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AI generation as a development tool in Europe: A double-edged sword?

AI-generálás mint fejlesztési eszköz Európában: Egy kétélű kard?

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KEYWORDS: AI generation; AI adoption; economic growth; employment growth; regions; EU

ABSTRACT: Europe is losing economic ground. Sluggish dynamism and deepening territorial polarisation have eroded its global standing just as artificial intelligence (AI) is rewriting the rules of the world economy. While AI is widely viewed as a potential source of productivity growth, competitiveness, and new economic opportunities, its regional consequences remain uncertain. Could AI generation - the innovation activity behind AI technologies - help reverse Europe's slide? We use a panel dataset of 224 NUTS2 regions across 26 European Union member states during the period 2011–2019 to investigate whether regional AI-related inventive capacity contributes to economic and employment growth and whether these effects are evenly distributed across space.

The empirical analysis combines several complementary approaches. We estimate region and year fixed-effects panel models to account for unobserved regional characteristics and common temporal shocks, while random-effects models are used as a benchmark. To address potential endogeneity arising from reverse causality and omitted time-varying factors, we employ System-GMM estimators. We further apply fixed-effects quantile regression to examine whether the effects of AI generation differ across the regional growth distribution. In addition, spatial econometric models are estimated as robustness checks to account for geographical dependence and potential spillover effects between neighbouring regions.

The results reveal three main findings. First, AI generation is positively associated with both regional economic growth and employment growth. Regions with stronger AI-related inventive capacity experience higher subsequent GDP per capita growth and employment expansion, suggesting that AI may be an important source of technological upgrading and regional development potential. Second, the benefits of AI generation are not distributed evenly across European territories. The strongest economic links are concentrated among regions already positioned near the technological and economic frontier, indicating that AI may reinforce existing patterns of regional advantage rather than automatically promoting convergence. Third, potential employment effects display a different spatial pattern: employment gains are more pronounced among intermediate-

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performing regions, suggesting that AI-related innovation may create broader labour-market opportunities beyond the most advanced innovation hubs.

These findings highlight the dual nature of AI-driven development. AI generation represents a significant opportunity for strengthening European competitiveness, but its benefits depend heavily on regional capabilities, including research capacity, skilled labour, and innovation ecosystems. Without targeted policies that broaden access to AI-related knowledge creation and strengthen the absorptive capacity of peripheral regions, AI may contribute to a widening rather than narrowing of Europe's territorial divide. The study contributes to debates on technology, regional development, and territorial inequality by demonstrating that the economic consequences of AI are shaped not only by technological progress itself but also by the uneven geography of innovation.

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KULCSSZAVAK: AI generálás; AI adopció; gazdasági növekedés; foglalkoztatásnövekedés; régiók; EU

ABSZTRAKT: Európa gazdasági térvesztésen megy keresztül. Lomha növekedési dinamikája és elmélyülő területi megosztottsága pont akkor ásta alá globális pozícióját, amikor a mesterséges intelligencia (AI) átírja a világgazdaság szabályait. Miközben az AI-ra széles körben a termelékenységnövekedés, versenyképesség és új gazdasági lehetőségek lehetséges forrásaként tekintenek, térbeli következményei még bizonytalanok. Alkalmas-e az AI-generálás – az AI technológiák mögött álló, azokat létrehozó innovációs tevékenység – Európa lecsúszásának megfordítására? Tanulmányunkban egy 224 NUTS2 régiót felölelő, 26 EU-tagországra kiterjedő paneladatbázist használunk a 2011–2019 közötti időszakban azzal a céllal, hogy feltárjuk, hozzájárulnak-e az AI-hoz kapcsolódó találmányok a gazdaság és foglalkoztatás növekedéséhez, illetve hogy ezek a hatások egyenletesen oszlanak-e el a térben.

Az empirikus vizsgálat több egymást kiegészítő megközelítést ötvöz. Fix hatású panelmodelleket becsülünk a meg nem figyelt regionális jellemzők és időbeli sokkok figyelembevételére, míg referenciaként véletlenszerű hatású modelleket alkalmazunk. A fordított oksági viszonyokból és időben változó tényezők kihagyásából eredő lehetséges endogenitás kezelésére System-GMM becslőket használunk fel. Ezeken túl fix hatású kvantilis regressziót alkalmazunk annak vizsgálatára, hogy az AI generálásának hatásai eltérnek-e a regionális növekedés eloszlása szerint. Végül térökonometriai modellbecsléseket végzünk a robusztussági ellenőrzés céljából, hogy figyelembe vegyük a szomszédos régiók közötti földrajzi függőségeket és lehetséges spillover-hatásokat.

Az eredmények három fő megállapítás felé mutatnak. Egyrészt az AI-generálás pozitív összefüggést mutat mind a gazdasági növekedéssel, mind a javuló foglalkoztatással. Azok a régiók, ahol erősebb az AI-hoz kapcsolódó szabadalmi aktivitás, magasabb egy főre eső GDP-növekedést és foglalkoztatásbővülést mutatnak, amely arra utal, hogy az AI a technológiai feljebb lépés és regionális fejlődési potenciál lényeges forrása lehet. Másrészt az AI-generálás előnyei nem egyenletesen oszlanak meg az európai régiók között. A legerősebb gazdasági kapcsolódások azokban a régiókban koncentrálódnak, amelyek eredendően a technológiai és gazdasági élvonalba sorolhatók; ez pedig arra utal, hogy az AI valószínűleg inkább megerősíti a meglévő regionális versenyelőnyöket, mintsem automatikusan elősegítené a felzárkózást. Harmadrészt a lehetséges foglalkoztatási hatások eltérő térbeli mintázatot mutatnak: a foglalkoztatás növekedése hangsúlyosabb a közepes teljesítményű régiókban, amely arra utal, hogy az AI-hoz kapcsolódó innováció a legfejlettebb innovációs csomópontokon túlmutatóan is szélesebb bázisú munkaerőpiaci lehetőségeket teremthet.

Az eredmények rávilágítanak az AI-alapú fejlődés duális hatására. Az AI-generálás jelentős lehetőséget kínál az európai versenyképesség erősítésére, előnyei azonban nagymértékben függenek a regionális képességeken, beleértve az innovációs kapacitásokat, képzett munkaerőt, illetve innovációs

ökoszisztémákat. Az AI-hoz kapcsolódó tudástermeléshez való hozzáférést, illetve a perifériku régiók abszorpciós kapacitását javító szakpolitikák hiányában az AI inkább elmélyítheti, mint csökkentheti Európa területi megosztottságát. A tanulmány hozzájárul a technológiák, regionális fejlődés, valamint területi egyenlőtlenségek körül folyó vitákhoz, bemutatva hogy az AI gazdasági hatásait nem csupán maga a technológiai fejlődés, hanem az innováció egyenlőtlen földrajza is formálja.

Introduction

Europe is being left behind. Once a quarter of global GDP, the European Union (EU) now accounts for just 16%. This is a slide that betrays a deeper malaise of anaemic dynamism, limited innovative capacity, and a deepening territorial divide between dynamic cores and struggling peripheries (Rodríguez-Pose 2018; Iammarino, Rodríguez-Pose, Storper 2019; Diemer et al. 2022; European Commission 2024). The divide cuts particularly deep in Central and Eastern Europe, where two decades of rapid GDP catch-up since EU accession have not been matched by parallel gains in innovation capacity.

Into this gloomy picture has stepped artificial intelligence. AI is reshaping industries, labour markets, and entire economies (Rampersad 2020; Parteka, Kordalska 2023; Zhang 2023) and Europe's policymakers have been quick to identify it as a possible tonic. The Draghi (2024) Report places AI at the heart of the EU's strategic plan for revival and the Letta (2024) report echoes this diagnosis. The problem, of course, is that the EU is starting from behind. China filed roughly 70% of the world's AI patents over the past decade. The United States accounted for 11%. The European Patient Office, by contrast, filed less patents than its Japanese or Korean counterparts (WIPO 2024). Europe is not leading the AI race. It is trying to stay in it.

This paper asks two questions about AI generation, the creation and development of AI-related inventions, as distinct from AI adoption, the deployment and use of those technologies in firms, sectors, and labour markets. The two have different geographies, different drivers, and different consequences for regional development (Babina et al. 2024; Bonfiglioli et al. 2024). AI generation tends to concentrate in a small number of well-resourced innovation hubs, whereas AI adoption can diffuse far more widely. Our focus is squarely on AI generation. Within this focus, the paper asks whether AI generation delivers tangible regional development benefits - in the form of stronger economic and employment growth - and whether AI generation can help close the EU's deepening territorial divide, or is more likely to widen it.

Neither question has an obvious answer. The literature is broadly bullish on AI's aggregate effects, treating it as a driver of growth (Agrawal, Gans, Goldfarb 2018; Cockburn, Henderson, Stern 2019; Lu 2021), employment expansion (Frey, Osborne, 2017; Bessen 2018), and productivity (Aghion et al. 2019; Brynjolfsson, Rock, Syverson 2019; Furman, Seamans 2019; Czarnitzki, Fernández, Rammer 2023). But aggregate effects need not survive the journey to the regional scale. A technology that lifts national output may do so by reorganising activity within

national territories rather than by expanding the pie everywhere. There are also dissenting voices. Berg, Buffie and Zanna (2018) and Acemoglu (2021) flag the risk that AI substitutes faster than it complements. Frank et al. (2019) warn that the labour-market effects are likely to be highly heterogeneous and a growing strand of work cautions that AI generation, like other capital-intensive innovation, will reproduce - and may amplify - existing patterns of spatial inequality (Kemeny, Petralia, Storper 2022; Cicerone et al. 2023; Xiao, Boschma 2023). The answer to both questions, in short, is genuinely open. In this paper, we accordingly propose the hypotheses that the economic and employment effects of AI-related invention are heterogeneous across regions, with stronger effects expected in regions possessing greater innovation capabilities and higher levels of economic development.

