EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Jonathan Bothner, Paloma Lopez-Garcia, Daphne Momferatou, Ralph Setzer

Why is Europe lagging behind in high tech sectors? The role of institutional and regulatory quality

No 3185

Abstract

This paper investigates the relationship between institutional and regulatory quality, and high-tech sector investment. Using data from 25 European Union (EU) countries from 2004 to 2019 (extended to 2023 for artificial intelligence-specific analyses), the study examines how institutional governance, labour market regulations, and business regulations influence investments in innovative, high-tech, and artificial intelligence-intensive sectors. The findings reveal that better institutional quality and less burdensome regulations are associated with higher investment shares in innovative, high-tech, and artificial intelligence industries. Raising EU countries' institutional and regulatory quality to the level of the current EU frontier could raise the share of investment in high-technology sectors by as much as 50%, hence notably narrowing the existent EU-US investment gap. These results highlight the importance of effective governance and efficient regulations in fostering investment, innovation, and therefore long-term productivity growth.

Keywords: Institutional quality, regulatory frameworks, risky technology, innovation, artificial intelligence, investment

JEL codes: C23, E02, L51, O38

Non-technical summary

Since the mid-1990s, European Union (EU) countries have experienced slower productivity growth compared to the United States (US). This divergence is closely linked to an innovation gap, as highlighted by Draghi (2024). While the US has prioritized investments in innovative and high-technology sectors such as in information and communication technologies (ICT), artificial intelligence (AI), cloud computing, and biotechnology, Europe has remained focused on traditional mid-tech sectors. This difference in the sectoral focus of investment, including research and development (R&D), has constrained Europe's productivity growth due to the more limited spillover effects of mid-tech investment compared to high-tech investment and innovation (Fuest et al., 2024).

The paper investigates the role of institutional and regulatory quality in shaping investment patterns in innovative sectors across the EU. Institutional and regulatory quality is particularly crucial for disruptive, high-tech sectors because these sectors inherently carry higher risks and greater uncertainties. Investments in disruptive technologies often involve significant trial-and-error processes, higher rates of project failures, and rapid scaling needs. Consequently, burdensome regulations, rigid employment protection laws, and inefficient institutions disproportionately increase the costs and complexities associated with failure and restructuring, deterring investment. In contrast, mid-tech sectors typically involve lower risk and fewer innovation-driven disruptions, making regulatory constraints less critical to their investment decisions.

The study uses three key indicators of institutional and regulatory quality: i) the Institutional Delivery Index, derived from the Worldwide Governance Indicators (WGI), which captures broader aspects of institutional quality, including the rule of law, control of corruption, regulatory quality, and government effectiveness, ii) the OECD Employment Protection Legislation (EPL) Index on the stringency of labour market regulations on dismissals, and iii) the World Bank Starting a Business Score, which assesses the administrative burden placed on entrepreneurs when establishing a business. The analysis links these institutional and regulatory indicators to sectoral investment shares. The sectors are classified in terms of their level of technological advancement and innovativeness using three different approaches: the Eurostat taxonomy, the patent intensity, and the AI intensity of sectors. Using data from 25 EU countries spanning 2004 to 2019 (extended to 2023 for AI-specific analyses), the study investigates how the quality of institutions, labour market regulations, and business regulations, influence investment patterns in high-tech, innovative, and AI-intensive sectors.

The results consistently show that higher institutional quality and lower regulatory barriers are associated with increased investment in high-tech, innovative, and AI-intensive sectors. Improving institutional and regulatory quality across the EU to the best-performing country's level could increase the share of investment in high-tech sectors by up to almost 8 percentage points, i.e. up to 50%, narrowing the respective investment gap to the US by about the same extent. Moreover, enhancing institutional governance could boost investment in AI-intensive sectors by over 7 percentage points.

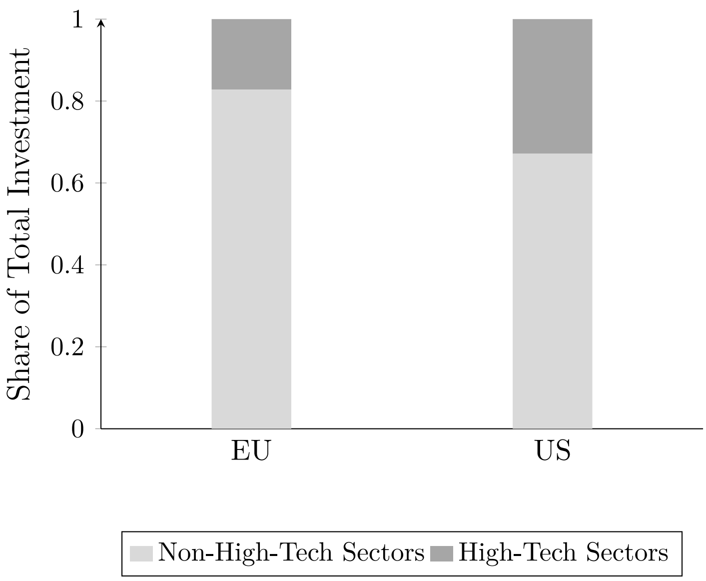
The results underline the importance of institutional and regulatory reforms in promoting innovation and investment in high-tech sectors. Strengthening governance, reducing corruption, making labour markets more flexible, and simplifying procedures for starting and managing businesses would significantly encourage investment in high-tech sectors. Such reforms could play an essential role in increasing Europe's competitiveness and productivity growth, by helping to close the investment gap with the US.

1 Introduction

Since the mid-1990s, European Union (EU) countries have experienced slower productivity growth than the United States (US). This productivity growth gap is closely linked to an innovation gap (Draghi, 2024). Notably, research and development (R&D) expenditures in Europe, particularly from the private sector, lag behind those in the US. Furthermore, there is a stark difference in the composition of investment and R&D expenditures between the two regions. The US prioritises innovative high-tech sectors like ICT, AI, cloud computing or biotech, which boosts productivity across the economy. By contrast, Europe continues to concentrate on mature mid-tech sectors, which limits the potential for positive productivity spillovers across the economy (Fuest et al., 2024).

Indeed, Figure 1 illustrates that in 2021 approximately 17 % of market sector gross fixed capital formation in EU countries was concentrated in sectors classified as high-tech by Eurostat. The corresponding share in the United States was nearly double, reaching 33 %, in the same year.

Figure 1: High-tech vs non-high-tech sector investment share of market sector investment in the EU and in the US in 2021.



Note: Authors' own calculations using EU KLEMS data on gross fixed capital formation at 2-digit NACE industry level. Market sectors are all NACE sectors except NACE sectors O (public adminstraction, defence and compulsary social security), P (education), Q (human health and social work activities) and T (activities of households as employers). We further exclude NACE sectors A (agriculture, forestry and fishing) and L (real estate activities) from the definition of market sectors. For the purpose of this figure, high-tech sectors include NACE sectors C20–C21 (chemicals and pharmaceuticals), C26 (Manufacturing of computers) and J (Media and information and communication technology). The EU high-tech sector investment share is based on the 17 EU countries for which data on gross fixed capital formation is available for these three NACE codes in the EU KLEMS dataset. These countries are Austria, Belgium, Bulgaria, Czechia, Germany, Denmark, Finland, France, Greece, Hungary, Italy, Luxembourg, Latvia, Netherlands, Portugal, Romania and Slovakia.

These differences in sectoral composition significantly contribute to the divergence in productivity growth between Europe and the US. Data from EU KLEMS illustrate that the ICT sector alone explains about 48 % of the average annual hourly productivity growth gap between the EU and the US from 2000–2019 (see Annex Table A1). This is the result of both the ICT sector's higher productivity growth and its greater size in the US than in the EU. These insights raise an important question: Why are EU countries lagging behind in disruptively innovative high-tech sectors?

One potential explanation lies in Europe's institutional and regulatory environment. High-tech sectors are inherently risky, characterized by trial-and-error and high rates of project and firm failures (Coatanlem and Coste, 2024, 2025). The expected profitability of investment in such sectors depends crucially on the costs of failure and restructuring (Bartelsman et al., 2016; Coatanlem and Coste, 2025; Saint-Paul, 2002). Institutions and regulations which influence these costs play therefore a critical role in determining investment in innovative high-tech sectors, more so than in traditional sectors. Coatanlem and Coste (2024) argue that restrictive employment protection legislation, which increases restructuring costs for European firms, can explain the smaller size of the high-tech sector in Europe and the relative scarcity of breakthrough innovations compared to the US. This is in line with the model by Saint-Paul (2002) which suggests that countries with high firing costs will specialize in secondary innovation, i.e. innovation which improves existing products, whereas countries with low firing costs will specialize in primary innovation which introduces new products. Similarly, Bartelsman et al. (2016) develop a model in which high-risk activity depends on firing costs and they provide empirical evidence that risky sectors are larger in countries with less restrictive labour market regulation.

This paper seeks to contribute to the existing literature by empirically examining how investment in innovative sectors, relative to investment in less innovative sectors, responds to measures of institutional and regulatory quality in EU countries over the period 2004 – 2019 (until 2023 for some AI-specific analyses). In particular, we explore the relative effect of the quality of institutions, summarised by the Institutional Delivery Index (which is composed of four Worldwide Governance Indicators by the World Bank), labour market regulations, as captured by the OECD Employment Protection Legislation (EPL) index, and business regulations, proxied by the World Bank's Starting a Business score. While the comparison with the US in the introduction serves to benchmark and illustrate the magnitude of the EU's investment gap in innovative sectors, the empirical analysis in this paper focuses on determinants of relative sectoral investment allocation within the EU, in innovative versus non-innovative sectors.

Our results indicate that better institutional governance and less burdensome regulations are associated with higher investment shares of high-tech sectors, sectors with high patent activity and AI-intensive sectors. Specifically, we estimate that raising all EU countries' institutional or regulatory delivery to the EU frontier could increase the investment share of high-tech sectors by up to 7.9 percentage points, equivalent to about 50% of the 2021 investment share of high-tech sectors. This would then close the respective investment gap with the US by almost 50%. For AI intensive sectors, the corresponding increase in the investment share could reach over 7 percentage points.

These findings have important policy implications. First, our results highlight the critical role of the institutional and regulatory frameworks in promoting investment in high-tech and innovative sectors. Institutional reforms that strengthen governance and reduce regulatory burden can help create a more favourable environment for innovation and investment in high-tech activities.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature, situating our analysis within the existing research. Section 3 outlines the methodology applied, details the different approaches used for the classification of sectors according to their innovativeness, and presents our measures of institutional and regulatory quality. Section 4 presents the results of the estimations using an instrumental variable (IV) approach to address potential endogeneity concerns, different sector classifications and different institutional indicators. It also includes simple back-of-the-envelope calculations to gauge the economic implications of these estimates. Section 5 assesses the robustness of the results to alternative control variables, dependent variables, and country samples. Section 6 concludes by summarising the key findings and discussing policy implications.

2 Literature

Institutional frameworks have been extensively discussed as an important determinant of economic growth (Rodrik et al., 2004; Acemoglu et al., 2005). North (1991) emphasizes the role of institutions in decreasing uncertainty and thus promoting investment and innovation which leads to growth. Institutional frameworks thus alter the incentive structure of individuals, encouraging or discouraging different kinds of behavior.

One important determinant of growth affected by institutional quality is innovation. Several studies have examined how institutions promote or hinder Schumpeterian 'creative destruction'. A prominent strand of literature focuses on institutions which regulate competition and market entry of firms. There are two lines of argument regarding the effect of competition on innovation. One argument focuses on the reduced monopoly rents an innovator can expect with increased competition. If regulatory entry barriers are low, successful innovation will be succeeded by imitators, decreasing the innovator's rents. This decreases the incentive to innovate (Aghion and Howitt, 1992). On the other hand, a competitive environment may induce a firm to be innovative in order to gain an advantage over its competitors. This would imply a positive effect of competition on innovative activity (Aghion et al., 2001). Aghion et al. (2009) examine how firm entry affects the innovation incentives of incumbents. They use firm-level data from the UK and exploit policy reforms at the UK and at the EU level which affect entry of foreign firms. Their findings suggest that foreign firm entry is related to increased innovation incentives in industries which are close to the technology frontier but not in industries which are less technologically advanced.

One of the most important institutions governing the functioning of the labour market is the Employment Protection Legislation (EPL) and has therefore received particular attention in the literature. The relationship between EPL and innovation is complex and remains widely debated. On the one hand, stringent EPL has been argued to foster innovation by promoting job security and reducing the risk of opportunistic behavior by employers. On the other hand, EPL can increase labor market rigidity, increase operational costs, and reduce firms' incentives to engage in risky investments in R&D.

On the positive side, Acharya et al. (2013, 2014) argue that dismissal laws—by limiting employers' ability to arbitrarily fire employees or expropriate the returns from innovative activities—build trust and collaboration between employers and employees. This trust, they claim, encourages employees to engage in innovative activities. Their empirical evidence, based on country-level changes in dismissal laws in the United States, the United Kingdom, France, and Germany, suggests that stringent dismissal laws particularly benefit innovation-intensive industries. On the negative side, however, EPL can impose costs that dampen innovation. Riphahn (2004) shows that protections against layoffs during probationary periods reduce the productivity of new hires, as they weaken incentives for performance, thereby undermining innovation. Bradley et al. (2017) find that unionisation which often results into strong termination protection, creates misaligned incentives and hinders corporate innovation by discouraging R&D investment, fostering employee shirking, and reducing wage inequality. Furthermore, stricter EPL can limit firms' ability to adjust their workforce in response to economic shifts or evolving technological demands, increasing operational rigidity and costs. This disincentivizes firms from pursuing high-risk, high-reward innovation projects. Francis et al. (2018) provide firm-level evidence that enhanced labour protections negatively impact innovation through mechanisms such as inventor shirking and distortions in labor mobility. They also find that the negative impact is more pronounced in firms that heavily rely on external financing and firms that have high R&D intensity. Saint-Paul (2002) highlights the importance of examining the differential impact of EPL across sectors, arguing that EPL may benefit industries with stable employment structures while hindering innovation in sectors that rely on high labor mobility and frequent workforce reallocation. Similarly, Bozkaya and Kerr (2014) use firm-level data to demonstrate that stringent EPL in European countries reduces venture capital investment, a critical driver of innovation, particularly in high-volatility sectors (energy, biotech, computers). Bartelsman et al. (2016) further explores the differential effects of EPL across sectors, developing a model that shows how firing costs reduce the sorting of firms into sectors with risky technology. They corroborate their findings with empirical evidence for OECD countries for the 1995-2005 period, using a diff-in-diff approach.

