated with a lower probability of adoption. Estimates are reported as marginal effects evaluated at the sample means.

A potential concern is that employment protection legislation may be correlated with technology adoption for reasons unrelated to firms' adjustment costs, for example if countries with lower adoption rates are more likely to maintain stricter labor regulation. Several features of the empirical design help to mitigate this concern. First, employment protection legislation varies primarily at the national level and changes infrequently over time, whereas adoption of advanced technologies varies substantially across firms, sectors, and technology types within countries. Second, the analysis controls for observable country characteristics related to adoption capacity, including an indicator for innovation leaders based on the European Innovation Scoreboard, as well as sector fixed effects and a rich set of firm-level controls. Third, the patterns documented in the data differ sharply across technologies within the same institutional environment: EPL is negatively associated with the adoption of some technologies (such as AI and digital security) but not others (such as robotics or cloud computing). This heterogeneity is difficult to reconcile with a generic omitted-variable explanation and is instead consistent with mechanisms operating through technology-specific adjustment and restructuring requirements.

D. Correlation between EPL and innovation

Table D.1 reports multilevel probit estimates relating employment protection legislation and product market regulation to firms' innovation outcomes, following the empirical specification described in Appendix C. Innovation activities are reported as binary indicators capturing whether the firm introduced during the past 12 months a new or significantly improved product or service (product innovation); a new or significantly improved production process (process innovation); a new management organization or business model (management innovation); a new method for marketing or selling products (marketing innovation); an innovation for which a patent was granted or applied. Overall, the results indicate no systematic association between EPL and innovation activity. Across the five innovation measures, the EPL coefficients are statistically insignificant, with the sole exception of management innovation, where collective dismissal protection enters with a negative coefficient significant at the 1 percent level.

The negative association for management innovation is consistent with the view that collective dismissal rules can impede organizational restructuring. Management innovations - such as changes in organizational design, reporting structures, or performance systems - often require task reallocation or the elimination of redundant functions. When dismissal rules impose high severance costs, lengthy consultation requirements, or administrative approval procedures, the expected costs of reorganizing the workforce increase. Firms may therefore postpone or forgo organizational changes, reinforcing persistence in managerial practices and slowing adaptation to competitive pressures (Nicoletti and Scarpetta 2005; Griffith and Macartney 2014).

Table D.1. Employment protection and innovation

	(1) Product Innovation	(2) Process Innovation	(3) Management Innovation	(4) Marketing Innovation	(5) Patented innovation
EPL	-0.012	0.005	-0.035***	-0.032	0.012
	(0.022)	(0.018)	(0.013)	(0.021)	(0.013)
PMR	0.023	0.020	0.059	0.065	0.024
	(0.052)	(0.038)	(0.053)	(0.080)	(0.036)
Startup	0.513***	0.310***	0.301***	0.393***	0.073***
	(0.029)	(0.028)	(0.025)	(0.036)	(0.018)
Scaleup	0.061***	0.042***	0.051***	0.037***	0.011**
	(0.008)	(0.009)	(0.008)	(0.010)	(0.004)

Notes: Delta-method standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The EPL indicator refers to collective dismissals (regular contracts), and the PMR indicator to the medium level indicator on barriers to trade and investment. Startup and scaleup are dummy variables taking value 1 if the firm is a startup or scaleup, and 0 otherwise. Controls for firm productivity (details are included in Appendix B), perceived business environment in terms of availability of staff with the right skills, export status, sector, firm age, ownership, and firm size are included. The model also includes a dummy taking value 1 if the country is an innovation leader according to the European Innovation Scoreboard 2025 and 0 otherwise (European Commission 2025d). The total number of observations is 12,096 and 29 countries are included in the analysis. Reported coefficients from the multilevel mixed-effects probit regression model refer to average marginal effects. Further details about the quantitative procedure can be found in Appendix C.

For the remaining innovation outcomes, the lack of statistical significance mirrors the broader literature, where evidence on the EPL-innovation link is mixed and often non-robust across specifications. Similarly, the coefficients on PMR are uniformly insignificant, suggesting that barriers to trade and investment do not exhibit a systematic relationship with innovation activity.