To address these questions, we draw on patent data covering AI-related innovation across 224 NUTS2 regions in 26 EU countries from 2011 to 2019. We combine fixed-effects panel estimators (with random-effects as a benchmark) and System-GMM specifications with fixed-effect quantile regression to capture both the average effect of AI generation on regional development and its distributional consequences across the regional growth distribution. We focus on the pre-COVID, pre-generative-AI window deliberately. The 2011–2019 period is the formative phase during which European AI capabilities were laid down. Understanding this period is necessary if we are to make sense of the post-2022 generative-AI surge that builds on it. The COVID disruption that followed would, in any case, contaminate measurement of AI's regional effects.

Three findings stand out. First, AI generation is, on average, good for European regions. It lifts both economic and employment growth. Second, the economic returns are heavily skewed towards regions already near the top of the growth distribution. Third, employment gains, by contrast, cluster in middling regions rather than only in leaders. Overall, AI generation is a partial answer to Europe's regional problem. It raises the EU's aggregate output, but its growth-enhancing effects in the period studied accrue most powerfully where Europe is already strongest.

The contribution of the paper is twofold. Conceptually, we place AI generation within the broader debate on technology and territorial inequality. Empirically, we provide one of the first systematic regional-level analyses of AI generation's economic and employment consequences in the EU, deploying quantile methods to surface distributional effects that mean-based analysis would miss. The policy implication is uncomfortable. Europe may need a certain amount of AI generation to revive its competitiveness, just as the Draghi (2024) and Letta (2024) reports urge. But more AI, on the current geography, will mean more regional inequality. Without a deliberate effort to widen the territorial base of AI generation the technology that promises to lift Europe's economy could just as easily deepen the divisions that already threaten it (Lee 2024; Rodríguez-Pose, Dijskstra, Poelmann 2024).

The remainder of the paper is structured as follows. Section 2 develops the theoretical framework and main hypotheses. Section 3 describes the data and methodology. Section 4 presents the results. Section 5 concludes.

AI and development

Two geographies, one technology

We adopt the standard taxonomy in defining AI as a class of computational technologies that perform tasks typically associated with human cognition - pattern recognition, prediction, classification, decision-making, and natural-language processing - through machine learning, deep learning, and related algorithmic techniques (Cockburn, Henderson, Stern 2019; WIPO 2024). Within that class, our focus is on the innovation activity behind such technologies.

AI generation refers to the innovation activity that produces AI-related technologies - patents, prototypes, algorithmic frameworks, datasets - and the firms, universities, and labs in which that activity takes place. It anchors the regional capabilities (talent, know-how, ecosystems) that help make sustained adoption possible.

Why treat AI generation as anything other than another instance of innovation? Two features distinguish it. First, AI is a candidate general-purpose technology (Petralia 2020; Gherhes et al. 2022). Its applications cut across industries and its productivity gains compound through downstream adoption. Second, AI generation is unusually capital- and talent-intensive. Modern foundation models require compute, data, and engineering scale that most firms - let alone most regions - cannot match. While some digital and Industry 4.0 technologies have shown wider regional applicability (Corradini, Santini, Vecciolini 2021), AI generation belongs firmly to the more concentrated end of the spectrum. The combination matters for regional development. As a candidate general-purpose technology, AI's regional benefits could in principle spread widely. But its concentrated supply side means those benefits will be unevenly captured.

Two strands of theory inform our expectations about the geography of AI generation. First, AI generation as path creation rather than path dependence: a substantive break from existing technological trajectories that requires a wholesale reconfiguration of talent, infrastructure, and institutions (Boschma, Lambooy, 1999; Geels 2002; Martin, Sunley 2006; MacKinnon et al. 2019; Xiao, Boschma, 2023). The character of that path creation varies. It can be incremental, building on local technological diversification (Boschma 2017; Antonietti, Montresor 2021), or genuinely disruptive, propagating across multiple sectors and platforms (Gherhes et al. 2022). Either way, the seed conditions matter. Knowledge relatedness within the regional economy and the diversity of the

local technology base shape both the likelihood and the form of AI emergence (Bathelt, Malmberg, Maskell 2004; Frenken, Van Oort, Verburg 2007; Buarque et al. 2020).

The second strand is that Krugman (1991) and a generation of subsequent work (Duranton, Puga 2004; Combes, Gobillon 2015) have documented how thick labour markets, dense input–output linkages, and localised knowledge spillovers concentrate economic activity in a small number of locations and sustain that concentration over time. For an activity as input-hungry as AI generation - requiring specialised talent, deep capital, abundant compute, and a thick web of complementary firms and institutions -the agglomeration logic predicts spatial concentration with unusual force.

These two strands converge on a similar empirical expectation. They differ in mechanism. The former emphasises path-creation and knowledge relatedness. The latter emphasises increasing returns to spatial co-location. Both, applied to AI, predict a sharply uneven map.

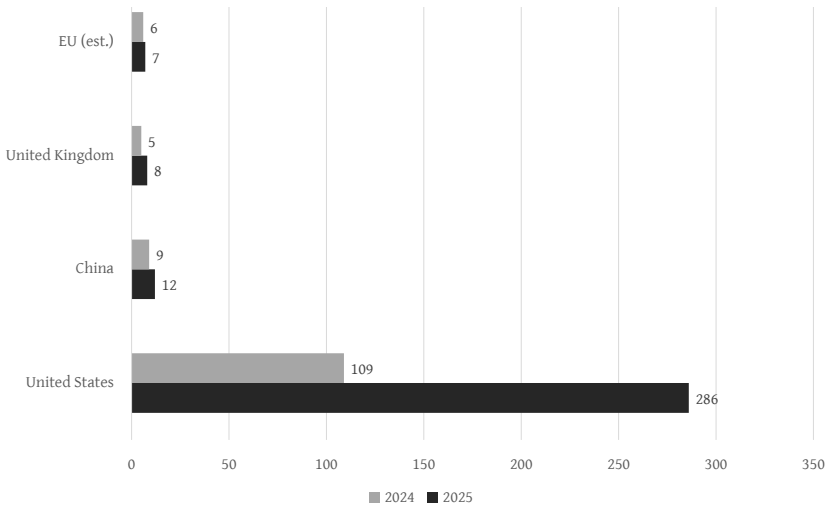
The European AI lag

Europe is far from being at the front of the AI race. Although AI investment has been growing globally - in the United States it rose seventeen-fold between 2001 and 2019 - Europe is being outspent and out-patented. China has led the world in AI patent filings every year since 2017 (WIPO 2024). Its share of global AI patents over the past decade is around 70%. The US accounts for 11%. Germany, Europe's strongest AI-patenting country, registers about 1% of the total global AI patents. The rest of the EU contributes barely more (WIPO 2024). The headline figures need a small caveat. China's patent count partly reflects domestic filing incentives that need not equate to technological leadership. US AI strength is concentrated in commercial deployment and frontier model development as much as in patent filings (Cath et al. 2018; Zeng 2021). Even so, the broad ordering - China and the United States first, Europe second-tier and below South Korea and Japan - is uncontentious .

Investment is being scaled up in response. The Commission's 2018 Coordinated Plan committed up to €20 billion in EU-level AI funding by 2030 (European Commission 2018a). When public and private flows are combined, the World Economic Forum (2022) projected that total European AI spending could reach €22.4 billion by 2025. The Commission has updated its position several times since: with the AI Act, which entered into force in 2024 as the world's first comprehensive horizontal AI regulation (European Union 2024), with the Letta (2024) report on the Single Market, which calls for a step-change in EU AI investment, and with the Draghi (2024) Report, which places AI at the heart of the European competitiveness agenda. Member states have followed. Germany has earmarked up to €5 billion for AI development under its national strategy (Bundesregierung 2023), much of it directed

to Baden-Württemberg and Bavaria. France's €1.5 billion "AI for Humanity" plan is anchored in the Paris region (French Government 2018). Most other governments and private investors across the EU cannot match these commitments at scale. The disparity is starkest in Central and Eastern Europe. Most CEE member states have adopted national AI strategies, but at far smaller scale, more recently, and with a heavier reliance on EU rather than domestic financing. The result is a continent in which AI generation capacity is not just lagging behind global competitors, but increasingly concentrated within Europe's existing innovation cores, with the bulk of CEE regions on the wrong side of the divide. On the whole, however, the European AI workforce remains thin by global standards (Figure 1).

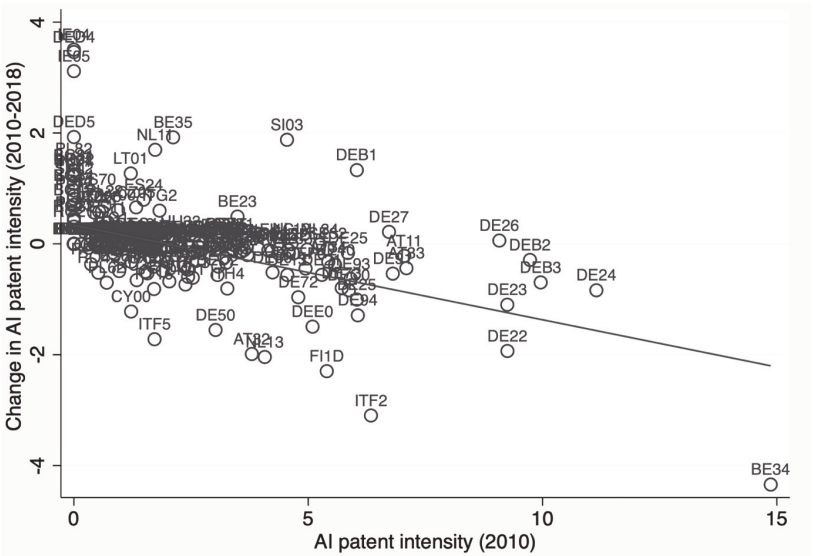
Figure 1: Private AI investment in the EU, UK, China, and the US (2024–2025, $ billion)
Magánszektorbeli AI beruházások az EU-ban, Egyesült Királyságban, Kínában és az Egyesült Államokban (2024–2025, milliárd USD)



Sources: Stanford AI Index 2025 & 2026; authors' estimates from European venture data

Inside Europe, AI generation is concentrated in a small number of regions. Figure 2 maps AI patent intensity in 2010 and its change to 2018 across European regions. Two patterns stand out. AI-related innovation outputs in less advanced regions have grown, but from a very low base. And several initially strong regions, including German strongholds such as Upper Bavaria and Lüneburg, have failed to pull further ahead. Some have even slipped backwards. Europe's AI generation is concentrated, but it is also stagnant relative to its global competitors.