Our study is closely related to the literature emphasizing the differential sectoral impacts of regulations, like EPL, as they might be better suited for certain types of activities than for others. Specifically, we investigate how institutional and regulatory burdens which could be related to the cost of adjustments in the face of failure impact relative investment allocation across sectors. This research question is linked to the recent public policy discussion about structural factors underlying the productivity growth gap between Europe and the US (Draghi, 2024). Several authors attribute this gap partly to differences in the sectoral allocation of economic activity. Fuest et al. (2024) point out that in the US, a higher share of R&D expenditures occurs in innovative high-tech industries than in the EU. This, they argue, leads to disruptive innovations which boost productivity taking place in US high-tech sectors. In contrast, innovation in EU countries is incremental in nature and takes place in mature mid-tech industries, a phenomenon that is referred to as the 'middle-technology trap' (Dietrich et al., 2024; Fuest et al., 2024).

We contribute to the literature by examining how institutional and regulatory frameworks influence the decision to invest in high-technology or disruptive sectors, rather than in mature technologies across sectors in EU countries. While our empirical approach is close to that of Bartelsman et al. (2016), we build upon their work by using a broader range of institutional and regulatory indicators and of innovativeness classifications. Specifically, we use three different institutional indicators and three distinct classification methods for high-tech sectors to inquire how various institutional dimensions affect investment in innovative sectors, relative to investment in other sectors. Moreover, we apply an IV approach, instrumenting institutions using legal origins, to address potential issues of endogeneity. By looking at differential impacts on innovative sectors in particular, we intend to support an ongoing policy discussion with empirical evidence.

3 Data and Methodology

3.1 Empirical methodology

We estimate the following model:

$$Inv_{cit} = \alpha + \beta IF_{ct} + \gamma IF_{ct} \times Innovative_i + \theta X_{cit} + \delta_i + \lambda_t + \epsilon_{cit}. \tag{1}$$

Models of similar form have been used in previous studies to explore the differential impacts of country-specific structural factors across sectors (Rajan and Zingales, 1996;

Bartelsman et al., 2016).

Here, Inv_{cit} is the gross fixed capital formation in sector i in country c in year t as a percentage share of total market sector gross fixed capital formation in country c in year t. We use data on gross fixed capital formation in current prices disaggregated at the 2-digit NACE sector level.

Two potential sources for data on gross fixed capital formation are the 2025 release of the EU KLEMS dataset (Bontadini et al., 2023) and Eurostat. The two datasets differ slightly in their coverage of countries, sectors and years. While the EU KLEMS data have longer reporting lags and are less disaggregated for some non-manufacturing sectors, we use the gross fixed capital formation data from EU KLEMS for most of our analysis. This choice is motivated by the fact that Eurostat investment data in manufacturing is available at a disaggregated sector level for only 14 EU countries.

The sample includes observations on up to 28 market sectors in 25 EU countries[1] over the time period from 2004 until 2019. As specified further below, some of the AI-specific analyses are extended to 2023. We consider market sectors as defined by the EU KLEMS, i.e. all sectors excluding real estate activities, public administration and defence, compulsory social security, education, human health and social work activities, activities of households as employers and activities of extraterritorial organizations and bodies. We further exclude agriculture, forestry and fishing. Table A2 in the Annex lists all the sectors included in the baseline analysis. The choice of sectors to be included and the levels of sector aggregation are based on data availability in the EU KLEMS dataset.

IF_{ct} is a measure of an institutional factor in country c in year t and $Innovative_i$ is a variable that indicates the innovativeness of sector i which is used to moderate the impact of the institutional variable. We discuss the innovativeness classifications and the institutional indicators in detail in Sections 3.2 and 3.3, respectively. By estimating the coefficient γ on the interaction term and controlling for sector- and year-fixed effects, we can estimate the differential impact of an increase in the institutional and regulatory quality on the investment share of an innovative sector relative to a non-innovative sector.

Our unit of observation is the country-sector-year cell. The institutional factor IF_{ct} varies both across countries and over time, while $Innovative_i$ varies across sectors and is constant across countries and years. The interaction term $IF_{ct} \times Innovative_i$ thus varies across countries, sectors and years. The parameter which is primarily of interest to us is γ and it is identified by cross-country variation and within-country over-time variation of the institutional variable.

The vector X_{cit} includes control variables. Keep in mind that our dependent variable is the within-country share of a sector's investment and our variable of interest – the interaction term $IF_{ct} \times Innovative_i$ – varies at the country-, sector- and year-level. Any omitted variable raising concerns about endogeneity should also exhibit variation at the

[1] Cyprus and Malta are excluded due to limited data availability.

country- and sector level. That is, since the dependent variable is expressed as a sector's within-country share, variables varying at the country-level may give rise to endogeneity concerns if they affect the investment in sectors classified as innovative differently than investment in other sectors.

In our baseline specification of the model, we control for the value added growth of sector i in country c in year t to account for the sector's cyclical position in a given year. To further address potential omitted variable bias, we conduct robustness checks by including further control variables. First, we account for the possibility that investment in innovative sectors is disproportionately attracted by favourable taxation policies. Second, since institutional quality is correlated with economic development, our estimates on the institutional measures might partially capture the effect of other characteristics of wealthier economies on investment in innovative sectors.

To address these concerns, we re-estimate the models while incorporating additional controls for a country's corporate tax rate and its gross domestic product (GDP) per capita, as well as the interactions between these variables and the respective $Innovative_i$ measures. Historical data on corporate tax rates is obtained from the Tax Foundation (2024). Data on GDP per capita is sourced from the World Development Indicators of the World Bank (2025). Summary statistics on all variables used in the empirical analysis are provided in Table A3 in the Annex.

3.2 Classifying Sectors by Innovativeness

We employ three distinct methods to classify the innovativeness of sectors. The first method categorizes sectors as either high-tech or non-high-tech, based on the Eurostat high-tech aggregation by NACE Rev. 2 at 2-digit level. A sector is considered high-tech if it is either classified as a high-technology manufacturing sector or as a high-tech knowledge-intensive service sector. Specifically, the following sectors are classified as high-tech: C21 (Manufacture of basic pharmaceutical products and pharmaceutical preparations), C26 (Manufacture of computer, electronic and optical products), J58–J60 (Publishing activities; motion picture, video and television programme production, sound recording; Programming and broadcasting activities), J61 (Telecommunications) and J62–J63 (Computer programming, consultancy and related activities; Information service activities)[2]. In this first approach, we estimate the model specified in equation (1) using a dummy variable as the moderating innovativeness classification. The dummy takes a value of one if a sector is classified as high-tech, and zero otherwise.

[2]As the EU KLEMS dataset only provides data on the aggregate across the three media sectors J58–J60 we consider the entire aggregate to be high-tech, even though J58 (Publishing activities) is not considered high-tech by the Eurostat categorization. Moreover, NACE code M72 (Scientific research and development) is also classified as high-tech by Eurostat. However, since the sector M (Professional, Scientific and Technical Activities) is not disaggregated any further in the EU KLEMS data, we cannot consider it a high-tech sector in our baseline analysis.

In our second classification approach, we assess sectoral innovativenes on the basis of patenting activity. We rely on patent data from the US to mitigate possible endogeneity issues. Using data on 18,085,696 patent applications from the United States PatentsView database of the U.S. Patent and Trademark Office (2025) we match the International Patent Classification (IPC) codes of the patent applications with 15 NACE codes employing the concordance scheme by Van Looy et al. (2014). For each sector, we calculate the average patent share by dividing the number of patents attributed to its NACE code in a given year by the total number of patent applications which could be matched to any NACE code in the respective year. Next, we calculate the average patent share for each sector over the period from 2004 to 2024 and use this as the innovation measure in equation (1).

As a third classification approach, we focus on the specific case of AI-intensive sectors. To examine the differential impact of institutional variables on investment in sectors with high AI intensity relative to sectors with low AI intensity, we rely on the taxonomy developed by Calvino et al. (2024). Calvino et al. (2024) conduct their classification by ranking 2-digit NACE sectors in OECD countries with respect to four measures capturing different dimensions of AI intensity: (1) AI human capital demand, measured by AI-related online vacancies, (2) AI innovation, measured by AI-related patents, (3) AI use, measured by firms' AI adoption and (4) sectoral AI exposure based on an indicator initially developed by Felten et al. (2021) which measures the extent to which AI can perform the tasks associated with occupations in a sector. Under this taxonomy, a sector is considered highly AI-intensive if it ranks in the top quartile for at least two of these four indicators and avoids falling into the bottom quartile for any of them[3]. Since the AI-part of our analysis requires a different sector aggregation that is not available in the EU KLEMS dataset, we use data from Eurostat which allows us to extend the sample until 2023.

Note that Calvino et al. (2024) refine the AI exposure measure by considering sector-specific barriers to AI adoption, such as cost, skills, and regulatory constraints. However, since our analysis aims to investigate how institutional quality influences investment in AI-intensive sectors, including regulatory barriers in the measure of AI intensity could introduce endogeneity issues. Regulatory barriers themselves reflect the institutional environment, potentially biasing our results. To address this concern, we reconstruct the AI-intensity classification by excluding the regulatory barriers component from the measure. The composition of sectors identified as highly AI-intensive remains unchanged

[3]The seven NACE sectors classified as highly AI intensive are C26 (Manufacture of computer, electronic and optical products), J58–J60 (Media), J61 (Telecommunications), J62–J63 (Computer programming, consultancy and related activities; Information service activities), K (Financial and Insurance Activities), M69–M71 (Legal and accounting acivities; Activities of head offices; management consultancy activities; Architectural and engineering activities; technical testing and analysis) and M72 (Scientific research and development).

with this adjustment. Additionally, we perform a supplementary exercise in which we estimate the model in equation (1) using the sectoral rankings of each of the four subindices individually as the variable moderating the impact of institutions on sectoral investment shares. This approach allows us to examine how different aspects of AI intensity affect the link between institutions and investment. In this exercise we rely on the non-adjusted AI exposure measure by Felten et al. (2021) excluding regulatory barriers, as previously explained.

3.3 Institutional indicators

We consider three indicators of institutional quality and regulatory stringency in our analysis. The first is the "Institutional Delivery" Index (Helliwell and Huang, 2008; Masuch et al., 2017) which is the simple mean of the four Worldwide Governance Indicators (WGI) "Rule of Law", "Control of Corruption", "Regulatory Quality" and "Government Effectiveness" (Kaufmann et al., 2011; Kaufmann and Kraay, 2024). The Institutional Delivery Index is a broad institutional indicator and reflects how well national institutions deliver a level playing field for all economic actors, prevent rent extraction and waste of resources, and ensure sound economic incentives to invest, innovate, and provide public goods.

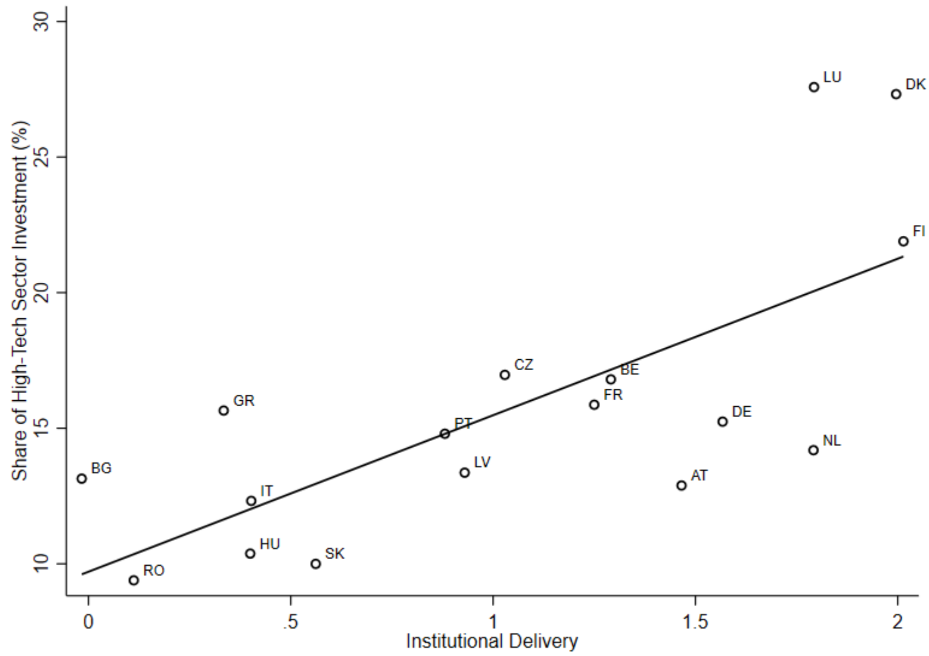
In addition, we look at two more narrowly defined, regulatory quality indicators, which capture more specific aspects of a country's regulatory framework. The first is the EPL index by the OECD (2020)[4]. This indicator measures the strictness of regulations on collective and individual dismissals. The second is the Starting a Business score by the World Bank (2020). This indicator measures the administrative burden placed on entrepreneurs when starting a business.