Finally, startup and scaleup indicators enter with positive and highly significant coefficients, which is partly mechanical given that innovation is embedded in their definitions. Notably, the estimated effects are substantially larger for startups than for scaleups, with the strongest association observed for product innovation.

E. Definition of firm types

Table E.1 describes the classification of firms into mutually exclusive types based on technology adoption, productivity, and employment dynamics. The definitions are constructed to ensure close comparability between the Eurobarometer data and the model economy.

Table E.1. Firm-type classification in the data and the model

Firm type	Definition in Eurobarometer data	Definition in model economy
Zombies	No adoption (Q14) and firm in first productivity quantile	No adoption and firm in first productivity quantile
Marginal non-adopters	No adoption (Q14) and firm in second or third productivity quantile	No adoption and firm in second or third productivity quantile
Low-productive adopters	Adoption (Q14) and firm in first, second or third productivity quantile	Adoption and firm in first, second or third productivity quantile
Expanding adopters	Adoption (Q14), increasing employment (Q4_1) and firm in fourth or fifth productivity quantile	Adoption, increasing employment and firm in fourth or fifth productivity quantile
Frontier stars	Adoption (Q14), increasing employment (Q4_1) and firm in sixth productivity quantile	Adoption, increasing employment and firm in sixth productivity quantile
Downsizing adopters	Adoption (Q14), decreasing employment (Q4_1) and firm in fourth, fifth or sixth productivity quantile	Adoption, decreasing employment and firm in fourth, fifth or sixth productivity quantile
Highly productive holdouts	No adoption (Q14) and firm in sixth productivity quantile	No adoption and firm in sixth productivity quantile
Other:		
Stable adopters	Adoption (Q14), stable employment (Q4_1) and firm in fourth, fifth or sixth productivity quantile	Adoption, stable employment and firm in fourth, fifth or sixth productivity quantile
Productive holdouts	No adoption (Q14) and firm in fourth or fifth productivity quantile	No adoption and firm in fourth or fifth productivity quantile

Notes: Productivity quantiles in the Eurobarometer data are defined as described in Appendix B. In the model economy, productivity quantiles are defined analogously using the distribution of firm-level productivity z. Adoption in the Eurobarometer data is based on firms reporting the use of at least one relevant technology in Question 14. Employment changes are measured using Question 4_1 and classified as increasing, decreasing, or stable. The same classification rules are applied in the model economy, ensuring consistency with the definitions used in the data. Firm types labeled “Other” are not reproduced in the model economy and are reported for completeness.

F. Model calibration and parameter values

Table F.1 summarizes the parameter values used in the quantitative implementation of the model. Panel A reports technology-specific parameters governing productivity gains, factor bias, retraining needs, experience retention, and fixed adoption costs across the three technological trajectories considered in the paper. Panel B reports institutional parameters that affect adoption and restructuring costs under alternative labor market regimes. Panel C lists remaining parameters that are common across all scenarios. Together, these parameters discipline firms' adoption incentives, the allocation of R&D across technological trajectories, and the comparison between market and socially optimal outcomes.

Table F.1. Model parameters by technology and institutional regime

Panel A. Technology-specific parameters

Parameter	Description	AI-P	AI-T	MDT
α_O	Production elasticity of labor under old technology	0.65	0.65	0.65
α_N	Production elasticity of labor under new technology	0.6	0.5	0.65
T_O	Efficiency multiplier old technology	1	1	1
T_N	Efficiency multiplier new technology	1.2	1.5	1.04
τ	Retraining cost per retained worker	0.3	0.3	0.1
ρ	Experience retention rate	0.65	0.65	0.9
κ	Fixed adoption cost	0.03964	0.03964	0.00448
P_L	License fee	0.04	0.04	0.007
ν	Innovation arrival rate	0.008	0.005	0.1

Panel B. Institutional parameters

Parameter	Description	Baseline	High EPL	Flexicurity
EPL	Employment protection index	2.4	3	2.4
b	Worker outside option	0.7	0.7	0.7
β	Worker bargaining power	0.5	0.5	0.5
η_ϕ	EPL sensitivity of fixed costs	0.25	0.25	0.15
S	Severance-cost intercept	-4.22	-4.22	-4.22
η_ψ	EPL sensitivity of severance costs	2.36	2.36	3