Figure 2: AI patent intensity in 2010 and its change between 2010 and 2018 across European regions
AI szabadalmi intenzitás az európai régiókban 2010-ben, valamint változása 2010 és 2018 között



Notes: Horizontal axis: AI patents per million inhabitants in 2010. Vertical axis: change in AI patents per million inhabitants between 2010 and 2018.
Source: Authors's construction

The literature attributes Europe's underperformance to a familiar cocktail: a shortage of large technology firms, limits on skilled talent, and uneven access to risk capital (Docquier, Rapoport 2012; Bundy 2017; Cooke 2017; Acemoglu, Restrepo 2018; Agrawal, Gans, Goldfarb 2018; Carriço 2018; Aghion, Jones, Jones 2019). Newer scholarship adds two further constraints: the rising cost of computing, and the regulatory uncertainty that has accompanied - and which the AI Act has now partly resolved - the absence of a coherent EU-wide framework (European Union 2024). Overall, AI development in Europe has further to travel than headline investment numbers suggest, and the territorial implications of AI generation for economic and labour-market performance remain, at this stage, an open empirical question.

AI generation as a regional development tool: what we know and what we don't

AI generation should boost local economic performance through localised knowledge spillovers, additional investment, complementary economic activity, and rising demand for skilled labour (Romer 1986; Acemoglu, Restrepo 2018; Haenlein, Kaplan 2019; Lu 2021). The micro-level evidence is broadly supportive.

Brynjolfsson and McAfee (2017) and Korinek (2023) show how machine learning and large language models improve decision-making and create new business models, even where productivity gains are uneven in the short run. Czarnitzki, Fernández and Rammer (2023) document significant AI-related productivity gains at the firm level in Germany, while Furman and Seamans (2019) point to AI's broader macroeconomic potential.

How does local AI generation drive regional performance specifically, as opposed to AI activity elsewhere that a region merely benefits from? Four mechanisms link the two. First, AI patents reflect new products and processes developed by firms in the region, raising local productivity directly (Czarnitzki, Fernández, Rammer 2023; Babina et al. 2024). Second, AI-generating firms attract STEM talent, driving up local skill levels and wages (Buarque et al. 2020; Kemeny, Storper 2020). Third, AI activity generates within-region knowledge spillovers, lifting the productivity of adjacent non-AI firms and supporting regional innovation systems more broadly (Audretsch, Feldman 2004; Storper, Venables 2004). Fourth, AI-generating firms tend to be high-growth and well-capitalised, contributing directly to regional GDP and employment, and attract complementary investments (in computing, in capital, in supplier networks) that further entrench local AI capability. The four mechanisms work in the same direction. Local AI generation should, on average, raise local growth and employment.

At the regional level, the empirical literature is younger, patchier, and tilted overwhelmingly towards one question: where AI emerges rather than what it does once it arrives. Most of this work concerns the antecedents of regional AI activity. Buarque et al. (2020) map the rise of AI clusters across European regions and find them concentrated where knowledge bases run deepest. Xiao and Boschma (2023) show that strong ICT foundations make regions more likely to develop AI capabilities, while Antonietti and Montresor (2021) place AI-related Key Enabling Technologies within familiar regional diversification logics. A second strand foregrounds agency and policy: Gherhes et al. (2022) trace how deliberate system-building underpinned AI's emergence in Montreal. Beyond Europe and North America, Liu et al. (2020) and Yang and Huang (2022) chart, respectively, China's AI manufacturing footprint and the spatial distribution of its AI policy.

What this body of work establishes is a rich account of the conditions under which AI takes root. But there is near silence on what follows. The few attempts to look downstream are suggestive rather than conclusive. Cicerone et al. (2023) find that local AI knowledge supports green-tech specialisation, hinting at spillovers but at one remove from growth or employment outcomes. Capello, Ciappei and Lenzi (2024) tackle the automation–wage inequality nexus across regions, but the lens is automation broadly rather than AI specifically. The first-order question – whether AI reshapes the economic trajectories of the places that host it – remains largely open.

In particular, two gaps in this body of work motivate our analysis. First, almost all of it concerns the determinants of AI generation rather than its consequences for regional development. Second, where consequences are studied, the focus is typically on the average effect, not on distributional effects across the regional growth distribution. We address both gaps. We estimate the average effect of AI generation on regional economic and employment growth across the full EU NUTS2 panel, and we use quantile methods to recover its distributional fingerprint.

The link between AI generation and employment is more contested than the link to growth. One strand of literature emphasises substitution: AI-related technologies will replace humans in routine and even non-routine tasks, raising unemployment (Carriço 2018; Berg, Buffie, Zanna 2018). A more nuanced reading suggests that automation primarily displaces low- and medium-skilled jobs while complementing high-skilled work (Acemoglu, Restrepo 2018; Frank et al. 2019; Acemoglu et al. 2022; Bonfiglioli et al. 2024; Yang, Kim 2024). A third view stresses job creation in AI-adjacent activities: generative AI alone is projected to create 12 million high-skilled positions in the US by 2030 (McKinsey Global Institute 2023), and AI-related activity expands demand throughout upstream and downstream supply chains (Caselli et al. 2025). The aggregate effect, in other words, is not theoretically determined.

On balance, we expect the growth and complementarity effects to outweigh the displacement effects in the European context, where labour markets remain relatively tight and structural change tends to be gradual. We therefore propose:

Hypothesis 1: AI generation is a driver of regional development in Europe, raising both economic and employment growth.

The dark side: AI generation and territorial inequality

But all that glitters is not gold. AI generation's potential to deepen inequality - across people and across places - has not received the attention it deserves (Piketty 2014; Frank et al. 2019; Acemoglu 2021; Rodríguez-Pose, You 2026). Three mechanisms link AI generation to widening territorial divides.

First, AI generation is highly capital-intensive. It requires specialised talent, robust infrastructure, and substantial finance. These are resources that are not available everywhere at scale (Kinkel, Baumgartner, Cherubini 2022; World Economic Forum 2022). Second, AI generation builds on existing knowledge endowments: regions with strong digital, green, or scientific bases can recombine that knowledge to produce AI-related innovation, while regions without such bases cannot (Cicerone et al. 2023). Third, the returns to AI generation accrue most powerfully where complementary assets - skilled labour, dense innovation systems, deep capital markets - are already present (Kemeny, Petralia, Storper 2022; Xiao, Boschma 2023). The pattern is familiar from earlier waves of innovation. Disruptive technologies tend to enrich the regions that need them least.

There is a secondary mechanism worth flagging. AI generation tends to cluster where general patenting does. AI patents follow the same regional hierarchy as innovation more broadly (Buarque et al. 2020; Xiao, Boschma 2023). This is precisely the point. The territorial concentration of AI generation is not anomalous. It is a sharper version of a pattern that has shaped European regional development for decades. What is at stake is whether AI, as a candidate general-purpose technology, will eventually broaden its geography or merely entrench the existing one. Our robustness specifications include a control for non-AI patent intensity to disentangle the two, and the AI coefficient survives.

It is worth distinguishing the inequality mechanisms that flow from AI generation specifically from those associated with AI adoption (Rodríguez-Pose, You 2026). For part of the literature, both can widen regional disparities, but through different channels. AI adoption may widen disparities downstream by displacing routine workers in regions specialised in routine activities (Acemoglu, Restrepo 2020; Bonfiglioli et al. 2024). AI generation widens disparities upstream, through the prerequisites for generating AI: talent, capital, infrastructure, complementary firms – which cluster in a small number of well-resourced hubs that capture the bulk of the rents (Kemeny, Storper 2020). The two reinforce one another: regions that generate AI also tend to adopt early (Corradini, Santini, Vecciolini 2021). Our empirical strategy isolates the generation channel by holding regional-level fixed effects and other innovation activity constant, while still allowing the geographic concentration of AI generation to drive cross-regional differences in returns.

The geography of AI activity remains concentrated in high-tech hubs across both developed and emerging economies (Yang, Huang 2022; Cicerone et al. 2023; McKinsey Global Institute 2023; Xiao, Boschma 2023). France's "AI for Humanity" strategy, launched in 2018 with €1.5 billion in public investment, has flowed disproportionately to the Paris region (French Government 2018), which by early 2023 had absorbed roughly 15% of all European AI venture capital (EY 2024). Microsoft's recent French AI investment is similarly Paris-centred (Microsoft EMEA 2024). Lyon, Marseille, and the rest of the country have seen comparatively little. AI activity in the Paris region alone is estimated to contribute 1–2% of annual GDP growth, a clear illustration of how AI generation can concentrate economic returns in already-dynamic territories. The mirror image is visible in Central and Eastern Europe. Regions outside CEE capital cores generate AI patents at a fraction of the EU average and capture an even smaller share of European AI venture capital. The same agglomeration logic that lifts the Paris region depresses, by complement, the AI prospects of the EU's eastern half.

Labour markets reproduce these inequalities. AI-driven automation primarily threatens routine and lower-skilled work (Autor 2015; Frey, Osborne 2017; Bonfiglioli et al. 2024), exposing regions specialised in such activities to a heightened risk of stagnation. Acemoglu and Johnson (2024) document how AI-

related activity has tended to widen worker inequality. The regional dimension of this effect, which Yang and Kim (2024) document for South Korea, is likely to be at least as strong in Europe, where the gap between high-tech metropoles and structurally weaker regions is already wide and politically charged (Rodríguez-Pose 2018; Rodríguez-Pose, Dijkstra, Poelmann 2024).

Taken together, these mechanisms suggest:

Hypothesis 2: The geographical concentration of AI generation across Europe widens economic and employment disparities between regions.

Methods

Unit of analysis and time frame

We focus on 224 NUTS2 regions in 26 EU member states, the level at which most relevant socio-economic data are harmonised. The period of analysis runs from 2010 to 2019. Three reasons argue for this window.