For a first visual inspection, Figure 2 shows the correlation between the institutional delivery index and the share of a country's investment in high-tech sectors for EU countries in 2021. The positive relation lends support to the idea that investment in innovative high-tech sectors is fostered by a high-quality institutional environment. Figures A1 and A2 in the Annex present similar relationships showing how institutional quality is positively associated with investment in sectors characterised by high patent activity and in AI-intensive sectors, respectively.

Table A4 in the Annex shows the variations of the institutional indicators between and within countries. Institutional conditions tend to change only slowly over time, hence the institutional delivery index varies much more across countries than within countries over time. However, the EPL index and especially the Starting a Business Score also exhibit substantial variation within a country over time. These patterns of within-country

[4]We use the second version of the EPL index as it is the most recent version with data for all years covered by our sample.

Figure 2: Institutional Delivery and high-tech sector investment share in 2021.



Note: The shares of high-tech sector investment are calculated using EU KLEMS data on gross fixed capital formation. High-tech sectors include NACE sectors C21 (Pharmaceuticals), C26 (Manufacturing of computers) and J (Media and information and communication technology). The figure includes the 17 EU countries for which data on gross fixed capital formation is available for these three NACE codes in the EU KLEMS dataset.

over-time variation are also illustrated by the developments of the EU-wide averages of the indicators over time, shown in Figures A3, A4, and A5 in the Annex. While the average Institutional Delivery index exhibited little variation over the time period from 2004 until 2019, there are substantial increases discernible for the other two indicators. In our approach, we exploit both sources of variation of the institutional indicators, the variation over countries and the variation over time.

3.4 Instrumenting Institutional Factors

We apply an instrumental variable (IV) approach to address endogeneity concerns and try to identify the causal differential effect of institutions on sectoral investment shares. We instrument the institutional measures using binary legal origin indicators. The idea behind this approach is that countries' legal systems differ with regard to their underlying ideologies and the intentions with which they were set up.

La Porta et al. (1999) classify countries by five legal origins: English common law, French civil law, German civil law, Scandinavian law and Socialist law. Legal origin theory typically argues that the historic intentions of a legal system affect the laws and regulations of countries that have adopted them (La Porta et al., 1997, 1998, 1999). Socialist law is said to be aimed at securing the power of the state and at the extraction of resources from the population. Civil law, with its various sub-classifications, is also intended to maintain the state's power, though with more restraint than Socialist law. English common law, on the other hand, intends to restrain government intervention and emphasizes individual liberties and property rights (La Porta et al., 1999). In particular, English common law and French civil law are often juxtaposed due to their quite different proclivities towards state intervention and regulation (Glaeser and Shleifer, 2002).

The studies by La Porta et al. (1997, 1998, 1999, 2008) provide evidence that legal origin can indeed explain variation in countries' institutional frameworks. Several studies have thus used legal origins as IVs for institutions (Glaeser et al., 2004; Acemoglu and Johnson, 2005; Williamson and Kerekes, 2011; Masuch et al., 2017). Legal origin has also been shown to explain cross country differences in labour market regulation (Botero et al., 2004) and regulatory entry barriers Djankov et al. (2002).

We define four dummy variables indicating four different legal origins of the countries in our sample. The legal origins are classified in accordance with La Porta et al. (1999)[5]. Since we are concerned about endogeneity of the institutional indicators, two regressors in the model in equation (1) need to be instrumented: IF_{ct} and $IF_{ct} \times Innovative_i$. We

[5]The four legal origin indicators are French (Belgium, Spain, France, Greece, Italy, Luxembourg, Netherlands, and Portugal), German (Austria and Germany), Scandinavian (Denmark, Finland, and Sweden) and Socialist (Estonia, Poland, Lithuania, Latvia, Slovenia, Slovak Republic, Bulgaria, Czechia, Croatia, and Hungary). The only country in our sample with its legal origin in English common law is Ireland, hence there is no separate indicator for this legal family.

thus have two first stage regressions which take the following forms:

$$\begin{aligned} IF_{ct} = \alpha + \beta_1 French_c + \beta_2 German_c + \beta_3 Socialist_c + \beta_4 Scandinavian_c \\ +\gamma_1 French_c \times Innovative_i + \gamma_2 German_c \times Innovative_i + \gamma_3 Socialist_c \times Innovative_i \\ +\theta X_{cit} + \delta_i + \lambda_t + \epsilon_{ct}. \end{aligned} \tag{2}$$

$$\begin{aligned} IF_{ct} \times Innovative_i = \alpha + \beta_1 French_c + \beta_2 German_c + \beta_3 Socialist_c + \beta_4 Scandinavian_c \\ +\gamma_1 French_c \times Innovative_i + \gamma_2 German_c \times Innovative_i + \gamma_3 Socialist_c \times Innovative_i \\ +\theta X_{cit} + \delta_i + \lambda_t + \epsilon_{ct}. \end{aligned} \tag{3}$$

.

The second stage regression then takes the following form with $\hat{IF}_{ct}$ being the value of IF_{ct} predicted by the model in equation (2) and $IF_{ct} \times In\hat{n}ovative_i$ being the the value of $IF_{ct} \times Innovative_i$ predicted by the model in equation (3):

$$Inv_{cit} = \alpha + \beta \hat{IF}_{ct} + \gamma IF_{ct} \times In\hat{n}ovative_i + \theta X_{cit} + \delta_i + \lambda_t + \epsilon_{cit}. \tag{4}$$

There are no country fixed effects in equations (1) through (4) as these would absorb the effects of the legal origin variables in the first stage regressions. However, the omission of country fixed effects is not likely to be a concern since our dependent variable Inv_{cit} is the share of investment of a sector within a country.

Throughout this analysis we cluster standard errors at the country level. Alternatively, one could cluster at the sector level. In our case, clustering at the country level is essential in the 2SLS estimations, since the dependent variable in the first stage indicated by equation (2) varies by country but not by sector. Clustering by country is also appropriate given the second stage: our dependent variable is expressed as a sector's within-country share of gross fixed capital formation and hence the residuals will be correlated within country cells.

The two requirements for our instruments to be valid is that they are relevant and exogenous. Relevance implies that the instruments must be correlated with the endogenous regressors in equation (1), while exogeneity requires that the instruments are not correlated with the error term.

To address the concern of weak instruments, we report the relevant F-statistics for the 2SLS estimations in this study. Since we have multiple endogenous variables, we rely on the corrected conditional F-statistic suggested by Sanderson and Windmeijer (2016) to evaluate the strength of each instrument individually. Additionally, we report the

Kleibergen and Paap (2006) F-statistic to assess the overall strength of both instruments for each 2SLS regression. As suggested by Baum et al. (2007) we follow the conventional rule of thumb and consider instruments to be sufficiently strong if the relevant F-statistics are larger than 10. The results of the first stage regressions for our baseline estimations, using the binary high-tech classification, the patent share and the AI intensity classification, respectively, are presented in Tables A5, A6, and A7 in the Annex. The F-statistics are all above the conventional threshold, providing reassurance about the relevance of the instruments.

The second requirement for instrument validity, the exogeneity condition, may be violated if the legal origin of countries affects our dependent variable through other channels which are correlated with institutional quality. To mitigate this concern, we ensure the robustness of our main results by incorporating additional covariates to control for potential confounding factors. Specifically, in a robustness check, we further control for a country's GDP per capita and corporate tax rate as well as their interactions with the innovativeness measures.

4 Empirical Results

Table 1 presents the results of estimating the model specified in equation (1) with OLS and 2SLS, applying the Eurostat high tech sector classification. Columns (1) and (2) display the results for the Institutional Delivery index, columns (3) and (4) show the results for the EPL index and columns (5) and (6) present the findings for the Starting a Business score. Each institutional indicator is defined such that higher values represent more efficient institutions. To facilitate interpretation, all institutional variables are standardized to have a mean of zero and a standard deviation of one. This means the estimated coefficients on the interaction of the respective institutional indicator with the high-tech dummy variable can be interpreted as the average differential impact of a one-standard deviation increase in the institutional variable on the investment share of high-tech sectors relative to non-high-tech sectors. The results consistently show that more efficient institutional frameworks, as captured by all three institutional indicators, are positively associated with a relatively higher share of investment in high-tech sectors.

We conduct a back-of-the-envelope calculation to illustrate the economic implications of the differential response of investment to changes in the institutional factors reported in Table 1. The 2SLS estimate of 0.924 on the interaction of the institutional indicator with the high-technology dummy in column (2) implies that a one-standard deviation increase in institutional delivery is, on average, associated with a 0.924 percentage-point increase in a high-tech sector's investment share relative to that of a non-high-tech sector.

The coefficient on the non-interacted institutional indicator of -0.211 reflects the marginal impact of a one standard deviation increase in institutional delivery on a non-

Table 1: Results for Eurostat High-Tech Sector Classification

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Institutional Factor	-0.135***	-0.211***	-0.122**	-0.309***	-0.094**	-0.518***
	(0.042)	(0.056)	(0.053)	(0.080)	(0.041)	(0.146)
Institutional Factor×High-Tech	0.793***	0.924***	0.674***	1.098***	0.449**	2.315***
	(0.197)	(0.216)	(0.193)	(0.202)	(0.173)	(0.552)
Value Added Growth	0.510***	0.494***	0.566***	0.576***	0.525***	0.493***
	(0.135)	(0.134)	(0.103)	(0.108)	(0.123)	(0.122)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9315	9315	7745	7745	9267	9267
R-squared	0.61	0.66	0.62	0.62	0.60	0.58
First stage, dependent variable: Institutional Factor						
SW multivariate F test of excluded instruments		43.74		37.41		1828.42
First stage, dependent variable: Institutional Factor ×High-Tech						
SW multivariate F test of excluded instruments		191.38		40.23		6153.63
Kleibergen-Paap Wald rk F statistic		51.63		33.67		4411.16

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

high-tech sector's share of investment. Therefore, the estimated marginal impact of a one standard deviation increase of institutional delivery on a high-tech sector's share of investment, reported in Table A8 in the Annex, is $-0.211 + 0.924 = 0.713$ percentage points. Using the same method, the marginal impacts of a one-standard-deviation increase in the EPL index and the Starting a Business score on a high-tech sector's investment share are 0.789 and 1.797 percentage points, respectively.

These marginal impacts represent the average impact per high-tech sector. Since our sample includes five sectors classified as high-tech for this analysis, a one standard deviation increase in institutional delivery is associated with a total increase of $0.713 \times 5 = 3.565$ percentage points in the investment share across all high-tech sectors. Similarly, a one standard deviation increase in the EPL index or the Starting a Business score corresponds, on average, to an increase in the high-tech sector investment share of $0.789 \times 5 = 3.945$ or $1.797 \times 5 = 8.985$ percentage points, respectively.

To provide a more concrete interpretation of the results, we simulate the effects of raising each EU country's institutional indicators to the EU frontier, as summarised in Table 2. The analysis uses 2021 as the reference year, as it is the most recent year with sufficient data on sectoral gross fixed capital formation from the EU KLEMS dataset. For 17 EU countries with complete data on high-tech sector investment—defined by NACE codes C21, C26, and J—we calculate each country's high-tech sector investment share and total investment in high-tech sectors (in EUR). Using the estimated marginal effects, we evaluate the increase in each country's high-tech investment share resulting from aligning its institutional indicators with the EU frontier.

The predicted post-reform high-tech investment shares are then converted into absolute investment amounts (in EUR), which are summed across all countries to estimate the total increase in high-tech sector investment. The results suggest that raising each EU country's Institutional Delivery Index to the EU frontier would increase the high-tech sector investment share by 4.59 percentage points.

Similarly, aligning each country's EPL index and Starting a Business score with their respective EU frontiers is estimated to raise the high-tech sector investment share by 7.60 and 7.92 percentage points, respectively.

Table 2: Back-of-the-envelope calculation of the estimated increases in the high-tech investment share due to institutional and structural improvements in percentage points.

	Per-sector Impact (1 SD)	**Total Impact (1 SD)**	**Improving Institutions to the EU frontier**
Institutional Delivery	0.713	$0.713 \times 5 = 3.565$	4.59
EPL	0.789	$0.789 \times 5 = 3.945$	7.60
Starting a Business	1.797	$1.797 \times 5 = 8.985$	7.92

A comparison to the investment shares of high-tech sectors in EU countries puts this into perspective: In 2021, high-tech sectors' investment accounted for 15.12% of total market sector investment across 17 EU countries[6]. Thus, the estimated increases due to raising each country's institutional indicators to the frontier are substantial, ranging from about 30% of the 2021 high-tech investment share (for the Institutional Delivery index) to about 50% of the 2021 share (for the Starting a Business score). Figure 3 illustrates these projected increases in high-tech sectors' investment shares for each of the three institutional indicators.

Next, we examine the role of institutional factors for investment in sectors which are more innovative, as indicated by their share of patent applications filed at the USPTO. Table 3 presents the results. The 2SLS estimate on the interaction term between the institutional variable and the patent share is positive and statistically significant at the 1 % level for Institutional Delivery and the EPL index. For the Starting a Business score, the 2SLS estimate is significant at the 10 % level.

[6]The high-tech sector investment share is the authors' own calculation using data from EU KLEMS. The investment share was computed considering only those EU countries for which there was data available on investment in all high-tech sectors in 2021, which are Austria, Belgium, Bulgaria, Czechia, Germany, Denmark, Finland, France, Greece, Hungary, Italy, Luxembourg, Latvia, Netherlands, Portugal, Romania, and Slovakia. The high-tech sector investment share reported here differs slightly from the share shown in Figure 1 due to a difference in the composition of high-tech sectors. In Figure 1 NACE sector C20 (chemicals) is considered a high-tech sector along with NACE sector C21 (pharmaceuticals), even though according to the Eurostat classification and in our analysis only NACE sector C21 is considered as high-tech. This is because there is no disaggregation of these two sectors in the US data, hence in Figure 1 we summed them both up under high-tech to make the comparison between Europe and the US possible.