Panel C. Other parameters

Parameter	Description	Value
$\bar{L}$	Labor supply	10,000
ξ	Planner weight on unemployment	0.7

Notes: Panel A reports technology-specific parameters governing productivity gains, factor bias, retraining needs, experience loss upon adoption, and fixed adoption costs. Panel B reports institutional parameters that affect adoption and restructuring costs. Under flexicurity, employment protection remains in place, but the sensitivity of fixed adoption costs to EPL (η_ϕ) is reduced, reflecting lower ex ante regulatory frictions, while severance costs increase (i.e. higher η_ψ), reflecting stronger ex post income protection for displaced workers. The worker outside option b is held constant across regimes to isolate the role of adoption frictions. Panel C reports remaining parameters common across all scenarios.

The arrival rate of new technologies, ν, differs across technological trajectories to reflect heterogeneity in the speed and scalability of innovation. AI-based technologies are characterized by substantial fixed development costs, long development cycles, and significant uncertainty, which we capture through lower arrival rates for both process-augmenting AI (AI-P) and transformational AI (AI-T). In contrast, modular digital technologies

(MDT) - such as incremental automation, software upgrades, or modular digital tools - are developed and diffused more rapidly, often building on existing platforms and requiring smaller, more frequent innovation steps. We therefore assign a higher arrival rate to MDT to reflect its incremental and scalable nature.

Importantly, differences in ν affect the timing and frequency of innovation rather than the productivity gains conditional on adoption. As a result, the calibration does not mechanically favor any particular technology in welfare terms. Instead, it allows the model to capture empirically observed differences in innovation dynamics while letting adoption incentives and institutional frictions determine the equilibrium direction of technological change.

To clarify the role of individual ingredients, Table F.2 summarizes how key assumptions map into qualitative implications. In particular, the combination of (i) technologies that become labor-saving at scale and (ii) severance costs that rise with EPL is central for generating high-productivity holdouts and a non-monotone adoption profile.

Table F.2. Mapping model ingredients to qualitative implications

Model ingredient	Qualitative implication
Fixed adoption cost κ and licensing fee P_L	Low-productivity firms do not adopt
Experience loss $(1-\rho)$ and retraining cost τ	Adoption can be costly even without layoffs
New technology more labor-saving at high z	High-z adopters may downsize
Severance cost scaled by $\psi(EPL)$	Downsizing becomes disproportionately costly under high EPL
Interaction of downsizing + severance	Generates “frontier holdouts” and non-monotone adoption
Flexicurity lowers η_ϕ and increases η_ψ	Shifts employment protection from ex ante adoption barriers toward ex post adjustment costs