First, this is the formative phase of AI generation in Europe. AI emerged as a serious policy concern (Cath et al. 2018; Aghion, Jones, Jones 2019) and AI patent filings began their European trajectory during this decade. Understanding the dynamics of this build-up phase is essential for interpreting what came afterwards. Second, the window ends just before the COVID-19 pandemic, which distorted both economic and labour-market dynamics for several years and would contaminate the link between AI generation and regional outcomes. Third, our period predates the 2022 generative-AI breakthrough and that is by design. The post-2022 surge has been built on regional capabilities laid down during the 2010s. Analysing the buildup phase is thus a precondition for understanding the dynamics that produced today's leaders. We, however, acknowledge the obvious limitation. Our results do not capture the post-2022 generative-AI period, and we return to it in the conclusion.

Because the effects of AI generation tend to materialise with a lag, we use a one-year lag for AI patenting variables in the main specification. We acknowledge that one year is short for a deep-impact technology. To gauge whether our results survive longer transmission delays, we re-estimate the models with two-year lags in the robustness checks (Tables D1 and D2). The main findings hold.

The result is a region-year panel that allows us to address two questions: a) whether AI generation has shifted economic and employment growth across European regions and b) whether it has done so evenly across the regional growth distribution.

Variables and data

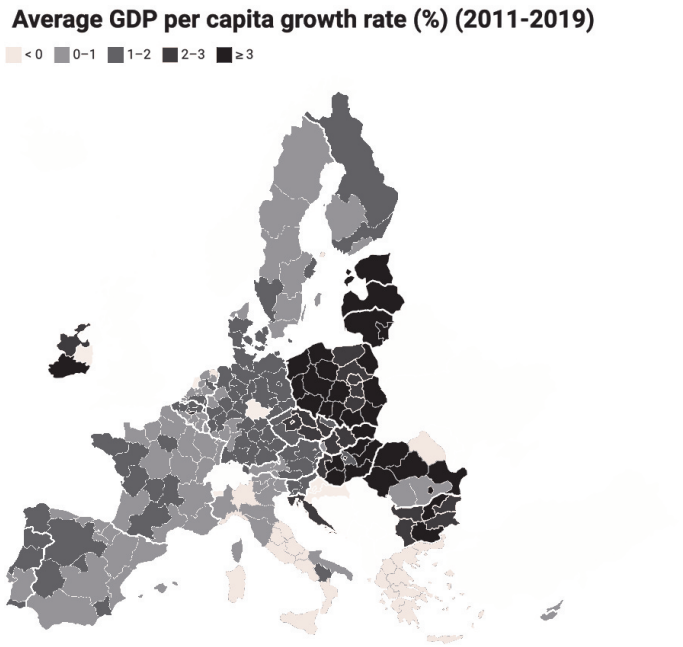
Dependent variables

We measure economic performance through GDP per capita growth (equation 1) and labour-market dynamics through employment growth (equation 2):

$$\text{GDPpc growth} = \ln\frac{\text{Real GDP per capita}_{it}}{\text{Real GDP per capita}_{i(t-1)}} * 100 \quad (1)$$

Figure 3 shows the spatial variation in average GDP per capita growth across European regions during 2011–2019. The contrast is striking. Many regions in Central and Eastern Europe have grown rapidly. Western and Northern regions show more moderate gains and parts of Italy (including high-income Lombardy and Liguria), much of Greece, and north-eastern Romania experienced negative average growth. Europe's growth map is not a story of north-south or east-west, but of cores and peripheries within both.

Figure 3: Average annual GDP per capita growth in European NUTS2 regions (2011–2019, %)
Az egy főre eső GDP átlagos éves növekedése az európai NUTS2 régiókban (2011–2019, %)



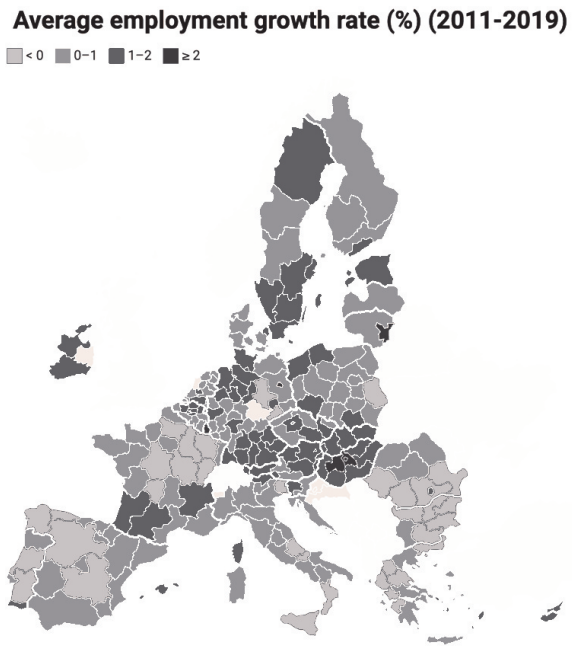
Source: Authors' calculations using Eurostat data

Employment dynamics are captured through the annual change in total employment (ages 15 to 64) within each NUTS2 region (Hartog, Boschma, Sotarauta 2012):

$$\text{Employment growth} = \frac{\text{Total employment}_{it} - \text{Total employment}_{i(t-1)}}{\text{Total employment}_{i(t-1)}} * 100 \qquad (2)$$

Figure 4 shows the corresponding pattern. The variation is more muted than for GDP per capita. Employment declines cluster in regions of substantial outmigration —southern Romania, large parts of Bulgaria (Sofia excepted), Lubelskie in eastern Poland— and in areas of long-running demographic or industrial decline, including parts of Portugal, central and western Spain, central and eastern France, and the former East Germany. Capital regions such as Berlin, Budapest, and Vilnius tell a different story.

Figure 4: Average annual employment growth in European NUTS2 regions (2011–2019, %)
A foglalkoztatás átlagos éves növekedése az európai NUTS2 régiókban (2011–2019, %)



Source: Authors' calculations using Eurostat data

Independent variable of interest

We capture AI generation through AI-related patent intensity. or the number of AI-related patent applications granted by the European Patent Office per million inhabitants. AI patents are identified using the WIPO IPC classification system, summarised in Appendix A1 (Xiao, Boschma, 2023). We draw on patent data from the OECD RegPAT dataset (August 2022 version), which fractionalises patents to inventors' regional addresses. This means that a patent with two inventors located in different regions contributes 0.5 to each region's count. This is the standard treatment in the regional innovation literature (Acs, Anselin, Varga 2002) and avoids attributing all of a multi-region invention to the location of the lead inventor.

Patent data have well-known limitations. They capture only a subset of innovation activity, particularly understating innovation in software-heavy and service domains where patent filings are less prevalent. They vary in their economic significance: a small share of patents accounts for the majority of citation-weighted value (Pakes, Griliches 1980; Hall, Jaffe, Trajtenburg 2005). And they are imperfectly comparable across jurisdictions, as filing incentives and standards differ. Even so, AI-related patents granted by the European Patent Office offer the most consistent cross-regional measure of AI generation available and have been used widely in recent regional AI studies (Buarque et al. 2020; Cicerone et al. 2023; Xiao, Boschma 2023). Appendix A2 reviews how different categories of AI-related innovation can plausibly affect economic and employment outcomes.

Two facts stand out in the geography of AI generation. AI generation is concentrated in a small number of regions, primarily in Germany and the Netherlands. Their AI strength tends to build on a pre-existing ICT base (Doloreux, Turkina 2021). And growth in AI-related innovation has occurred primarily in regions starting from a low base, while several formerly strong German regions have lost ground. The pattern is consistent with Figure 1 and reinforces the broader picture: European AI generation is spatially concentrated and globally underperforming.

Control variables

We control for a standard set of regional development drivers. Physical capital is captured through the share of gross fixed capital formation in nominal GDP (Levine, Renelt 1992). Human capital is measured as the share of the adult population with tertiary education (Krueger, Lindahl 2001). R&D intensity is the share of R&D expenditure in GDP (Griliches 1980). The initial level of regional GDP per capita controls for convergence dynamics. Finally, we include ageing - proxied using the share of residents aged 65 and over - to take demographic pressures into account (Maestas, Mullen, Powell 2023). Variables are log-transformed where

appropriate to reduce the influence of outliers. Data are drawn from Eurostat. Definitions and sources are reported in Appendix B.

Four additional concerns motivate further controls in the robustness checks (Table G1). First, AI generation might simply track general innovation capacity. We therefore add a control for non-AI patent intensity. Second, AI activity may concentrate in regions with deeper ICT and STEM bases. Hence, we add measures of ICT employment and the share of STEM-trained workers. Third, prior AI activity may shape current AI generation through path dependence. We thus add the lagged stock of AI patents. Fourth, regional industrial structure shapes both economic and employment dynamics, meaning that we control for the share of manufacturing and the share of services in total employment. The main results survive these additions.

Models and identification

For economic performance, we estimate equation (3); for employment growth, equation (4):

$$\text{GDPpc growth}_{it} = \alpha_1 * \text{AI}_{it-1} + \alpha_2 * \text{Controls}_{it-1} + \mu_i + \tau_t + \varepsilon_{it} \quad (3)$$

$$\text{Employment growth}_{it} = \alpha_1 * \text{AI}_{it-1} + \alpha_2 * \text{Controls}_{it-1} + \mu_i + \tau_t + \varepsilon_{it} \quad (4)$$

AI denotes AI patent intensity; Controls is the vector of control variables; μ_i and τ_t are region and time fixed-effects respectively, and ε_{it} is the error term. All explanatory variables are lagged by one year. Longer lags are explored in the robustness checks.

Our preferred specification is fixed effects. Fixed effects strip out time-invariant regional characteristics - institutional quality, geography, deep cultural drivers - that almost certainly correlate with both AI generation and regional economic performance. We report random-effects estimates as a benchmark, but we treat them as such. The Hausman test rejects independence of the regional effects from the regressors at conventional levels in both equations, formally identifying the fixed-effects estimator as the appropriate choice (Hausman, Taylor 1981; Cameron, Trivedi 2005). The random-effects coefficients are reported for transparency, not for primary interpretation.