Figure 3: High-tech sectors' investment share and predicted change under institutional and structural reforms

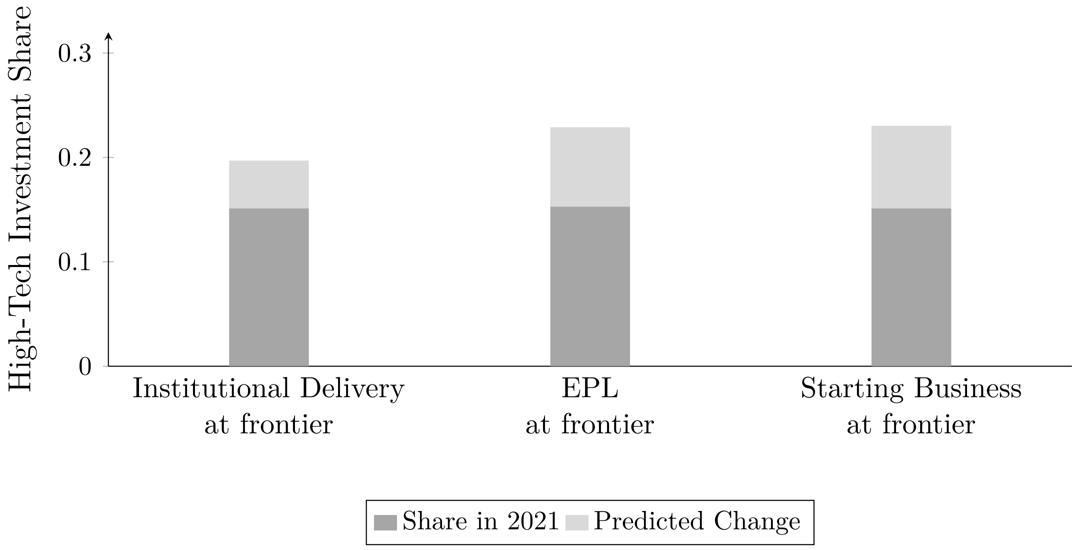


Table A9 in the Annex reports the corresponding marginal effects of an increase in the various institutional indicators on the investment shares of the lowest-ranking and the highest-ranking sectors, in terms of patent shares. The differential impact on the highest-ranking sector relative to the lowest-ranking sector is reported as well.

The results of the 2SLS estimations suggest that an increase in any of the three institutional indicators is associated with a statistically significant relative increase of the share of investment allocated to the sector with the highest patent share. These findings suggest that improvements in institutional frameworks have a disproportionately stronger effect on investment in sectors with higher patenting activity.

Third, we examine the differential impact of institutional frameworks on investment in AI intensive sectors compared to less AI-intensive sectors. As described in Section 2, we estimate the model in equation (1) using the binary AI intensity classification by Calvino et al. (2024) as the moderating variable. Table 4 presents the results.

For two out of the three indicators, we find the estimate on the interaction of the institutional indicator with the AI-intensity dummy to be positive and statistically significant at the 1% level. For the EPL index, the estimate on the interaction is also positive; however, it is not significant at the 10% level.

Table A10 reports the corresponding estimated impacts on the investment share of AI-intensive and non-AI-intensive sectors. To gauge the economic implications of these estimates, in Table 5 we conduct another back-of-the-envelope calculation of the expected change in the seven AI-intensive sectors' investment shares resulting from elevating EU countries' institutional and structural indicators to frontier levels. The calculation follows the same methodology as the one presented in Table 2 which analysed the expected increase in high-tech sector investment. Our results suggest that raising institutional and

Table 3: Results for Patent Shares

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Institutional Indicator	-0.089	-0.083	0.115	0.139	-0.107	-0.119
	(0.104)	(0.122)	(0.100)	(0.156)	(0.126)	(0.267)
Institutional Indicator × Patent Share	0.059***	0.066***	0.044*	0.081***	0.025	0.110*
	(0.016)	(0.022)	(0.021)	(0.030)	(0.015)	(0.063)
Value Added Growth	0.532***	0.530***	0.693***	0.752***	0.587***	0.652***
	(0.153)	(0.146)	(0.109)	(0.095)	(0.138)	(0.113)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	4323	4323	3688	3688	4314	4314
R-squared	0.34	0.34	0.29	0.27	0.30	0.22
First stage, dependent variable: Institutional Factor						
SW multivariate F test of excluded instruments		64.03		38.01		889.97
First stage, dependent variable: Institutional Factor ×Patent Share						
SW multivariate F test of excluded instruments		51.80		43.49		857.52
Kleibergen-Paap Wald rk F statistic		104.21		34.42		518.72

Notes: Standard errors in parentheses are clustered at the country level. The Patent Share is centered around its sample-mean so the estimate on the non-interacted institutional indicator is the estimated effect at the mean. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

regulatory frameworks to frontier levels would lead to an increase of AI-intensive sectors' investment share between 2.14 and 7.60 percentage points. With AI intensive sectors' accounting for approximately 28.5% of total investment in 2021, these estimates indicate significant relative increases of roughly 7.5%, 24.4%, or 26.7% in the investment share, depending on whether the EPL index, the Starting a Business score, or the institutional delivery index is raised to the frontier level. Figure 4 shows the magnitudes of these impacts in relation to AI intensive sectors' investment share, across 18 EU countries in 2021[7].

Calvino et al. (2024) base the AI-intensity classification used above on four subindices. Those sectors which rank consistently high across four indices measuring different aspects of AI intensity – AI human capital, AI innovation, AI exposure and AI use – get classified as highly AI intensive. To see whether our main results vary across sub-dimensions of AI intensity, we estimate the model in equation (1) using the sectoral ranking of the four subindices reported by Calvino et al. (2024) as the variable moderating the effect of the institutional variable. The four panels of Table A11 in the Annex show the results of this exercise for the four AI intensity subindeces[8].

[7]The 18 EU countries for which there was data available from Eurostat on investment in all seven AI intensive sectors in 2021 and which could thus be considered in this calculation are Austria, Belgium, Bulgaria, Czechia, Denmark, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, Latvia, Netherlands, Portugal, Romania, Sweden, and Slovakia

[8]For the specification using the AI exposure ranking, we use the sectoral ranking with respect to the

Table 4: Results for AI Intensity

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Institutional Indicator	-0.182**	-0.256***	-0.051	-0.247*	-0.235***	-0.596***
	(0.061)	(0.088)	(0.084)	(0.126)	(0.068)	(0.159)
Institutional Indicator×AI Intensive	0.845***	0.967***	0.227	0.415	0.618***	2.019***
	(0.193)	(0.204)	(0.206)	(0.344)	(0.176)	(0.537)
Value Added Growth	0.928***	0.913***	1.200***	1.194***	1.021***	1.161***
	(0.188)	(0.186)	(0.262)	(0.266)	(0.212)	(0.202)
Sector-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	7182	7182	6038	6038	7125	7125
R-squared	0.60	0.60	0.60	0.60	0.60	0.58
First stage, dependent variable: Institutional Factor						
SW multivariate F test of excluded instruments		45.47		43.18		2411.50
First stage, dependent variable: Institutional Factor ×AI-intensive						
SW multivariate F test of excluded instruments		29.75		9.12		1040.70
Kleibergen-Paap Wald rk F statistic		34.47		20.70		231.23

Notes: Standard errors in parentheses are clustered at the country-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Back-of-the-envelope calculation of the estimated increase in AI intensive sectors' investment share changes due to institutional and structural improvements in percentage points.

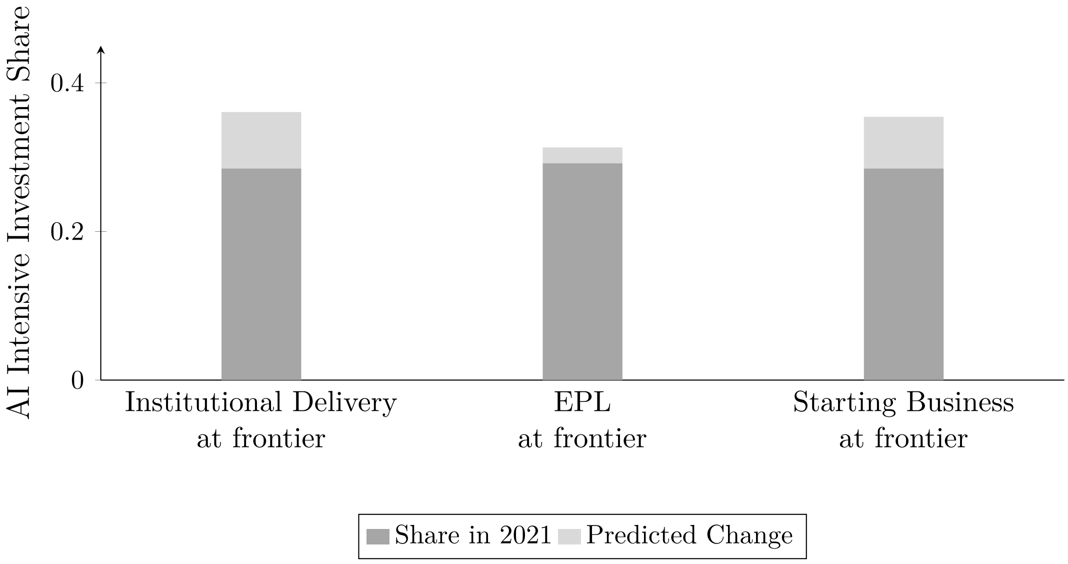
	Per-sector Impact (1 SD)	**Total Impact (1 SD)**	**Improving Institutions to the EU frontier**
Institutional Delivery	0.711	$0.711 \times 7 = 4.977$	7.60
EPL	0.168	$0.168 \times 7 = 1.176$	2.14
Starting a Business	1.422	$1.422 \times 7 = 9.954$	6.96

For three out of the four AI intensity indicators – AI Human Capital, AI Exposure, and AI Use – the estimated coefficients on the interaction term of interest are positive and statistically significant at the 5% level for all three institutional indicators. An exception is the AI Innovation indicator. Here, the 2SLS estimate on the interaction of the institutional indicator with the intensity rank is not statistically different from zero for the EPL index. This could reflect the fact that AI-related patenting might be more affected by factors other than labor market regulation, like human capital or access to capital.

Similar to Table A11, the four panels of Table A12 in the Annex show the estimated marginal effects of the different institutional indicators on the lowest ranking sector and

non-barrier-adjusted AI exposure measure by Felten et al. (2021) instead of the barrier-adjusted exposure measure by Calvino et al. (2024) to mitigate the issue that the absence of regulatory barriers determines the AI intenstity classification, as discussed in section 2.

Figure 4: AI intensive sectors' investment share and predicted change under institutional and structural reforms



on the highest ranking sector according to each of the four AI intensity rankings. Also, each panel shows the respective estimated differential impact on the highest ranking sector relative to the lowest ranking sector. The significance levels of the estimated differential impacts mirror those of the institutional interaction terms in Table A11. Overall, the results indicate that sectors with a higher AI intensity are more strongly affected by institutional framework conditions than sectors with low AI intensity. This appears to be particularly the case for sectors in which AI applications are used rather than invented, as indicated by the insignificant estimate for the EPL index in the specification using the AI Innovation indicator.

One might argue that in the time period from 2004 to 2019, over which the baseline regressions were conducted, AI technology had not yet reached the level of relevance it holds in more recent years. Concequently, the concept of AI intensity which we allow to moderate the impact of the institutional and structural indicators may have been less meaningful during that earlier timeframe. To address this concern, we re-estimate the model in equation (1), focusing on the effects of institutional indicators on AI intensity, while using a more recent sample covering the years 2019 to 2023. This period captures a time in which the emergence of AI technology was further advanced than in earlier years and non-regulatory barriers to firms' adoption were lower. The investment data for these regressions is from Eurostat since the EU KLEMS data only extends to 2021.

Moreover, since the most recent years for which the EPL index and the Starting a Business score are available are 2019 and 2020, respectively, we assume the institutional indicators to be non-time-varying in these specifications. Specifically, we use the average value of each indicator for a country across the entire sample period and apply this average to all five years under consideration.

Table 6 shows the results of these estimations. The 2SLS estimates on the interaction

Table 6: Results for AI Intensity (2019 – 2023)

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Institutional Indicator	-0.311***	-0.540***	-0.266	-0.637***	-0.312**	-0.747***
	(0.108)	(0.165)	(0.174)	(0.245)	(0.136)	(0.274)
Institutional Indicator×AI intensive	0.931***	1.254***	0.382	0.682*	0.710**	1.605***
	(0.212)	(0.318)	(0.280)	(0.356)	(0.309)	(0.498)
Value added growth	0.451	0.408	0.831	0.759*	0.388	0.309
	(0.477)	(0.456)	(0.487)	(0.459)	(0.483)	(0.438)
Sector-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1676	1676	1484	1484	1676	1676
R-squared	0.60	0.59	0.62	0.61	0.59	0.58
First stage, dependent variable: Institutional Factor						
SW multivariate F test of excluded instruments		23.23		63.54		5387.57
First stage, dependent variable: Institutional Factor × AI-intensive						
SW multivariate F test of excluded instruments		11.42		6.15		685.85
Kleibergen-Paap Wald rk F statistic		13.26		18.51		118.08

Notes: Standard errors in parentheses are clustered at the country-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

term of interest are positive and statistically significant at the 1% level for the Institutional Delivery index and the Starting a Business score. Column (4) shows that the 2SLS estimate on the interacted EPL index is significant at 10% level, while it was insignificant in the baseline estimations presented in Table 4, underscoring the importance of institutional quality in fostering investment in AI-intensive sectors during the more recent period, when AI technology has become increasingly prominent.