G. Auxiliary graphs

Figure G.1. Labor demand under old and new technology, AI-P trajectory

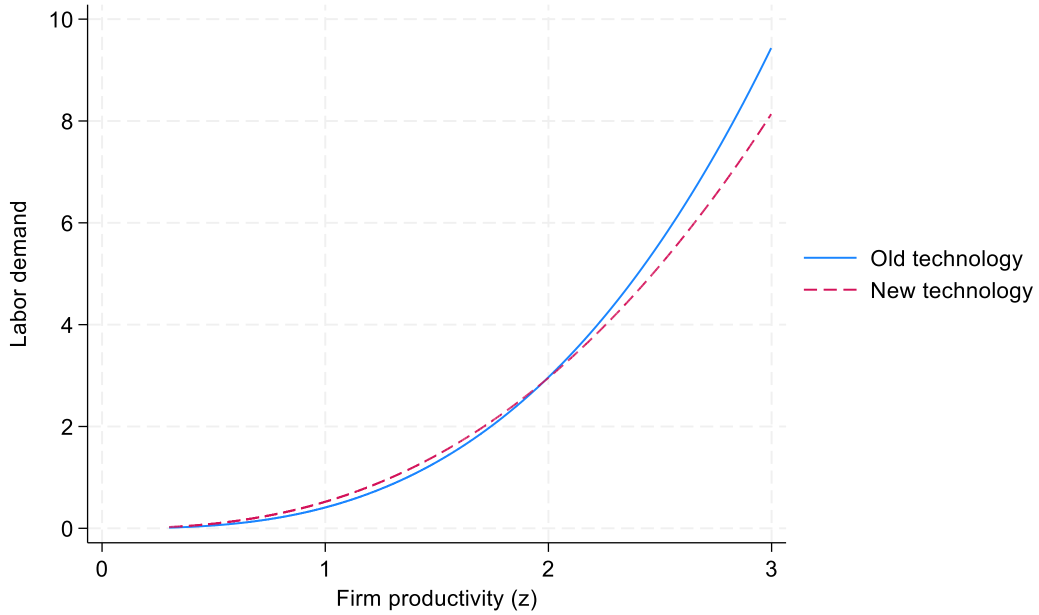


Figure G.2. Cost of restructuring components, AI-P trajectory

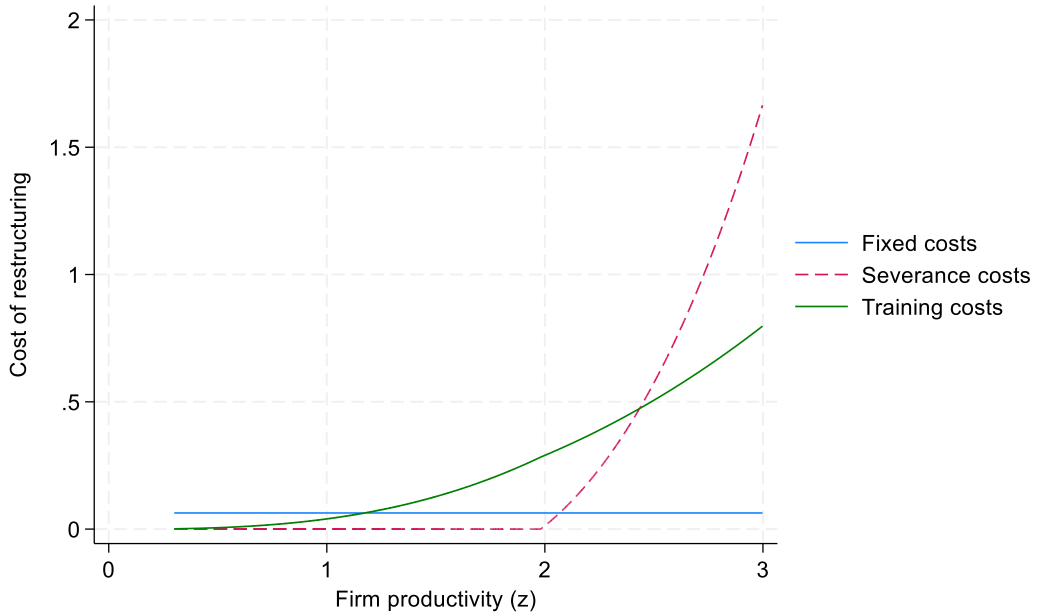


Figure G.3. Labor demand under old and new technology, AI-T trajectory

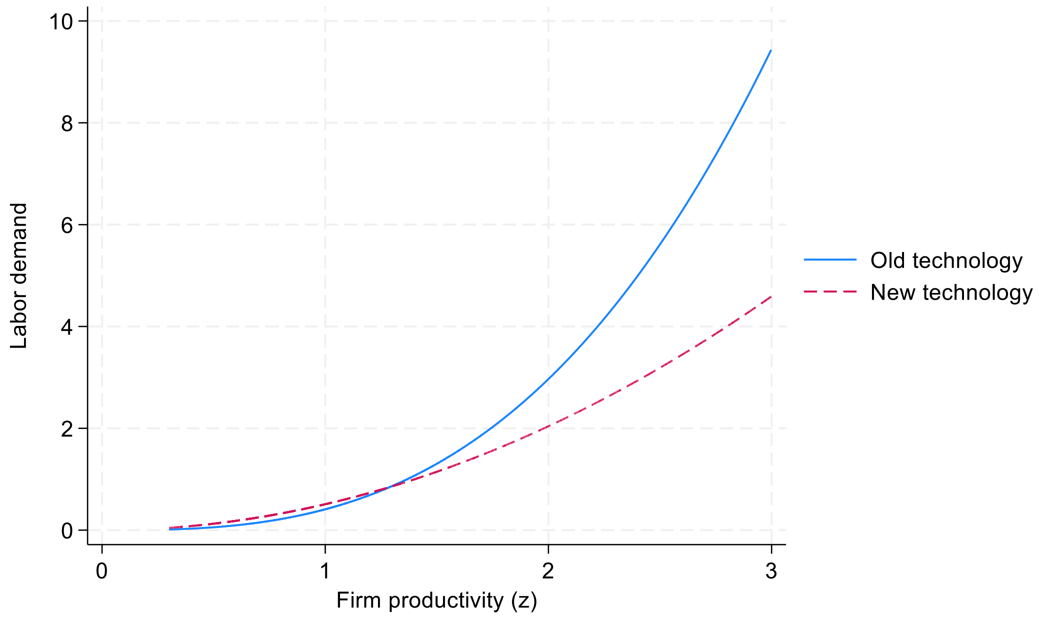