Reverse causality is a real concern. Regions that grow strongly may attract AI investment and talent, just as AI generation may drive growth. We address remaining identification concerns in three ways. First, we strengthen the fixed-effects design by adding region-year interactions in column (3) of Tables 2 and 3, allowing for region-specific time trends. Second, in the robustness checks (Table E1) we include country-by-year fixed effects to absorb macroeconomic shocks affecting groups of regions (Bonfiglioli et al. 2024). Third, we estimate System-GMM dynamic panel models in the appendix (Table F1) to address potential

reverse causality and weak exogeneity. We implement the estimator following Arellano and Bover (1995) and Blundell and Bond (1998): lagged levels of AI patent intensity and the dependent variables from t–2 onwards instrument the differenced equations, while lagged differences instrument the level equations. To prevent instrument proliferation we collapse the instrument matrix and cap lag depth, keeping the number of instruments well below the number of regions (Roodman 2009). The Hansen J test of overidentifying restrictions fails to reject the null of valid instruments, and the Arellano–Bond AR(2) test fails to reject the null of no second-order autocorrelation in the differenced residuals. Standard errors use the Windmeijer (2005) finite-sample correction. None of these checks is a panacea. System-GMM relies on lag exogeneity assumptions that are difficult to verify directly in short panels (Barzotto et al. 2019). A shift-share (Bartik-type) instrumental-variable strategy, leveraging pre-period regional exposure to AI-related technologies combined with EU-level shifts in AI funding, would be a natural complement (Goldsmith-Pinkham, Sorkin, Swift 2020). We discuss it as a future research direction in the conclusion.

To examine the second research question - whether AI generation widens regional disparities - we turn to fixed-effect quantile regression. The translation from H2 to the empirical test is direct. H2 says AI generation raises growth more in regions already at the upper end of the regional growth distribution than at the lower end. That is precisely what quantile regression estimates. The AI coefficient at each quantile of the conditional distribution of regional growth. A coefficient that rises with the quantile is direct evidence of widening disparities. A flat coefficient indicates that AI is distributionally neutral. We use the fixed-effect variant (Machado, Santos Silva 2019) for the same reason we prefer fixed effects in the mean regressions: to absorb time-invariant regional heterogeneity that would otherwise bias the estimates. Tables 4 and C1 and C2 (the latter two in the appendix) report the results.

Descriptive statistics

Table 1 summarises the panel. Across European regions, average GDP per capita growth is 1.25%, ranging from –14.14% to 8.22%. Employment growth averages a more modest 0.69%, with a range from –4.32% to 4.85%. AI patent intensity is generally low but unevenly distributed, peaking at 35.71 patents per million people. Among the controls, physical capital averages 21% of GDP, tertiary education 27%, and R&D intensity 1.6%. Regional GDP per capita varies by an order of magnitude (from €6,800 to €79,000 in PPS) and the share of the population aged 65 or over reaches 53.83% in the oldest region. Europe's regions, in short, differ in almost every dimension that matters.

Table 1: Descriptive statistics
Leíró statisztikák

Variable	*Obs*	*Mean*	*Std. dev*	*Min*	*Max*
GDPpc growth (2011-2019)	2,016	1.25	2.60	-14.14	8.22
Employment growth (2011-2019)	2,016	0.69	1.65	-4.32	4.85
AI (2010-2018)	2,016	2.39	2.62	0.00	35.71
Physical capital (%) (2010-2018)	2,016	20.81	4.51	7.03	69.50
Educational attainment (%) (2010-2018)	2,016	27.23	8.70	9.00	58.40
R&D intensity (%) (2010-2018)	2,016	1.59	1.29	0.06	9.35
GDP per capita (PPS) (2010-2018)	2,016	25,983	10,137	6,800	79,000
Ageing (%) (2010-2018)	2,016	33.40	6.28	15.97	53.83

Source: Authors' construction

Results

AI generation, economic growth, and employment

Tables 2 and 3 report the panel results. Column (1) of each uses random effects with year dummies; column (2) is fixed effects (our preferred specification); column (3) adds region-year interactions to allow for region-specific time trends. We focus on the fixed-effects results in the discussion.

We begin with the variable of interest. The coefficient on AI generation is positive and significant at the 1% level across all specifications and both dependent variables. In the preferred fixed-effects column of Table 2, a one-unit increase in AI patent intensity (one additional AI patent per million inhabitants) is associated with 0.14 percentage points higher annual GDP per capita growth. The effect is meaningful at the regional scale and economically significant given the modest mean AI patent intensity of 2.39 in our sample. Two channels are likely at work. AI generation drives innovation and creative output, sustaining economic expansion. And it allows substitution of low- and medium-skilled labour, supporting productivity (Aghion, Jones, Jones 2019; Czarnitzki, Fernández, Rammer 2023).

Table 2: AI and economic growth
AI és gazdasági növekedés

GDPpc growth	*Random-effect*	*Fixed-effect*	*Fixed-effect*
	(1)	(2)	(3)
AI	0.124***	0.140***	0.117***
	(0.0360)	(0.0159)	(0.0174)
Ln(Physical capital)	-1.191*	-2.956***	-2.978***
	(0.617)	(0.905)	(0.839)
Ln(Educational attainment)	1.572***	2.622***	2.384***
	(0.370)	(0.854)	(0.788)
R&D intensity	0.202**	0.0177	-0.001
	(0.0837)	(0.128)	(0.123)
Ln(GDPpc)	-2.472***	-12.69***	-13.48***
	(0.332)	(2.489)	(2.385)
Ln(Ageing)	-3.087***	16.99***	19.10***
	(0.591)	(3.281)	(3.532)
Constant	34.83***	70.31***	-219.6*
	(4.294)	(26.03)	(126.5)
Region fixed-effects	NO	YES	YES
Year fixed-effects	YES	YES	YES
Region*Year	NO	NO	YES
Observations	224	224	224
N(regions)	2,016	2,016	2,016

*Notes: The Hausman test statistic is significant (chi2 = 344.87***), rejecting the null hypothesis and identifying the fixed-effect specification as preferred. The random-effects column is reported as a benchmark. Robust standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*
Source: Authors' construction

Table 3 tells a similar story for employment. Higher AI patent intensity is associated with higher employment growth across the EU at the 1% level in all three specifications. The fixed-effects coefficient implies a one-unit rise in AI patent intensity is linked to roughly 0.07 percentage points higher annual employment growth. The result cuts against the more catastrophist accounts of automation and employment (Acemoglu, Restrepo 2020). On aggregate, AI generation appears to add jobs, both directly in AI-related activities, and indirectly through complementary sectors and adjacent high-quality positions (Brollo 2024; Bonfiglioli et al. 2024).

Table 3: AI and employment growth
AI és foglalkoztatásnövekedés

AI	0.0521***	0.065***	0.0648***
	(0.0173)	(0.018)	(0.0224)
Ln(Physical capital)	-0.423*	-1.241***	-1.338***
	(0.238)	(0.483)	(0.479)
Ln(Educational attainment)	0.347**	1.002*	1.020*
	(0.147)	(0.581)	(0.555)
R&D intensity	0.0948***	-0.064	-0.0350
	(0.0300)	(0.070)	(0.0655)
Ln(GDPpc)	0.402***	-4.510***	-5.320***
	(0.147)	(1.144)	(1.171)
Ln(Ageing)	-1.573***	8.101***	10.47***
	(0.208)	(2.501)	(2.658)
Constant	1.388	17.88	-217.8**
	(1.611)	(12.49)	(88.60)
Region fixed-effects	NO	YES	YES
Year fixed-effects	YES	YES	YES
Region*Year	NO	NO	YES
Observations	224	224	224
N(regions)	2,016	2,016	2,016

*Notes: The Hausman test statistic is significant (chi2 = 98.73***), rejecting the null hypothesis and identifying the fixed-effect specification as preferred. The random-effects column is reported as a benchmark. Robust standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*
Source: Authors' construction

The control variables behave broadly as expected. Initial GDP per capita is consistently negative and significant, indicating overall convergence across European regions. Physical capital displays the negative sign predicted by Solow (1956), reflecting decreasing returns to capital accumulation. Educational attainment is positive and significant, confirming the established link between human capital and growth (Krueger, Lindahl 2001). R&D intensity is significantly positive in the random-effects benchmark but not in the fixed-effects model. This is a sign that R&D's contribution to growth is captured largely by between-region rather than within-region variation.

So far, so good for Hypothesis 1. AI generation looks like a useful tool for European regional development, at least on an aggregate level.

But where do the gains land?

The aggregate story, however, masks, however, a more uncomfortable distributional one. Table 4 reports fixed-effect quantile regression results for both dependent variables (full estimates in Appendix C).

For GDP per capita growth, the AI coefficient is positive at every quantile, but only significant at the 70th and 80th percentiles. The further up the regional

growth distribution one looks, the larger the coefficient becomes. AI generation is delivering economic gains, but the gains are concentrated in regions that are already growing strongly, typically those with the smart infrastructure, deep talent pools, and dense innovation networks needed to commercialise AI. The implication is that AI generation in its current form is reinforcing the existing centralisation of economic dynamism, rather than offsetting it (Iammarino, Rodríguez-Pose, Storper 2019; Rodríguez-Pose, Dijkstra, Poelmann 2024).

For employment growth, the picture is different. The AI coefficient is positive across all quantiles, but significance clusters in the middle of the distribution, at the 40th, 50th, 60th, and 70th percentiles. AI generation is associated with employment gains in regions of average labour-market performance, rather than only in the leaders or only in the laggards.