5 Robustness and Additional Results

5.1 Controlling for Confounding Variables

In this section we examine the robustness of the results by controlling for additional covariates, using alternative dependent variables, and modifying the sample of countries.

First, we address concerns that the exogeneity restriction of our IVs may be violated in our baseline estimations. The exogeneity restriction requires that our IVs, that is the legal origin dummies and their interactions with the sectoral innovativeness measures, affect the differential sectoral investment shares of innovative sectors only through their effect on the institutional measures and their respective interactions. It is plausible that legal origins have an effect on investment conditions through other channels than the institutional variables which we use. This would raise concerns about the validity of our instruments. To address this issue, we re-estimate the model in equation (1) while controlling for GDP per capita and the corporate tax rate, as well as for these variables' respective interactions with the three innovativeness measures.

Table A13 shows the results for the high-tech classification. The 2SLS estimates on the interaction of the institutional variables with the high-tech indicator remain similar in magnitude to the baseline estimates. For the Institutional Delivery index in column (1), the precision of the estimate on the interaction decreases due to the inclusion of the additional covariates, yet it remains significant at the 10% level.

For the EPL index in column (2), the relevant F-statistics are below the conventional threshold of 10, raising concerns about weak instruments in this specific specification. Nevertheless, the results are overall qualitatively consistent with the baseline results.

Tables A14 and A15 present analogous results using the sectoral patent share and the AI intensity indicator, respectively, as the moderating variable. In both cases, the baseline results prove robust, with the exception of the estimate on the interacted Institutional Delivery index when using the AI intensity indicator (column 1 in Table A15) which, while still positive, is not statistically significant at the 10% level.

5.2 Alternative Dependent Variables

We further test the robustness of our main results by employing alternative dependent variables in the estimation. First, we use the value added of sector i in country c in year t as a share of total market sector value added in country c in year t. This approach shifts the focus from examining the differential impact of institutional factors on investment in innovative sectors to analysing whether the relative economic size of innovative sectors compared to less innovative sectors is larger in countries with more efficient institutional environments. We obtain the data on sectoral value added in current prices from Eurostat.

The results, presented in Tables A16, A17 and A18 in the Annex for the three different sector innovativeness classifications, are consistent with our main results. Specifically, the value added in innovative and disruptive sectors increases relative to other sectors in countries with more efficient institutions and better regulatory frameworks.

As a second variation to the dependent variable, we use the R&D expenditure share of sector i in country c in year t as a share of total market sector R&D expenditure. The R&D expenditure data is obtained from the EU KLEMS dataset. This specification allows us to investigate whether more efficient institutions lead to a greater concentration of innovative activity—proxied by R&D expenditures—in disruptive sectors compared to traditional industries. Tables A19, A20 and A21 in the Annex report the results of estimating the model in equation (1) with this alternative dependent variable using as the moderating innovativeness variable the Eurostat high-tech classification, the patent share and the AI intensity classification, respectively.

Table A19 suggests that the results obtained using the Eurostat high-tech classification are in line with our main results. The positive and significant estimates on the interaction term suggest that more efficient institutions are associated with increased R&D expenditures in sectors classified as high-tech relative to other sectors. However, we do not find evidence that R&D expenditures in sectors with high patenting activity and in AI intensive sectors are affected more strongly by these institutional and regulatory factors, as the estimates on the on the interaction terms reported in Tables A20 and A21 are not statistically different from zero.

5.3 Resolving Insolvency Score

Thus far we have used three institutional and structural indicators (the institutional delivery index, the EPL index and the Starting a Business score) to examine the differential impact of institutions and regulations on investment in innovative sectors. These indicators can be interpreted as determinants of firms' start-up and rescaling costs and thus of the costs of project failure which according to Coatanlem and Coste (2024) strongly determine firms' profitability in disruptively innovative sectors.

In this section we re-estimate the model in equation (1), incorporating the Resolving Insolvency score of the World Bank (2020) as the structural indicator. This index measures the ease of resolving insolvency in a country and is composed of two subindices: the recovery rate in insolvency proceedings and the strength of the legal insolvency framework. The ease of resolving insolvency may serve as a proxy for firms' exit costs, complementing indicators such as starting and scaling a business. It may also capture the cost of project failure leading to a firm's exit.

Table A22 in the Annex presents the results of these estimations for the three classifications of innovativeness. The results suggest a positive differential impact of the insolvency indicator. The estimate on the interaction of the resolving insolvency score with the innovativeness measure is statistically significant at the 1% level in all three specifications.

Our results underline the importance of efficient insolvency frameworks for investment in innovative sectors. This is in line with the argument of Coatanlem and Coste (2024, 2025) that activity in these sectors is highly responsive to the costs of failure.

5.4 Excluding Ireland and Luxembourg

In a final robustness check, we drop Ireland and Luxembourg from the sample, due to their role as financial hubs. The investment data of these countries need to be interpreted with caution, since they are heavily affected by the activities of multinational enterprises and a large financial sector which, in the case of Ireland, show only limited links with domestic economic activity. Table A23 in the Annex shows the results of the 2SLS estimations without these two countries using the Eurostat high-tech sector classification as the moderating innovativeness classification. The estimates on the interactions of the high tech dummy with the institutional variables remain very similar in magnitude to those of the baseline estimates in Table 1.

Similarly, Tables A24 and A25 in the Annex show the results of the estimations using the sectoral patent share and the AI intensity classification as moderating innovativeness variables. Overall, the estimates confirm that the main findings of the analysis are not materially affected by the exclusion of Ireland and Luxembourg.

6 Conclusion

This study has provided evidence for the relation between institutional and regulatory quality and the share of investment in innovative sectors in EU countries. Stronger institutions and more efficient regulatory frameworks are associated with significantly higher investment shares in high-tech, patent-intensive, and AI-intensive sectors.

Our findings suggest that the EU's lag in technological dynamism and productivity goes beyond industrial composition or sectoral preferences. It is deeply rooted in the quality of governance and regulatory frameworks. This is particularly the case for highly innovative sectors, such as those relying heavily on AI, R&D, and disruptive technologies, which face a significantly higher probability of failure. These sectors are disproportionately affected by the costs and constraints of institutional setups, as they depend on adaptive and supportive frameworks to effectively manage risk, scale operations, and recover from setbacks.

Qualitatively, illustrative back-of-the-envelope calculations suggest that aligning the institutional and regulatory quality of all EU member states with the corresponding current EU frontier could raise the share of investment in high technology sectors by up to 50%, closing the respective gap to the US by about the same amount.

These findings are policy-relevant, as a significant portion of the productivity growth gap between the EU and the US can be attributed to the smaller size and slower productivity growth of innovative sectors in the EU (Draghi, 2024). Easing labor market rigidities, enhancing the rule of law, and reducing administrative burdens could significantly improve the investment climate for cutting-edge industries. In particular, reforming employment protection legislation and simplifying business start-up procedures could help reduce barriers to innovation and entrepreneurial risk-taking, enabling a more dynamic reallocation of resources toward frontier technologies. Such improvements in the regulatory and institutional framework will need to be complemented by other important enablers of innovation, such as access to finance, education and skill-upgrading systems, and robust digital infrastructure, to further close the investment gap to the US.

Looking ahead, future research could further build on this work by exploring the interaction between institutional reforms and these complementary enablers. Moreover, as AI and other general-purpose technologies continue to evolve rapidly, gaining deeper insights into the specific institutional factors that facilitate their diffusion will be critical for improving Europe's competitiveness on the global stage.

References

Acemoglu, D. and Johnson, S. (2005). Unbundling institutions. *Journal of political Economy*, 113(5):949–995.

Acemoglu, D., Johnson, S., and Robinson, J. A. (2005). Institutions as a fundamental cause of long-run growth. *Handbook of economic growth*, 1:385–472.

Acharya, V. V., Baghai, R. P., and Subramanian, K. V. (2013). Labor laws and innovation. *The Journal of Law and Economics*, 56(4):997–1037.

Acharya, V. V., Baghai, R. P., and Subramanian, K. V. (2014). Wrongful discharge laws and innovation. *The Review of Financial Studies*, 27(1):301–346.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., and Prantl, S. (2009). The effects of entry on incumbent innovation and productivity. *The review of economics and statistics*, 91(1):20–32.

Aghion, P., Harris, C., Howitt, P., and Vickers, J. (2001). Competition, imitation and growth with step-by-step innovation. *The Review of Economic Studies*, 68(3):467–492.

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

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

Baum, C. F., Schaffer, M. E., and Stillman, S. (2007). Enhanced routines for instrumental variables/generalized method of moments estimation and testing. *The Stata Journal*, 7(4):465–506.

Bontadini, F., Corrado, C., Haskel, J., Iommi, M., and Jona-Lasinio, C. (2023). Euklems & intanprod: industry productivity accounts with intangibles—sources of growth and productivity trends: methods and main measurement challenges. *The Luiss Lab of European Economics. https://euklems-intanprod-llee. luiss. it/(Data extracted on 21 February 2023).*

Botero, J. C., Djankov, S., Porta, R. L., Lopez-de Silanes, F., and Shleifer, A. (2004). The regulation of labor. *The Quarterly Journal of Economics*, 119(4):1339–1382.

Bozkaya, A. and Kerr, W. R. (2014). Labor regulations and european venture capital. *Journal of Economics & Management Strategy*, 23(4):776–810.

Bradley, D., Kim, I., and Tian, X. (2017). Do unions affect innovation? *Management Science*, 63(7):2251–2271.

Calvino, F., Dernis, H., Samek, L., and Ughi, A. (2024). A sectoral taxonomy of ai intensity. Technical report, OECD Publishing.

Coatanlem, Y. and Coste, O. (2024). Cost of failure and competitiveness in disruptive innovation. *IEP@ BU Policy Brief, Bocconi University.*

Coatanlem, Y. and Coste, O. (2025). Cost of failure, disruptive innovation and targeted flexicurity. *IEP@ BU Working Paper, Bocconi University.*

Dietrich, A., Dorn, F., Fuest, C., Gros, D., Presidente, G., Mengel, P.-L., and Tirole, J. (2024). Europe's middle-technology trap. In *EconPol Forum*, volume 25, pages 32–39. Munich: CESifo GmbH.

Djankov, S., La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2002). The regulation of entry. *The quarterly Journal of economics*, 117(1):1–37.

Draghi, M. (2024). The future of european competitiveness.

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217.

Francis, B. B., Kim, I., Wang, B., and Zhang, Z. (2018). Labor law and innovation revisited. *Journal of Banking & Finance*, 94:1–15.

Fuest, C., Gros, D., Mengel, P.-L., Presidente, G., and Tirole, J. J. (2024). Eu innovation policy: How to escape the middle technology trap. Technical report, ifo Institute-Leibniz Institute for Economic Research at the University of ....

Glaeser, E. L., La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2004). Do institutions cause growth? *Journal of economic Growth*, 9(3):271–303.

Glaeser, E. L. and Shleifer, A. (2002). Legal origins. *The Quarterly Journal of Economics*, 117(4):1193–1229.

Helliwell, J. F. and Huang, H. (2008). How's your government? international evidence linking good government and well-being. *British journal of political science*, 38(4):595–619.

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. *Hague journal on the rule of law*, 3(2):220–246.

Kaufmann, D. and Kraay, A. C. (2024). The worldwide governance indicators: Methodology and 2024 update (english). Policy Research working paper 10952, Washington, D.C.: World Bank Group.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of econometrics*, 133(1):97–126.

La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2008). The economic consequences of legal origins. *Journal of economic literature*, 46(2):285–332.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. (1999). The quality of government. *Journal of Law, Economics, and organization*, 15(1):222–279.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1997). Legal determinants of external finance. *The journal of finance*, 52(3):1131–1150.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1998). Law and finance. *Journal of political economy*, 106(6):1113–1155.

Masuch, K., Moshammer, E., and Pierluigi, B. (2017). Institutions, public debt and growth in europe. *Public sector economics*, 41(2):159–205.

North, D. C. (1991). Institutions. *The Journal of Economic Perspectives*, 5(1):97–112.

OECD (2020). Oecd indicators of employment protection — oecd. Available at: `https://www.oecd.org/en/data/datasets/oecd-indicators-of-employment-protection.html`. Accessed: 04-Oct-2024.

Rajan, R. and Zingales, L. (1996). Financial dependence and growth. National bureau of economic research, Cambridge, Mass., USA.

Riphahn, R. T. (2004). Employment protection and effort among german employees. *Economics Letters*, 85(3):353–357.

Rodrik, D., Subramanian, A., and Trebbi, F. (2004). Institutions rule: the primacy of institutions over geography and integration in economic development. *Journal of economic growth*, 9(2):131–165.

Saint-Paul, G. (2002). Employment protection, international specialization, and innovation. *European Economic Review*, 46(2):375–395.

Sanderson, E. and Windmeijer, F. (2016). A weak instrument f-test in linear iv models with multiple endogenous variables. *Journal of econometrics*, 190(2):212–221.

Tax Foundation (2024). 2024 corporate tax rates by country — tax foundation. Available at: https://taxfoundation.org/data/all/global/corporate-tax-rates-by-country-2024/. Accessed: 01-May-2025.

U.S. Patent and Trademark Office (2025). Data download tables — patentsview. Available at: https://patentsview.org/download/data-download-tables. Accessed: 16-Jan-2025.

Van Looy, B., Vereyen, C., and Schmoch, U. (2014). Patent statistics: Concordance ipc v8 – nace rev.2.

Williamson, C. R. and Kerekes, C. B. (2011). Securing private property: formal versus informal institutions. *The Journal of Law and Economics*, 54(3):537–572.

World Bank (2020). Doing business 2020: Comparing business regulation in 190 economies. World Bank Group.

World Bank (2025). World development indicators — databank. Available at: https://databank.worldbank.org/source/world-development-indicators. Accessed: 25-September-2025.