Figure G.4. Cost of restructuring components, AI-T trajectory

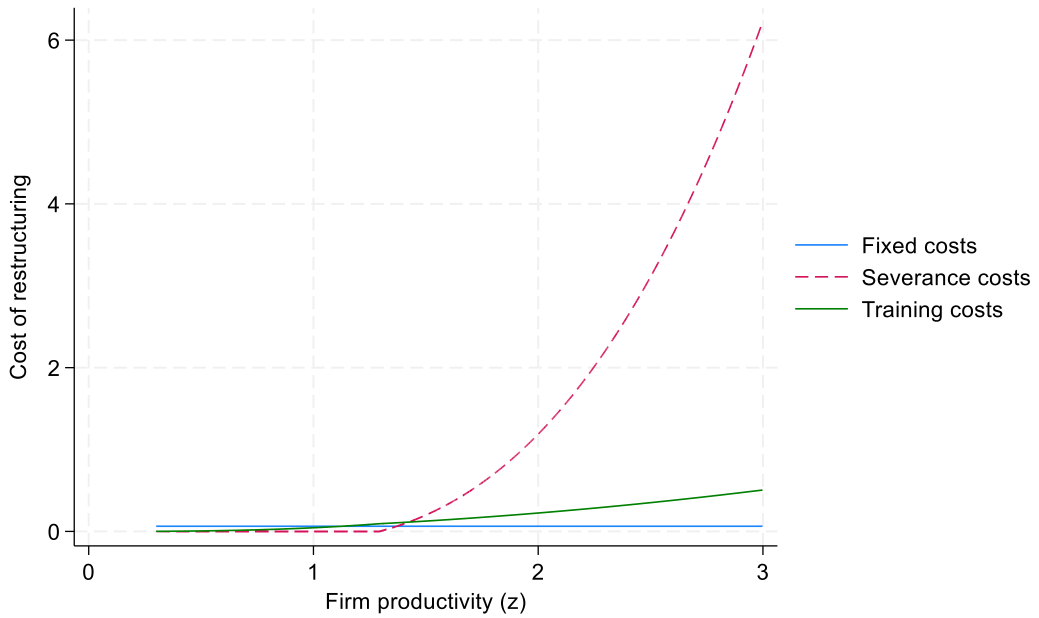


Figure G.5. Labor demand under old and new technology, MDT trajectory

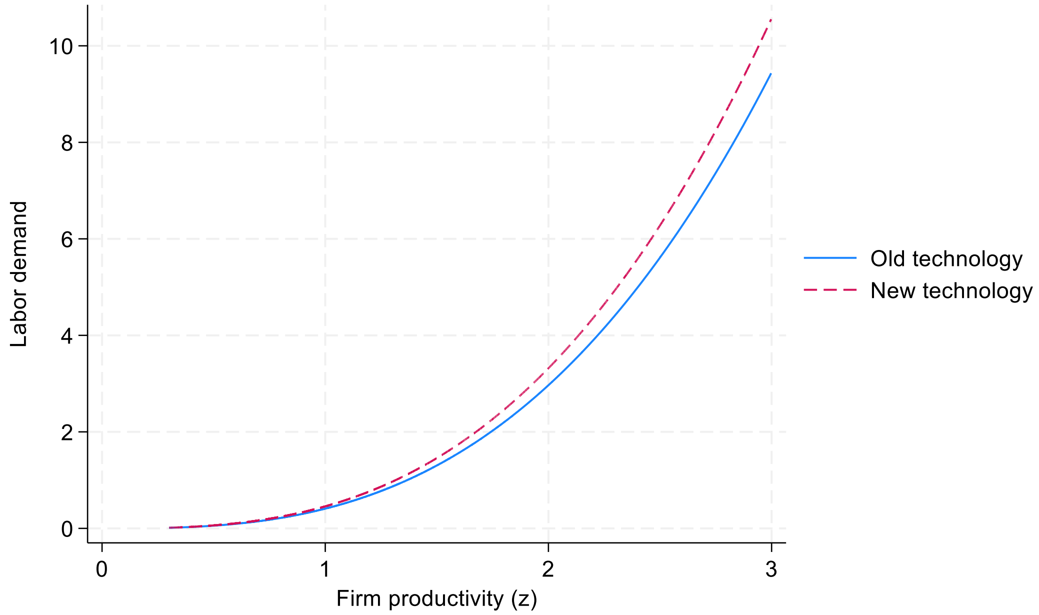
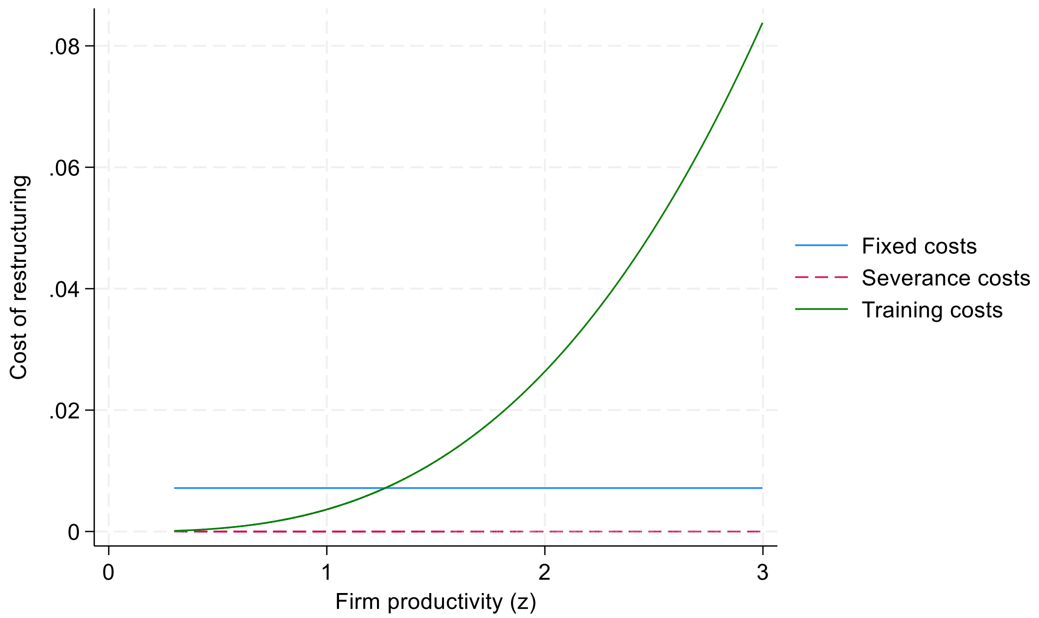


Figure G.6. Cost of restructuring components, MDT trajectory



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Labor market regulations play a key role in shaping firms' technology adoption. The paper finds that stricter employment protection reduces uptake of AI and similar technologies, with important implications for productivity, firm dynamics, and innovation.

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