The middle-distribution finding deserves a deeper look. Three mechanisms plausibly combine to produce it. At the bottom of the distribution, regions tend to be too thin in skills and infrastructure to translate AI generation into employment expansion: even if AI activity arrives, the absorptive capacity is missing (Yang, Kim 2024). At the top, regions that are already growing strongly may face binding labour-market constraints. AI's automating effects may also bite into employment more strongly where routine work is concentrated and where firms have the scale to substitute capital for labour at speed (Acemoglu, Restrepo 2020; Bonfiglioli et al. 2024). In the middle, both effects are weaker. The complementarity-substitution balance tips toward employment expansion. AI generation is large enough to create new jobs in adjacent activities, while labour markets are loose enough to absorb the new positions without bumping up against scale or skill constraints. The pattern echoes broader findings on the inverted-U relationship between innovation and employment growth (Bessen 2018; Caselli et al. 2025). Whatever displacement AI may cause, in this period it appears to be more than offset by complementary employment in middling regions (Acemoglu, Restrepo 2018).

In summary, the results support Hypothesis 1 in full and Hypothesis 2 only in part. AI generation is good for European growth and employment overall, but its distributional consequences are mixed: regressive in economic terms, more even - and more middle-loaded - in employment terms.

The robustness checks (Tables D1, D2, E1, E2, F1, G1, and G2 in the appendices) reinforce these findings. Table D1 reports Moran's I tests for spatial autocorrelation in regional GDP per capita growth and employment growth. The results indicate statistically significant positive spatial dependence for almost all years in the sample. These findings suggest that regional economic performance exhibits substantial spatial clustering. To account for spatial dependence, Table D2 presents estimates from a spatial autoregressive (SAR) model including both region and time fixed effects. AI remains positively and statistically significantly associated with both GDP per capita growth and employment growth.

Table 4 : Fixed-effect quantile regression: AI and territorial polarisation
Fix hatású kvantilis regresszió: AI és területi polarizáció

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
GDP per capita growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.221	0.054	0.081	0.102	0.123	0.141	0.158*	0.176*	0.195
	(0.157)	(0.184)	(0.144)	(0.117)	(0.098)	(0.090)	(0.092)	(0.104)	(0.124)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employment growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.053	0.056	0.059	0.061*	0.064*	0.067**	0.069*	0.072	0.075
	(0.066)	(0.052)	(0.043)	(0.037)	(0.033)	(0.034)	(0.038)	(0.045)	(0.056)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016
N(regions)	224	224	224	224	224	224	224	224	224

*Notes: Quantile values shown as decimals (0.1 = 10th percentile). Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*
Source: Authors' construction

This finding highlights the importance of spatial spillovers but does not alter the substantive conclusions regarding the effects of AI. Two-year lags preserve the positive average effect on both growth and employment, although the quantile effect on GDP per capita growth weakens. This is a sign that the growth-widening effect of AI may itself be relatively short-lived. Significant employment gains continue to concentrate in regions with healthier labour markets. System-GMM estimates address remaining endogeneity concerns and replicate the main results. Adding country-by-year fixed effects, controls for non-AI patent intensity, ICT employment, the share of STEM-trained workers, and the lagged AI patent stock produces the same overall pattern: AI generation lifts growth and employment on average, while its growth-enhancing effects remain concentrated in higher-quantile regions and its employment effects fade in the same set of robustness specifications.

Conclusion and discussion

This paper has examined the role of AI generation in regional development across the EU. Using data on 224 NUTS2 regions from 2011 to 2019, and a battery of panel-data and quantile estimators, it has asked two questions. Can AI generation drive economic and employment growth in Europe? And can it help close (or will it widen) the territorial inequalities that already plague the continent?

The answers are mixed, but they point in a single direction. On the first question, AI generation is, on aggregate, good for Europe. It raises both economic and employment growth. On the second, the picture is harder. The economic gains from AI generation accrue disproportionately to regions already at the technological frontier; those with the infrastructure, talent, and innovation systems to translate patents into productivity. Regions in the upper deciles of the growth distribution, including parts of Germany and the Netherlands, capture significantly larger growth coefficients than the rest. Employment gains, by contrast, appear more evenly distributed and concentrate in middling regions, supporting a more diversified pattern of employment expansion (Acemoglu, Restrepo 2018; Brollo 2024). AI generation is therefore a partial answer to Europe's regional development problem. It is useful, but not sufficient, and at risk of accentuating rather than narrowing the divides that already trouble the continent.

The findings broadly endorse the idea that AI generation can support European competitiveness and contribute to economic revival. But the endorsement comes with a caveat. The current geography of AI generation is intensely concentrated and the territorial pattern of returns is similarly, if not more, geographically skewed. Pushing AI development without simultaneously broadening its geographical base risks deepening the very inequalities that are already eroding political

support for European integration. Nowhere is this risk more salient than in Central and Eastern Europe, where the rapid economic catch-up that has defined the post-2004 period risks stalling unless innovation capacity, and AI generation in particular, can be rooted across the region rather than confined to a handful of capital areas.

The policy implication is straightforward, even if the politics are not. Europe needs more AI, but it also needs more of its regions to participate in AI generation, not just AI adoption, although that matters too (Babina et al. 2024; Lee 2024; Rodríguez-Pose, You 2026). That means investment in digital infrastructure, skills, and access to AI resources in less developed regions (Maestas, Mullen, Powell 2023). It means a deliberate effort to spread the human and financial capital prerequisites of AI generation more widely than current allocations suggest (French Government 2018; Bundesregierung 2023). The AI Act, as it beds down (European Union 2024), is more likely to govern AI's risks than to redistribute its rewards. The redistributive task remains to be designed. And it means recognising that AI's distributional consequences are themselves an economic problem: a more polarised Europe is, ultimately, a less competitive Europe (European Commission 2024).

Several limitations bound these conclusions. The 2011–2019 window precedes both the generative-AI boom and the COVID-induced reorganisation of European labour markets. The territorial dynamics of generative AI may differ in ways our data cannot speak to: the scale of compute and capital required to train frontier models exceeds anything that dominated our period, which could either further concentrate AI generation or - through more permissive open-weight ecosystems - democratise it. Patent data, though widely used, capture only a slice of AI-related innovation and underweight software-heavy and service-domain activity. The identification strategy relies on fixed-effects and System-GMM specifications that mitigate but do not eliminate endogeneity concerns. A shift-share or natural-experiment instrumental-variable strategy would be a valuable complement (Goldsmith-Pinkham, Sorkin, Swift 2020).

Future research could profitably extend the time horizon to capture the post-2022 generative AI period; deploy complementary measures of AI generation, including investment, skills, and AI workforce shares; pair AI generation with measures of AI adoption to map the joint geography of the two; and explore the policy levers most likely to broaden the territorial base of AI activity in Europe.

Despite these caveats, the broader message is hard to escape. AI generation holds genuine promise as a catalyst for European competitiveness. But promise does not mean that AI generation will deliver in the end. Realising AI's potential without deepening already-deep territorial divides will require more than market dynamics and headline funding announcements. It will require a deliberate, place-sensitive strategy that brings AI generation to the regions that, in its absence, will be left further behind. AI generation, in short, is both a tool of European renewal and a test of European cohesion. Europe will need to pass both.

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Appendix

Appendix A1. WIPO IPC categories for AI

The taxonomy used to identify AI-related patents follows the International Patent Classification (IPC) system as outlined by the World Intellectual Property Organization (WIPO). It distinguishes between AI techniques (e.g. fuzzy logic, deep learning, machine learning, neural networks, probabilistic graphical models, rule learning), AI functional applications (e.g. computer vision, augmented reality, character recognition, image and video segmentation, object tracking, scene understanding, control methods, knowledge representation, machine translation, natural language processing, robotics, and speech-related applications), and AI application fields (e.g. agriculture, banking and finance, e-commerce, enterprise computing, government, document and text processing, education, entertainment, industry and manufacturing, life and medical sciences, military, physical sciences and engineering, security, telecommunications, computer networks, and broadcasting). The full mapping of IPC codes to these categories is available in the OECD RegPAT documentation and in Xiao and Boschma (2023).

Appendix A1: WIPO IPC categories for AI
A WIPO IPC AI kategóriái

AI techniques	*IPC code*	*AI functional applications*	*IPC code*	*AI application fields*	*IPC code*	*AI*	*IPC code*
Fuzzy logic	G06N7/02	Computer vision	G06T7/00, G06K9/00, G06T1/20, G06T3/40, G06T9/00	Agriculture	A01	artific intelligen, computation intelligen, neural network, neuralnetwork,	A61B5/00, A63F13/67, B23K31/00, B25J9/16, B29C65/00,
Deep learning	G06N3/02	Augmented reality	G06T-019/20	Banking and finance	G06Q40/00	bayes network, bayesiannetwork,	B60W30/06, B60W30/10,
Machine learning (General)	G06N3/08, G06N99/00, G06K9/00	Character recognition	G06K9/00	E-commerce	G06Q20/00, G06Q30/00	chatbot, data mining, decision model, deep	B60W30/14, B62D15/02, B64G1/24,
Neural networks	G06N3/02, G06N7/04	Image and video segmentation	G06T7/10, G06T7/215	Enterprise computing	G06Q10/10	learning, deeplearning,	E21B41/00, F02D41/14,
Probabilistic graphical models	G06N7/00	Object tracking	G06T-007/246	Computing in government	G06Q50/26	genetic algorithm, inductive logic	F03D7/04, F16H61/00, G01N29/44,
Rule learning	G06N5/02	Scene understanding and Vision for robotics	G06T7/00	Document management and text processing	G06F17/21	programm, machine learning, machinelearning,	G01N33/00, G01R31/28, G01R31/36, G01S7/41, ,