A Annex

Table A1: Value added weighted average

Productivity annual average growth, 2000–2019, %	EU11	US	US minus EU11
Total Economy	0.9	1.6	0.62
Total excluding contribution from ICT	0.8	1.1	0.33
Total excluding contribution from ICT and Financial Services	0.7	0.9	0.22
ICT, of which	3.8	7.8	3.97
Manufacturing of computers and electronics	4.2	11.8	7.54
Information and Communication services	2.7	6.7	3.99
Financial and Insurance Services	1.3	1.8	0.48
Memo items, VA shares			
1999			
ICT, of which	3.8	3.6	-0.17
Manufacturing of computers and electronics	1.2	0.5	-0.69
Information and Communication services	2.6	3.2	0.52
Financial and Insurance Services	4.8	8.0	3.15
2019			
ICT, of which	6.2	9.5	3.23
Manufacturing of computers and electronics	1.6	1.6	0.03
Information and Communication services	4.6	7.8	3.21
Financial and Insurance Services	4.3	7.6	3.30

Source: EU KLEMS and ECB staff computations; EU11: sum of AT, CZ, BE, DE, DK, ES, FI, FR, IT, NL, SE. Sectoral contributions are based on corresponding shares of value added.

Table A2: NACE Sectors Included in the Analysis

NACE Code	**Sector Description**
B	Mining and Quarrying
C10–C12	Manufacture of food products, beverages and tobacco products
C13–C15	Manufacture of textiles, wearing apparel, leather and related products
C16–C18	Manufacture of wood, wood products (except furniture) and paper; Printing
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22–C23	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C24–C25	Manufacture of basic metals and fabricated metal products (except machinery and equipment)

NACE Code	Sector Description
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29–C30	Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment
C31–C33	Manufacture furniture and other manufacturing; Repair and installation of machinery and equipment
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage; waste management and remediation activities
F	Construction
G	Wholesale and retail trade
H	Transport and warehousing
I	Accommodation and food service activities
J58–J60	Publishing activities; motion picture, video and television programme production, sound recording; Programming and broadcasting activities
J61	Telecommunications
J62–J63	Computer programming, consultancy and related activities; Information service activities
K	Financial and Insurance Activities
M	Professional, Scientific and Technical Activities
N	Administrative and Support Service Activities
R	Arts, Entertainment and Recreation
S	Other Service Activities

Table A3: Summary Statistics

Variable	N	Mean	SD	Min	Max
Investment share (EU KLEMS)	9315	3.89	4.03	-4.59	35.41
Investment share (Eurostat)	9545	3.56	3.98	-4.59	43.65
High-tech	9315	0.15	0.36	0	1
Patent share	4323	6.39	9.39	0.16	38.54
AI intensive	7182	0.28	0.45	0	1
AI human capital rank	7182	12.07	6.92	1	24
AI innovation rank	7182	12.70	6.74	1	24
AI exposure rank	7182	12.28	7.07	1	24
AI use rank	6798	11.4	6.71	1	23
Institutional delivery	9315	1.09	0.63	-0.13	2.18
EPL	7745	1.90	0.45	0.61	2.89
Starting a Business score	9267	84.48	8.68	51.5	95.3
Value added growth	9315	0.02	0.14	-2.01	2.13
GDP per capita	9315	46.32	19.79	16.38	138.68
Corporate tax rate	9315	23.98	7.11	9	38.90
Resolving insolvency	9267	68.16	15.31	36.4	93.9
R&D investment share	7863	0.04	0.08	-0.50	1.15
Value added share	12137	3.26	3.90	-0.12	39.22

Notes: The summary statistics of the institutional indicators are those before standardization.

Table A4: Standard deviations of institutional indicators

Variable	SD Overall	SD Between	SD Within
Institutional delivery	0.63	0.62	0.10
EPL	0.45	0.42	0.17
Starting a Business score	8.68	5.89	6.37

Notes: The summary statistics of the institutional indicators are those before standardization.

Table A5: First Stage Results for Eurostat High-Tech Sector Classification

	Institutional Delivery	Employment Protection	Starting a Business
Dep. Var.: Institutions	(1)	(2)	(3)
French	-0.667***	-2.339***	-0.838***
	(0.290)	(0.239)	(0.249)
German	0.164***	-1.944***	-1.265***
	(0.034)	(0.265)	(0.033)
Socialist	-1.572***	-1.965***	-1.021***
	(0.164)	(0.292)	(0.197)
Scandinavian	0.668***	-0.676*	0.011
	(0.056)	(0.400)	(0.052)
French × High-Tech	-0.040	-0.114***	0.037
	(0.035)	(0.042)	(0.044)
German × High-Tech	-0.004	-0.045*	0.003
	(0.005)	(0.024)	(0.005)
Socialist × High-Tech	-0.113	-0.252	0.018
	(0.097)	(0.176)	(0.114)
Value added growth	0.114	-0.046	0.055
	(0.101)	(0.069)	(0.124)
Intercept	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	9315	7745	9267
R-squared	0.64	0.46	0.45
SW multivariate F test of excluded instruments	43.74	37.41	1828.42
	Institutional Delivery	Employment Protection	Starting a Business
Dep. Var.: Institutions × High-Tech	(1)	(2)	(3)
French	0.001*	-0.002	-0.002
	(0.000)	(0.001)	(0.003)
German	0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.000)
Socialist	-0.000	-0.006	-0.000
	(0.000)	(0.004)	(0.000)
Scandinavian	0.001*	-0.001*	-0.000
	(0.000)	(0.001)	(0.001)
French × High-Tech	-1.377***	-1.772***	-0.801***
	(0.312)	(0.439)	(0.248)
German × High-Tech	-0.508***	-1.313***	-1.272***
	(0.043)	(0.456)	(0.044)
Socialist × High-Tech	-2.352***	-1.516***	-1.013***
	(0.212)	(0.541)	(0.261)
Value added growth	0.035**	-0.040**	0.008
	(0.018)	(0.019)	(0.023)
Intercept	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	9315	7745	9267
R-squared	0.66	0.44	0.20
SW multivariate F test of excluded instruments	191.38	40.23	6153.63
Kleibergen-Paap Wald rk F statistic	51.63	33.67	4411.16

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A6: First Stage Results for Patent Shares

	Institutional Delivery	Employment Protection	Starting a Business
Dep. Var.: Institutions	(1)	(2)	(3)
French	-0.649**	-2.341***	-0.839***
	(0.294)	(0.247)	(0.262)
German	0.213***	-1.898***	-1.299***
	(0.069)	(0.276)	(0.075)
Socialist	-1.576***	-2.085***	-1.039***
	(0.170)	(0.341)	(0.215)
Scandinavian	0.712***	-0.583	0.008
	(0.081)	(0.389)	(0.085)
French × Patent Share	-0.001	-0.005	0.005
	(0.002)	(0.004)	(0.005)
German × Patent Share	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Socialist × Patent Share	-0.001	-0.002	0.000
	(0.001)	(0.002)	(0.001)
Value added growth	0.136*	-0.074	0.073
	(0.076)	(0.089)	(0.145)
Intercept	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	4323	3688	4314
R-squared	0.67	0.45	0.44
SW multivariate F test of excluded instruments	64.03	38.01	889.97
	Institutional Delivery	Employment Protection	Starting a Business
Dep. Var.: Institutions × Patent Share	(1)	(2)	(3)
French	-4.231***	3.036	0.407
	(0.593)	(2.447)	(0.723)
German	-4.145***	3.496	0.029
	(0.490)	(2.398)	(0.518)
Socialist	-4.218***	3.280	0.065
	(0.548)	(2.426)	(0.606)
Scandinavian	-4.126***	3.499	0.021
	(0.491)	(2.409)	(0.516)
French × Patent Share	-1.374***	-1.801***	-0.755***
	(0.327)	(0.463)	(0.252)
German × Patent Share	-0.491***	-1.265***	-1.304***
	(0.044)	(0.480)	(0.043)
Socialist × Patent Share	-2.285***	-1.454***	-1.040***
	(0.204)	(0.558)	(0.263)
Value added growth	0.561*	-1.064**	-0.597
	(0.339)	(0.475)	(0.480)
Intercept	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	4323	3688	4314
R-squared	0.68	0.45	0.17
SW multivariate F test of excluded instruments	64.03	43.49	857.52
Kleibergen-Paap Wald rk F statistic	104.21	34.42	518.72

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7: First Stage Results for AI Intensity

	Institutional Delivery	Employment Protection	Starting a Business
Dep. Var.: Institutions	(1)	(2)	(3)
French	-0.662**	-2.344***	-0.771***
	(0.305)	(0.213)	(0.233)
German	0.098***	-1.718***	-1.310***
	(0.018)	(0.198)	(0.012)
Socialist	-1.602***	-1.986***	-1.049***
	(0.176)	(0.313)	(0.230)
Scandinavian	0.609***	-0.669*	-0.008
	(0.046)	(0.370)	(0.047)
French × AI Intensive	-0.011	-0.039	0.028
	(0.015)	(0.024)	(0.029)
German × AI Intensive	0.003	0.062	-0.000
	(0.006)	(0.072)	(0.005)
Socialist × AI Intensive	-0.044	-0.068	0.000
	(0.029)	(0.051)	(0.036)
Value added growth	0.177	-0.212*	0.137
	(0.178)	(0.117)	(0.236)
Intercept	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	7182	6038	7125
R-squared	0.63	0.53	0.45
SW multivariate F test of excluded instruments	45.47	43.18	2411.50
	Institutional Delivery	Employment Protection	Starting a Business
Dep. Var.: Institutions × AI Intensive	(1)	(2)	(3)
French	0.160***	-0.184*	-0.005
	(0.036)	(0.103)	(0.013)
German	0.159***	-0.180*	0.001
	(0.036)	(0.102)	(0.012)
Socialist	0.158***	-0.187*	0.002
	(0.036)	(0.102)	(0.012)
Scandinavian	0.190***	-0.216*	0.001
	(0.016)	(0.116)	(0.014)
French × AI Intensive	-1.175***	-1.824***	-0.720***
	(0.334)	(0.382)	(0.236)
German × AI Intensive	-0.398***	-1.108***	-1.302***
	(0.111)	(0.342)	(0.037)
Socialist × AI Intensive	-2.142***	-1.482***	-1.037***
	(0.219)	(0.464)	(0.249)
Value added growth	0.047	-0.086	-0.082
	(0.047)	(0.054)	(0.072)
Intercept	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	7182	6038	7125
R-squared	0.63	0.52	0.17
SW multivariate F test of excluded instruments	29.75	9.12	1040.70
Kleibergen-Paap Wald rk F statistic	34.47	20.70	231.23

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8: Marginal Effects for Eurostat High-Tech Sector Classification

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Impact of 1 SD increase at:						
High-Tech = 0	-0.135***	-0.211***	-0.122**	-0.309***	-0.094**	-0.518***
	(0.042)	(0.056)	(0.053)	(0.080)	(0.041)	(0.146)
High-Tech = 1	0.658***	0.713***	0.552***	0.789***	0.355**	1.797***
	(0.176)	(0.180)	(0.156)	(0.174)	(0.144)	(0.448)
Differential Impact	0.793**	0.924***	0.674***	1.098***	0.449**	2.315***
	(0.197)	(0.216)	(0.193)	(0.202)	(0.173)	(0.552)

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A9: Marginal Effects for Patent Shares

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Impact of 1 SD increase at:						
Lowest Patent Share (C19)	-0.455***	-0.491***	-0.162	-0.367**	-0.261**	-0.803***
	(0.105)	(0.108)	(0.121)	(0.147)	(0.125)	(0.313)
Highest Patent Share (C26)	1.800***	2.022***	1.541**	2.747***	0.681	3.408
	(0.584)	(0.778)	(0.309)	(1.056)	(0.530)	(2.191)
Differential Impact	2.255***	2.514***	1.703*	3.114***	0.942	4.211*
	(0.629)	(0.828)	(0.823)	(1.134)	(0.562)	(2.411)

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A10: Marginal Effects for AI Intensity Classification

	Institutional Delivery		Employment Protection		Starting a Business	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Impact of 1 SD increase at:						
AI Intensive = 0	-0.182***	-0.256***	-0.051	-0.247*	-0.235***	-0.596***
	(0.061)	(0.088)	(0.084)	(0.126)	(0.068)	(0.159)
AI Intensive = 1	0.663***	0.711***	0.176	0.168	0.384***	1.422***
	(0.156)	(0.142)	(0.133)	(0.237)	(0.136)	(0.413)
Differential Impact	0.845**	0.967***	0.227	0.415	0.618***	2.019***
	(0.193)	(0.204)	(0.206)	(0.344)	(0.176)	(0.537)

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A11: Results for AI Intensity Subindicator Rankings

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS (1)	2SLS (2)	2SLS (3)
AI Human Capital			
Institutional Indicator	0.007	-0.160**	-0.035
	(0.053)	(0.062)	(0.099)
Institutional Indicator × Rank	0.072***	0.060***	0.152***
	(0.014)	(0.017)	(0.038)
Value Added Growth	0.905***	1.251***	1.146***
	(0.184)	(0.258)	(0.212)
Sector- & Year-FE	Yes	Yes	Yes
Number of Observations	7182	6038	7125
R-squared	0.60	0.60	0.57
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	53.22	238.98	3985.17
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	18.30	12.00	517.97
Kleibergen-Paap Wald rk F statistic	37.56	25.83	369.76
AI Innovation			
Institutional Indicator	0.020	-0.126**	-0.041
	(0.055)	(0.056)	(0.082)
Institutional Indicator × Rank	0.042***	0.013	0.080***
	(0.010)	(0.016)	(0.023)
Value Added Growth	0.937***	1.193***	1.030***
	(0.173)	(0.268)	(0.207)
Sector- & Year-FE	Yes	Yes	Yes
Number of Observations	7182	6038	7125
R-squared	0.60	0.60	0.59
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	47.61	1576.00	4096.43
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	56.95	672.56	2994.06
Kleibergen-Paap Wald rk F statistic	31.66	287.58	2549.64
AI Exposure			
Institutional Indicator	0.0512	-0.128**	-0.020
	(0.054)	(0.057)	(0.095)
Institutional Indicator × Rank	0.098***	0.046**	0.147***
	(0.015)	(0.021)	(0.044)
Value Added Growth	0.890***	1.196***	1.110***
	(0.171)	(0.263)	(0.223)
Sector- & Year-FE	Yes	Yes	Yes
Number of Observations	7182	6038	7125
R-squared	0.61	0.60	0.57
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	50.95	168.28	2706.37
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	10.56	16.78	345.98
Kleibergen-Paap Wald rk F statistic	40.76	23.11	238.99
AI Use			
Institutional Indicator	-0.043	-0.133**	-0.083
	(0.049)	(0.062)	(0.093)
Institutional Indicator × Rank	0.088***	0.064***	0.156***
	(0.019)	(0.022)	(0.046)
Value Added Growth	0.928***	1.191***	1.117***
	(0.182)	(0.261)	(0.220)
Sector- & Year-FE	Yes	Yes	Yes
Number of Observations	6798	5716	6744
R-squared	0.62	0.61	0.58
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	59.15	529.04	9453.92
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	37.67	32.16	263.52
Kleibergen-Paap Wald rk F statistic	39.93	23.38	922.15

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p <$ 0 1, ** 0 05, $^{***}p < 0.01$. Each AI intensity ranking is centered around its respective mean so the estimates on the non-interacted institutional indicator are the estimated effects at the mean.