AI techniques	IPC code	AI functional applications	IPC code	AI application fields	IPC code	AI	IPC code
		Control methods	G05B13/02, G05D1/00	Education	G21, H02, H01M8/04992, H03H17/02	natural language generation, natural language processing,	G06F9/44, G06F11/14, G06F11/22,
		Knowledge representation and reasoning	G06N5/00	Entertainment	A63	reinforcement learning, supervised learning, supervised training,	G06F15/00, G06F17/00, G06F19/00,
		Machine translation	G06F17/28	Industry and manufacturing	G06Q10/06, G06Q10/08, G06Q50/04, G06Q50/28	supervisedlearning, swarm intelligen, swarmintelligen, unsupervised learning,	G06G7/00, G06J1/00, G06K7/14, G06K9/00,
		Natural language processing	G06F17/27	Life and medical sciences	A61, G06F19/24, G06F19/00, G16H50/20	unsupervised training, unsupervisedlearning, semi-supervised	G06N3/00, G06N5/00, G06N7/00,
		Robotics	A61B34/00, B25J9/00	Military	B63G, G01S19/18, B64D7/00, F41, F42	learning, semi-supervised training, semisupervised learning,	G06N99/00, G06T1/20, G06T1/40, G06T3/40,
		Speaker recognition	G10L17/00	Physical sciences and engineering	C, D, E, F01, F03, F05, F07, F09, F11, F13, F15, F17	semisupervised training, semi supervisedlearning, semisupervisedlearning,	G06T7/00, G06T9/00, G08B29/18, G10L13/00,
		Speech processing	G10L25/00, G10L99/00	Security	G06F21/00, A61B5/117, H04W12/00	connectionis, expert system, transfer learning, transferlearning,	G10L15/00, G10L17/00, G10L25/00, G10L99/00,

AI techniques	*IPC code*	*AI functional applications*	*IPC code*	*AI application fields*	*IPC code*	*AI*	*IPC code*
		Speech recognition	G10L15/00	Anomaly detection and surveillance	H04W12/12, G06Q40/00, G08B13/00, G08B31/00	latent semantic analysis, latent dirichlet allocation, multi-agent system, hidden markov model,	G11B20/10, G16H50/20, H01M8/04992, H02H1/00,
		Speech synthesis	G10L13/00	Authentication	G06F21/30, H04W12/06	clustering, combinatorial explosion, comput	H02P21/00, H02P23/00,
				Cryptography	H04L9/00	creativity, deep blue,	H03H17/02,
				Cybersecurity	G06F21/00, H04W12/04, H04W12/08	descriptive model, inductive reasoning, overfitting, predictive	H04L12/24, H04L12/70, H04L12/751,
				Privacy / anonymity	H04W12/02	analytics, predictive	H04L25/02,
				Telecommunications	H04L12/70, H04L25/03, H04L25/02, H04L25/03, H04L12/24, H04L12/751, H04N21/466, H04R25/00	model, target function, test data set, training data set, validation data set, backpropagation, self learning, selflearning, objective function, feature selection, embedding, active learning, regression model, stochastic approach,	H04L25/03, H04N21/466, H04R25/00

AI techniques	*IPC code*	*AI functional applications*	*IPC code*	*AI application fields*	*IPC code*	*AI*	*IPC code*
				Computer networks / Internet	G06F13/00, H04L 29/00	stochastic technique, stochastic method,	G11B20/10, G16H50/20,
				Radio and Television broadcasting	H04H, H04N	stochastic algorithm, probabilist technique,	H01M8/04992, H02H1/00,
				Telephony	H04M	probabilist approach,	H02P21/00,
				Transportation	B60W30/06, B60W30/10, B60W30/12, B60W30/14, B62D15/02, B64G1/24, G06K9/00, G05D1/00	probabilist method, probabilist algorithm, recommend systemrobot, autonomous system, medical imag, healthcare, virtual assist, personali medic, precision medic, genomic screening, drug	H02P23/00, H03H17/02, H04L12/24, H04L12/70, H04L12/751, H04L25/02, H04L25/03, H04N21/466,
				Aerospace / Avionics	B64, F02K	discover, medical diagnos, drug creation, medication	H04R25/00
				Autonomous vehicles	B60W30/06, B60W30/10, B60W30/12, B60W30/14, B62D15/02, G05D1/00	manag, autonomous vehicle, transportation, driverless, smart car, smart cars, smart city, smart grid, automotive, agriculture,	

AI techniques	*IPC code*	*AI functional applications*	*IPC code*	*AI application fields*	*IPC code*	*AI*	*IPC code*
				Autonomous vehicles	B60W30/06, B60W30/10, B60W30/12, B60W30/14, B62D15/02, G05D1/00	irrigation system, fintech, banking, finance, economics, text analysis, speech analysis, hand writing analysis, handwriting analysis,	
				Driver / vehicle recognition	G08G1/017, G08G 1/054	facial analysis, face, text analytic, speech analytic,	
				Transportation / traffic engineering	G08G	hand writing analytic, handwriting analytic, facial analytic, face analytic, text recognition, speech recognition, hand writing recognition, handwriting recognition, facial recognition, face recognition, cybersecurity, predictive analysis, predictive analytic, predictive purchas, marketing analytic, video game	

Source: Authors' construction based on WIPO

Appendix A2. AI generation and economic outcomes — a literature snapshot

AI generation can plausibly affect economic and employment growth through three broad channels. First, machine learning and automated systems improve decision-making and enable new business models, even if their productivity benefits emerge gradually (Brynjolfsson, McAfee 2017; Czarnitzki, Fernández, Rammer 2023). Second, well-established applications such as ChatGPT —and large language models more generally— can automate micro-tasks, raising productivity and supporting longer-term economic gains (Korinek 2023). Third, AI-related innovation expands demand in upstream and downstream supply chains, generating employment in adjacent industries (Brollo 2024; Caselli et al. 2025). The net effect on aggregate growth and employment thus depends on the balance between substitution, complementarity, and the pace at which firms and workers adapt.

Appendix A2: A review for AI impact on macro-development
Áttekintés az AI makroszintű fejlődésre gyakorolt hatásairól

Citations	*Titles*	*AI categories*	*Topics*	*Findings*
Acemoglu, Restrepo (2018)	The race between man and machine: Implications of technology for growth, factor shares, and employment	AI functional application – automatic machine	Economic, employment, productivity growth, inequality	AI and automation increase production efficiency and reduce the cost, driving the productivity growth, but it shifts labour market, causing jobs in middle-skill positions are replaced by robots and machines, which also leads to an economic inequality.
Autor (2015)	Why are there still so many jobs? The history and future of workplace automation	AI functional application – automatic machine	Employment, productivity growth	Automation and robots will not make job loss in the economy, instead change the market structure and create other types of jobs. The replacement by robots create new opportunities can improve productivity, which also in turns yields new jobs.
Berg, Buffie, Zanna (2018)	Should we fear the robot revolution? (The correct answer is yes)	AI functional application – robots	Employment, productivity growth, inequality	Automation led by robots enhances local productivity but deteriorates inequality and deepen unemployment gap.
Brynjolfsson, Mcafee (2017)	Artificial intelligence, for real.	AI technique – machine learning / robotics	Economic; employment; productivity growth	AI untapped economic potentials are existing, and machine learning system improves decision-making and the creation of new business model, yielding a position influence on job market, but it cannot have an immediate impact on productivity.

Citations	*Titles*	*AI categories*	*Topics*	*Findings*
Capello, Ciappei, Lenzi (2024)	Unveiling the automation—wage inequality nexus within and across regions.	AI functional application – robots	Inequality	While automation might increase productivity and incomes in some high-skill industries, it tends to replace jobs previously performed by low- and medium-skill workers, deepening wage gaps. Only high-tech regions with high-level technological infrastructure get more returns from automation.
Caselli et al., (2025)	What workers and robots do: An activity-based analysis of the impact of robotization on changes in local employment.	AI functional application – robots	Employment, productivity growth	AI-powered robots are changing the labour market and helping human labour improve productivity. Robot-human collaboration can be applied in different sectors in the future.
Furman, Seamans (2019)	AI and the Economy	AI functional application – robots	Employment, productivity growth, inequality	AI and automation create jobs in high-skilled position, leading to job polarization. The impact from AI and robotics on productivity takes long time given the needed investment, workforce, and infrastructure.
Korinek (2023)	Generative AI for economic research: Use cases and implications for economists.	AI application – ChatGPT (large language models)	Economic profits; productivity	Case studies explain how generative AI automate micro-task to improve productivity and long-term profits.
Lavallin, Downs (2021)	Machine learning in geography–Past, present, and future.	AI technique – machine learning	Spatial geography	As one of the main technologies of artificial intelligence, machine learning's development history, current widespread application, and future further development are worthy of attention.

Citations	*Titles*	*AI categories*	*Topics*	*Findings*
Lu (2021)	The impact of artificial intelligence on economic growth and welfare	AI applications in different sectors	Economic, employment, productivity growth, inequality	AI technologies automate complicated tasks and then improve production process, positively influencing economic growth. AI knowledge spillovers across different sectors improve labour productivity and create more jobs. However, AI adoption exacerbates economic inequality.
Piketty (2014)	Capital in the Twenty-First Century	AI functional application – automation; robots	Economic growth, inequality	Robots replace human working but exacerbate inequality across regions.

Source: Authors' construction

Appendix B. Variable measurements and data sources

Appendix B: Variable measurements and data sources
Változók és adatforrások

Variables	*Measures*	*Sources*
GDPpc growth (%)	ln(Real GDP per capita$_{it}$)–ln(Real GDP per capita$_{it-1}$)*100	Eurostat
Employment growth (%)	(Total employment$_{it}$-Total employment$_{it-1}$) / Total employment$_{it-1}$*100	Eurostat
AI	The number of AI patent applications / total population (million individuals)	OECD RegPAT
Physical capital (%)	Natural logarithm of the share of gross fixed capital formation in nominal GDP (*100)	Eurostat
Educational attainment (%)	Natural logarithm of the proportion of the higher education (tertiary) population to the total population aged 25-64 (*100)	Eurostat
R&D intensity (%)	The share of R&D expenditure to GDP	Eurostat
GDP per capita	Natural logarithm of GDP per capita in PPS	Eurostat
Ageing (%)	Natural logarithm of the proportion of the elderly population aged 65 and above in the total population (*100)	Eurostat

Source: Authors' construction

Appendix C. Quantile regression: AI and territorial polarisation

Table C1: Quantile regression: GDP per capita growth
Kvantilis regresszió: az egy főre eső GDP növekedése