Table A12: Marginal Effects for AI Intensity Subindicator Rankings

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
AI Human Capital			
Impact of 1 SD increase at:			
Lowest Rank (I)	-0.790***	-0.829***	-1.719***
	(0.171)	(0.223)	(0.396)
Highest Rank (C26)	0.867***	0.559***	1.777***
	(0.177)	(0.178)	(0.498)
Differential Impact	1.657**	1.388***	3.495***
	(0.330)	(0.387)	(0.874)
AI Innovation			
Impact of 1 SD increase at:			
Lowest Rank (C22-C23)	-0.468***	-0.274	-0.974***
	(0.122)	(0.203)	(0.239)
Highest Rank (J58-J60)	0.491***	0.017	0.858***
	(0.!§))	(0.189)	(0.314)
Differential Impact	0.960***	0.291	1.832***
	(0.237)	(0.375)	(0.535)
AI Exposure			
Impact of 1 SD increase at:			
Lowest Rank (F)	-1.097***	-0.648***	-1.683***
	(0.162)	(0.245)	(0.460)
Highest Rank (J62-J63)	1.163***	0.412*	1.706***
	(0.207)	(0.244)	(0.565)
Differential Impact	2.260***	1.060**	3.388***
	(0.356)	(0.475)	(1.012)
AI Use			
Impact of 1 SD increase at:			
Lowest Rank (I)	-0.965***	-0.796***	-1.707***
	(0.197)	(0.261)	(0.454)
Highest Rank (J62-J63)	0.980***	0.601**	1.718***
	(0.232)	(0.244)	(0.578)
Differential Impact	1.944***	1.397***	3.425***
	(0.418)	(0.492)	(1.018)

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A13: Controlling for GDP p.c. and Taxes (High-Tech Classification)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Factor	-0.305***	-0.335***	-0.481***
	(0.063)	(0.097)	(0.126)
Institutional Factor × High-Tech	0.763*	0.918***	1.901***
	(0.402)	(0.231)	(0.485)
GDP per capita	0.005	0.000	0.001
	(0.004)	(0.005)	(0.004)
GDP per capita × High-Tech	0.026	0.036**	0.020
	(0.022)	(0.014)	(0.020)
Corporate Tax Rate	0.011	-0.007	-0.003
	(0.010)	(0.011)	(0.012)
Corporate Tax Rate × High-Tech	-0.034*	0.003	0.026
	(0.020)	(0.022)	(0.045)
Value added growth	0.518***	0.559***	0.501***
	(0.143)	(0.106)	(0.130)
Sector-FE	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes
Number of Observations	9315	7745	9267
R-squared	0.61	0.62	0.59
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	23.06	6.46	51.00
First stage, dependent variable: Institutional Factor × High-tech			
SW multivariate F test of excluded instruments	32.16	5.08	27.40
Kleibergen-Paap Wald rk F statistic	18.18	3.91	20.32

Notes: Standard errors in parentheses are clustered at the country-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A14: Controlling for GDP p.c. and Taxes (Patent Shares)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Indicator	0.461*	0.137	0.057
	(0.258)	(0.132)	(0.217)
Institutional Indicator×Patent Shares	0.132**	0.080**	0.047
	(0.062)	(0.036)	(0.051)
GDP per capita	-0.034*	-0.004	-0.002
	(0.018)	(0.006)	(0.007)
GDP per capita ×Patent Shares	-0.005	0.001	0.002**
	(0.004)	(0.001)	(0.001)
Corporate Tax Rate	-0.008	-0.015	-0.019
	(0.019)	(0.016)	(0.015)
Corporate Tax Rate ×Patent Shares	-0.000	0.001	0.000*
	(0.002)	(0.003)	(0.002)
Value added growth	0.444***	0.735***	0.569***
	(0.157)	(0.083)	(0.119)
Sector-FE	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes
Number of Observations	4323	3688	4314
R-squared	0.32	0.28	0.31
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	21.02	4.57	32.48
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	28.73	4.21	27.65
Kleibergen-Paap Wald rk F statistic	7.09	3.41	13.16

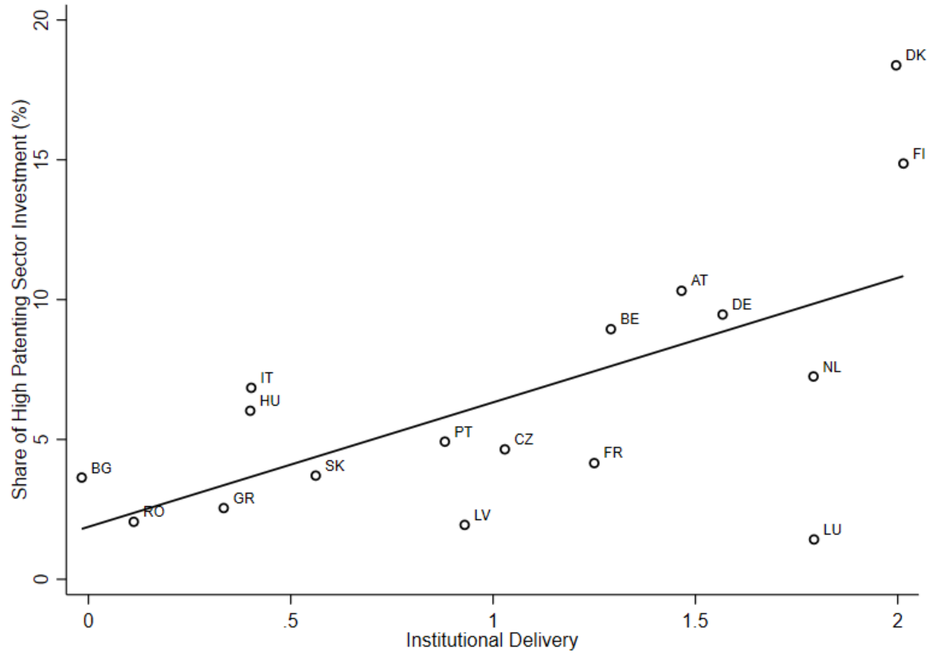
Notes: Standard errors in parentheses are clustered at the country-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A15: Controlling for GDP p.c. and Taxes (AI Intensity)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS (1)	2SLS (2)	2SLS (3)
Institutional Indicator	-0.304***	-0.329**	-0.639***
	(0.115)	(0.146)	(0.137)
Institutional Indicator×AI Intensity	0.493	0.553	1.641***
	(0.358)	(0.355)	(0.457)
GDP per capita	0.004	0.001	0.004
	(0.003)	(0.003)	(0.003)
GDP per capita ×AI Intensity	0.020**	0.022***	0.009
	(0.010)	(0.006)	(0.012)
Corporate Tax Rate	0.000	-0.021	-0.012
	(0.012)	(0.016)	(0.011)
Corporate Tax Rate ×AI Intensity	0.045	0.075**	0.076***
	(0.031)	(0.038)	(0.027)
Value added growth	0.989***	1.192***	1.198***
	(0.202)	(0.251)	(0.217)
Sector-FE	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes
Number of Observations	7182	6038	7125
R-squared	0.60	0.60	0.59
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	22.33	4.42	63.07
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	20.03	3.55	55.88
Kleibergen-Paap Wald rk F statistic	13.54	3.82	36.67

Notes: Standard errors in parentheses are clustered at the country-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure A1: Institutional delivery and high patenting sector investment share in 2021.



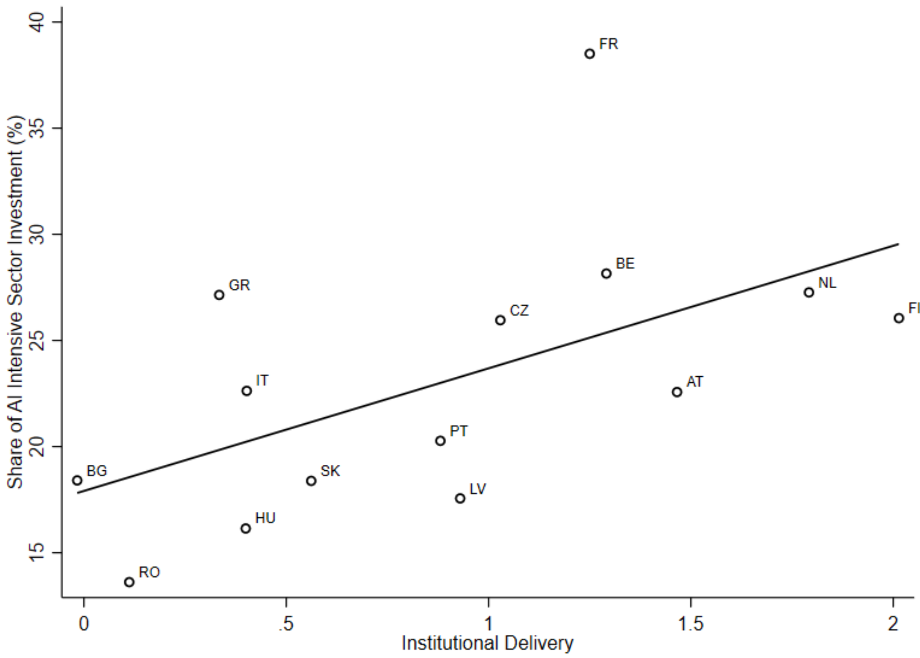
Note: For the purpose of this figure, we consider the 20 % of sectors with the highest patent shares to be high-patenting sectors. These are the sectors with NACE codes C21, C26 and C28. The figure includes all EU countries for which data on gross fixed capital formation is available for all three of these NACE codes in the EU KLEMS dataset.

Table A16: Results for Eurostat High-Tech Sector Classification (Value Added Share as Dependent Variable)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Indicator	-0.095**	-0.225***	-0.309**
	(0.048)	(0.077)	(0.122)
Institutional Indicator × High-Tech	0.430**	0.759***	1.242***
	(0.189)	(0.201)	(0.358)
Value added growth	0.356***	0.482***	0.353***
	(0.100)	(0.116)	(0.101)
Number of Observations	12,137	9786	12,062
R-squared	0.77	0.78	0.77
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	408.52	34.59	100,000.00
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	76.90	30.19	558.50
Kleibergen-Paap Wald rk F statistic	489.30	18.30	359.03

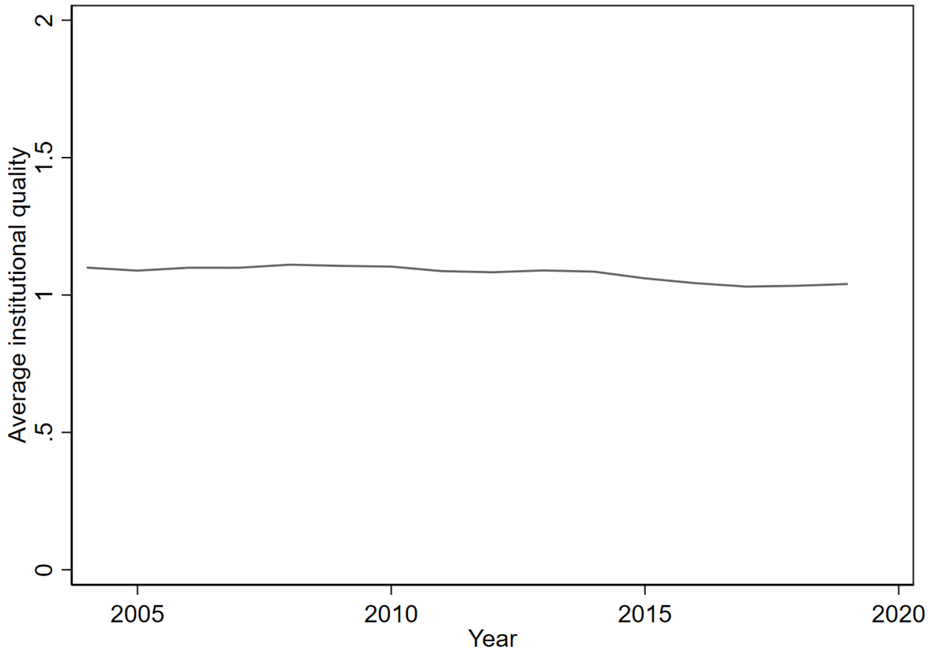
Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure A2: Institutional delivery and AI intensive sector investment share in 2021.



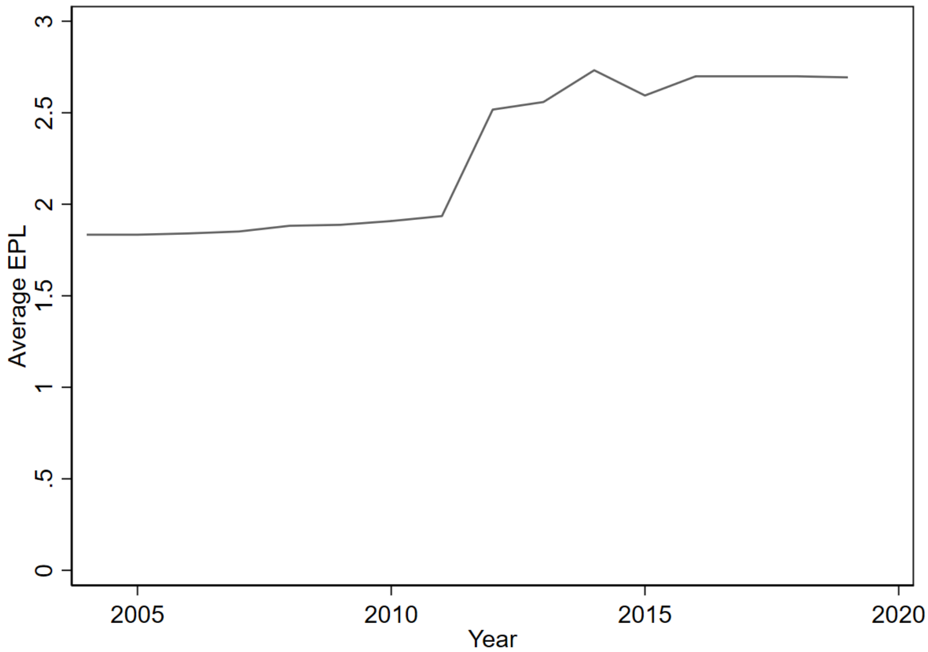
Note: The shares of AI intensive sector investment are calculated using data on gross fixed capital formation from Eurostat. We consider those sectors as AI intensive which are classified as highly AI intensive by Calvino et al. (2024). These include NACE sectors C26 (Manufacturing of computers) and J (Media and information and communication technology), K (Finance and insurance), M69–M71 (Legal, headoffice, architectural and engineering activities) and M72 (Scientific research and development). The figure includes the 14 EU countries for which data on gross fixed capital formation is available for all these NACE codes from Eurostat.

Figure A3: Average institutional delivery over time.



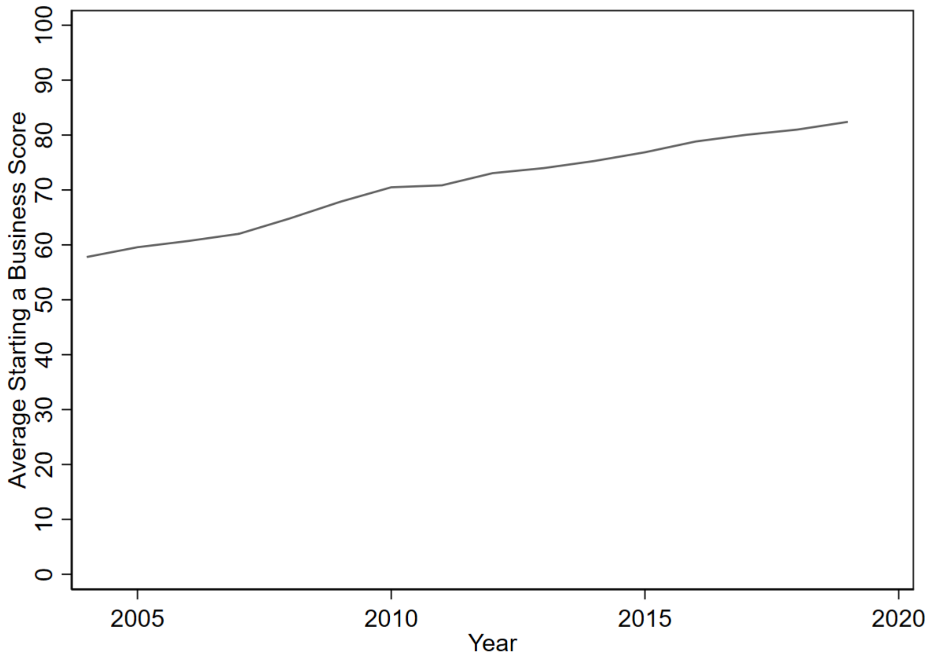
Note: Average of the institutional delivery index across all 27 EU countries from 2004 until 2019.

Figure A4: Average EPL over time.



Note: Average EPL across 24 EU countries from 2004 until 2019. There is no EPL data over this time period for Bulgaria, Cyprus and Romania. Estonia and Luxembourg are included from 2008 onwards. Slovenia is included from 2009 onwards. Latvia is included from 2012 onwards. Lithuania is included from 2014 onwards. Croatia is only in included in 2015.

Figure A5: Average Starting a Business Score over time.



Note: Average Starting a Business Score across 27 EU countries from 2004 until 2019. Luxembourg and Malta are included from 2007 onwards and Cyprus is included from 2009 onwards.

Table A17: Results for Patent Shares (Value Added Share as Dependent Variable)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Indicator	-0.038	0.203	-0.065
	(0.096)	(0.127)	(0.197)
Institutional Indicator × Patent Share	0.037***	0.039***	0.069***
	(0.009)	(0.010)	(0.026)
Value added growth	0.392***	0.538***	0.471***
	(0.134)	(0.133)	(0.165)
Number of Observations	5779	4656	5749
R-squared	0.66	0.64	0.60
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	277.41	34.35	21225.87
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	73.42	29.72	1863.30
Kleibergen-Paap Wald rk F statistic	203.89	18.93	1124.80

Notes: Standard errors in parentheses are clustered at the country level. The Patent Share is centered around its sample-mean so the estimate on the non-interacted institutional indicator is the estimated effect at the mean. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A18: Results for AI Intensity (Value Added Share as Dependent Variable)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS (1)	2SLS (2)	2SLS (3)
Institutional Indicator	-0.174**	-0.142	-0.441***
	(0.972)	(0.104)	(0.146)
Institutional Indicator × AI Intensive	0.662***	0.135	1.292***
	(0.227)	(0.381)	(0.402)
Value Added Growth	0.942***	1.201***	1.037***
	(0.151)	(0.174)	(0.180)
Number of Observations	9424	7596	9367
R-squared	0.77	0.77	0.77
First stage, dependent variable: Institutional Factor			
F test of excluded instruments	323.73	36.71	72551.97
SW multivariate F test of excluded instruments	351.42	34.37	80643.01
First stage, dependent variable: Institutional Factor × Patent Share			
F test of excluded instruments	371.31	29.65	71270.31
SW multivariate F test of excluded instruments	24.36	15.13	554.22
Kleibergen-Paap Wald rk F statistic	148.30	19.74	322.10

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A19: Results for Eurostat High-Tech Sector Classification (R&D Share as Dependent Variable)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS (1)	2SLS (2)	2SLS (3)
Institutional Indicator	-0.005**	-0.006***	-0.009***
	(0.002)	(0.001)	(0.003)
Institutional Indicator × High-Tech	0.020**	0.031***	0.046**
	(0.010)	(0.005)	(0.018)
Value added growth	-0.003	0.003	-0.002
	(0.005)	(0.004)	(0.005)
Number of Observations	7863	6757	7815
R-squared	0.51	0.53	0.48
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	48.16	3.95	226.31
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	105.33	35.61	482.92
Kleibergen-Paap Wald rk F statistic	39.03	2.05	147.68

Notes: Standard errors in parentheses, two-way clustered at the sector and country-year levels. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A20: Results for Patent Shares (R&D Share as Dependent Variable)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Indicator	0.003	0.005**	-0.001
	(0.003)	(0.002)	(0.006)
Institutional Indicator × Patent Share	0.002	0.002**	0.003
	(0.001)	(0.001)	(0.002)
Value added growth	0.004	0.011***	0.006
	(0.005)	(0.004)	(0.004)
Number of Observations	3723	3326	3714
R-squared	0.34	0.33	0.29
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	69.54	5.07	809.94
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	50.65	5.77	192.32
Kleibergen-Paap Wald rk F statistic	96.94	3.73	161.28

Notes: Standard errors in parentheses are clustered at the country level. The Patent Share is centered around its sample-mean so the estimate on the non-interacted institutional indicator is the estimated effect at the mean. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A21: Results for AI Intensity (R&D Share as Dependent Variable)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS (1)	2SLS (2)	2SLS (3)
Institutional Indicator	-0.000	-0.001	-0.007
	(0.003)	(0.004)	(0.006)
Institutional Indicator × AI Intensity	0.011	0.013	0.028
	(0.009)	(0.013)	(0.020)
Value added growth	0.004	0.015	0.009
	(0.009)	(0.011)	(0.009)
Number of Observations	5772	5020	5721
R-squared	0.32	0.30	0.29
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	57.12	7.17	183.68
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	146.12	53.38	203.17
Kleibergen-Paap Wald rk F statistic	39.57	20.22	154.04

Notes: Standard errors in parentheses, two-way clustered at the sector and country-year levels. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A22: Results for the Resolving Insolvency Index

	(1) High-Tech Classification	(2) Patent Share	(3) AI Intensive
Resolving Insolvency	-0.243***	-0.144	-0.308***
	(0.072)	(0.152)	(0.093)
Resolving Insolvency × Innovative	1.036***	0.073***	1.213***
	(0.319)	(0.021)	(0.218)
Value added growth	0.480***	0.534***	1.015***
	(0.122)	(0.134)	(0.203)
Number of Observations	9267	4314	7125
R-squared	0.60	0.31	0.59
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	30.45	27.58	27.65
First stage, dependent variable: Institutional Factor × Patent Share			
SW multivariate F test of excluded instruments	27.15	28.82	22.04
Kleibergen-Paap Wald rk F statistic	21.83	21.02	11.60

Notes: Standard errors in parentheses are clustered at the country level. The Patent Share is centered around its sample-mean so the estimate on the non-interacted institutional indicator is the estimated effect at the mean. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A23: Results for Eurostat High-Tech Classification (Excluding Ireland and Luxembourg)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS (1)	2SLS (2)	2SLS (3)
Institutional Indicator	-0.184***	-0.214***	-0.414***
	(0.050)	(0.051)	(0.103)
Institutional Indicator × High-Tech	0.896***	1.087***	2.239***
	(0.224)	(0.196)	(0.548)
Value added growth	0.416***	0.499***	0.430***
	(0.122)	(0.085)	(0.114)
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	8867	7361	8867
R-squared	0.64	0.66	0.61
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	51.09	2.74	247.21
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	757.57	34.46	376.29
Kleibergen-Paap Wald rk F statistic	53.07	2.47	146.59

Notes: Standard errors in parentheses are clustered at the country-level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A24: Results for Patent Shares (Excluding Ireland and Luxembourg)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Indicator	-0.053	0.203	-0.018
	(0.116)	(0.157)	(0.234)
Institutional Indicator × Patent Share	0.064***	0.077***	0.104
	(0.022)	(0.029)	(0.063)
Value added growth	0.526***	0.747***	0.646***
	(0.147)	(0.098)	(0.114)
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	4259	3636	4259
R-squared	0.34	0.27	0.23
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	85.42	4.87	1069.05
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	70.52	5.39	193.24
Kleibergen-Paap Wald rk F statistic	127.39	4.07	160.93

Notes: Standard errors in parentheses are clustered at the country-level. The Patent Share is centered around its sample-mean so the estimate on the non-interacted institutional indicator is the estimated effect at the mean. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A25: Results for AI Intensity (Excluding Ireland and Luxembourg)

	Institutional Delivery	Employment Protection	Starting a Business
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Institutional Indicator	-0.265***	-0.269*	-0.662***
	(0.096)	(0.143)	(0.172)
Institutional Indicator × AI Intensive	0.959***	0.535	2.244***
	(0.223)	(0.391)	(0.579)
Value Added Growth	0.815***	1.010***	1.079***
	(0.196)	(0.268)	(0.221)
Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of Observations	6672	5604	6672
R-squared	0.64	0.65	0.61
First stage, dependent variable: Institutional Factor			
SW multivariate F test of excluded instruments	51.51	4.32	177.54
First stage, dependent variable: Institutional Factor × AI-intensive			
SW multivariate F test of excluded instruments	57.82	5.55	190.19
Kleibergen-Paap Wald rk F statistic	69.06	4.21	150.39

Notes: Standard errors in parentheses are clustered at the country level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Acknowledgements

The authors thank Gert Bijnens, Yann Coatanlem, Oliver Coste, Ethan Ilzetzki, Wolfgang Modery, Chiara Osbat, Jesus Fernández Villaverde, an anonymous referee and participants of ECB workshops on artificial intelligence and on productivity for their comments and suggestions.

Jonathan Bothner
European Central Bank, Frankfurt am Main, Germany; University of Bayreuth, Bayreuth, Germany; email: bothner@googlemail.com

Paloma Lopez-Garcia
European Central Bank, Frankfurt am Main, Germany; email: paloma.lopez-garcia@ecb.europa.eu

Daphne Momferatou
European Central Bank, Frankfurt am Main, Germany; email: daphne.momferatou@ecb.europa.eu

Ralph Setzer
European Central Bank, Frankfurt am Main, Germany; email: ralph.setzer@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-7649-7 ISSN 1725-2806 doi:10.2866/0924871 QB-01-26-037-EN-N