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP per capita growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.221	0.054	0.081	0.102	0.123	0.141	0.158*	0.176*	0.195
	(0.157)	(0.184)	(0.144)	(0.117)	(0.098)	(0.090)	(0.092)	(0.104)	(0.124)
Physical capital	-2.808**	-3.117**	-3.066***	-3.027***	-2.988***	-2.956***	-2.924***	-2.890***	-2.854***
	(1.137)	(1.325)	(1.038)	(0.847)	(0.706)	(0.648)	(0.663)	(0.749)	(0.896)
Educational attainment	2.584**	2.663**	2.650**	2.640***	2.630***	2.622***	2.614***	2.605***	2.596***
	(1.157)	(1.348)	(1.056)	(0.861)	(0.718)	(0.660)	(0.674)	(0.761)	(0.911)
R&D intensity	-0.008	0.046	0.037	0.030	0.023	0.018	0.012	0.006	0.000
	(0.166)	(0.193)	(0.151)	(0.123)	(0.103)	(0.094)	(0.097)	(0.109)	(0.131)
GDPpc	-9.801***	-15.813***	-14.823***	-14.065***	-13.313***	-12.681***	-12.055***	-11.399***	-10.704***
	(2.840)	(3.308)	(2.592)	(2.117)	(1.766)	(1.622)	(1.657)	(1.871)	(2.238)
Ageing	13.370***	20.896***	19.657***	18.708***	17.767***	16.975***	16.192***	15.370***	14.501***
	(4.363)	(5.084)	(3.982)	(3.251)	(2.712)	(2.491)	(2.545)	(2.874)	(3.438)
Observations	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016
N(regions)	224	224	224	224	224	224	224	224	224
Region fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Source: Authors' construction

Table C2: Quantile regression: Employment growth
Kvantilis regresszió: a foglalkoztatás növekedése

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employment growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.053	0.056	0.059	0.061*	0.064*	0.067**	0.069*	0.072	0.075
	(0.066)	(0.052)	(0.043)	(0.037)	(0.033)	(0.034)	(0.038)	(0.045)	(0.056)
Physical capital	-1.074	-1.123*	-1.162**	-1.195**	-1.236***	-1.278***	-1.309***	-1.343**	-1.386*
	(0.841)	(0.669)	(0.552)	(0.473)	(0.421)	(0.437)	(0.491)	(0.580)	(0.715)
Educational attainment	0.140	0.395	0.594	0.766	0.976**	1.191***	1.353***	1.531***	1.750**
	(0.858)	(0.682)	(0.563)	(0.483)	(0.430)	(0.446)	(0.501)	(0.591)	(0.729)
R&D intensity	-0.156	-0.129	-0.108	-0.089	-0.067	-0.044	-0.027	-0.008	0.015
	(0.122)	(0.097)	(0.080)	(0.069)	(0.061)	(0.064)	(0.071)	(0.084)	(0.104)
GDPpc	-3.802**	-4.012***	-4.175***	-4.316***	-4.489***	-4.665***	-4.798***	-4.944***	-5.123***
	(1.867)	(1.485)	(1.225)	(1.050)	(0.935)	(0.969)	(1.089)	(1.286)	(1.586)
Ageing	7.047*	7.359**	7.602***	7.812***	8.070***	8.332***	8.531***	8.748***	9.015***
	(3.752)	(2.984)	(2.462)	(2.109)	(1.878)	(1.947)	(2.189)	(2.585)	(3.187)
Observations	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016
N(regions)	224	224	224	224	224	224	224	224	224
Region fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Source: Authors' construction

Appendix D. Robustness checks: spatial regression results

Table D1: Moran's I tests for spatial autocorrelation
Térbeli autokorreláció vizsgálata Moran-féle I-statisztikával

Dependent variable	*Year*	*Moran's I*	*Expected I*	*p-value*
GDPpc growth	2010	0.441	-0.004	0.000
GDPpc growth	2011	0.238	-0.004	0.000
GDPpc growth	2012	0.114	-0.004	0.007
GDPpc growth	2013	0.008	-0.004	0.394
GDPpc growth	2014	0.282	-0.004	0.000
GDPpc growth	2015	0.157	-0.004	0.000
GDPpc growth	2016	0.330	-0.004	0.000
GDPpc growth	2017	0.398	-0.004	0.000
GDPpc growth	2018	0.142	-0.004	0.001
Employment growth	2010	0.557	-0.004	0.000
Employment growth	2011	0.520	-0.004	0.000
Employment growth	2012	0.447	-0.004	0.000
Employment growth	2013	0.436	-0.004	0.000
Employment growth	2014	0.525	-0.004	0.000
Employment growth	2015	0.405	-0.004	0.000
Employment growth	2016	0.342	-0.004	0.000
Employment growth	2017	0.524	-0.004	0.000
Employment growth	2018	0.408	-0.004	0.000

Notes: The spatial weights matrix is row-standardized queen contiguity.
Source: Authors' construction

Table D2: AI and economic growth and employment growth: spatial autoregressive model
AI, gazdasági növekedés és foglalkoztatásbővülés: térbeli autoregressziós modell

	GDPpc growth	*Employment growth*
AI	0.107***	0.042***
	(0.027)	(0.018)
Physical capital	-1.557***	-0.363
	(0,374)	(0.248)
Educational attainment	1.471***	0.339
	(0.555)	(0.370)
R&D intensity	0.029	-0.041
	(0.096)	(0.064)
GDPpc	-10.114***	-2.562***
	(0.816)	(0.531)
Aging	13.404***	6.474**
	(1.906)	(1.271)
ρ	0.383***	0.569***
	(0.024)	(0.020)
Observations	2016	2016
N(regions)	224	224
Region fixed-effects	YES	YES
Time fixed-effects	YES	YES

*Notes: ρ denotes the spatial autoregressive parameter. Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Source: Authors' construction

Appendix E. Robustness checks: more lags

Table E1: The impact of AI on economic growth and employment growth

AI, gazdasági növekedés és foglalkoztatásbővülés

	GDPpc growth			*Employment growth*		
Two-year lags	*Random effect*	*Fixed effect*	*Fixed effect*	*Random effect*	*Fixed effect*	*Fixed effect*
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.0629*	0.0758***	0.225***	0.0467***	0.0599***	0.118***
	(0.0333)	(0.0247)	(0.0616)	(0.0122)	(0.0158)	(0.0148)
Ln(Physical capital)	0.124	-1.930**	-5.319***	-0.901***	-2.561***	-3.778***
	(0.535)	(0.760)	(0.991)	(0.213)	(0.470)	(0.522)
Ln(Educational attainment)	1.200***	0.0377	0.937	0.460***	0.281	0.654
	(0.294)	(0.708)	(1.092)	(0.146)	(0.447)	(0.523)
R&D intensity	0.102	-0.137	0.201	0.101***	-0.114**	0.0199
	(0.0753)	(0.105)	(0.161)	(0.0291)	(0.0559)	(0.0643)
Ln(GDPpc)	-1.897***	-8.317***	-17.11***	0.143	-6.864***	-10.28***
	(0.300)	(1.308)	(2.024)	(0.159)	(1.200)	(1.668)
Ln(Ageing)	-3.346***	13.89***	27.62***	-1.714***	7.319***	13.80***
	(0.621)	(3.042)	(4.724)	(0.207)	(2.267)	(2.713)
Constant	25.14***	40.38***	861.3***	5.250***	50.28***	130.1
	(3.794)	(12.77)	(170.7)	(1.695)	(12.89)	(90.76)
Region fixed-effects	NO	YES	YES	NO	YES	YES
Year fixed-effects	YES	YES	YES	YES	YES	YES
Region*Year	NO	NO	YES	NO	NO	YES
Observations	2,016	2,016	2,016	2,016	2,016	2,016
N(regions)	224	224	224	224	224	224

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.*

Source: Authors' construction

Table E2: Fixed-effect quantile regression: AI and territorial polarisation
Fix hatású kvantilis regresszió: AI és területi polarizáció

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP per capita growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.192	0.152	0.124	0.102	0.076	0.054	0.032	0.005	-0.028
	(5.401)	(4.213)	(3.373)	(2.719)	(1.973)	(1.300)	(0.674)	(0.212)	(1.139)
Ln(Physical capital)	-2.218	-2.118	-2.048	-1.993	-1.931	-1.875	-1.822	-1.753	-1.672
	(48.907)	(38.144)	(30.545)	(24.623)	(17.864)	(11.773)	(6.105)	(1.921)	(10.315)
Ln(Educational attainment)	0.885	0.593	0.386	0.226	0.042	-0.124	-0.280	-0.481	-0.719
	(49.050)	(38.256)	(30.635)	(24.695)	(17.916)	(11.808)	(6.123)	(1.927)	(10.345)
R&D intensity	-0.241	-0.205	-0.180	-0.160	-0.138	-0.117	-0.098	-0.073	-0.044
	(7.793)	(6.078)	(4.867)	(3.924)	(2.847)	(1.876)	(0.973)	(0.306)	(1.644)
Ln(GDPpc)	-0.844	-3.421	-5.241	-6.660	-8.281	-9.744	-11.115	-12.894*	-14.996
	(199.007)	(155.212)	(124.292)	(100.192)	(72.690)	(47.907)	(24.844)	(7.828)	(41.974)
Ln(Ageing)	19.730	17.716	16.294	15.185	13.918	12.774	11.702	10.312	8.669
	(200.922)	(156.706)	(125.488)	(101.156)	(73.389)	(48.368)	(25.081)	(7.894)	(42.376)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employment growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	-0.001	0.018	0.033	0.046	0.059*	0.072**	0.084**	0.099**	0.115*
	(0.071)	(0.055)	(0.045)	(0.038)	(0.035)	(0.036)	(0.041)	(0.049)	(0.061)
Ln(Physical capital)	-3.356***	-3.103***	-2.911***	-2.739***	-2.576***	-2.408***	-2.243***	-2.058***	-1.848**
	(0.879)	(0.687)	(0.561)	(0.477)	(0.437)	(0.447)	(0.505)	(0.610)	(0.758)
Ln(Educational attainment)	-0.095	0.024	0.115	0.197	0.274	0.354	0.432	0.520	0.619
	(0.862)	(0.674)	(0.550)	(0.468)	(0.428)	(0.438)	(0.495)	(0.598)	(0.744)
R&D intensity	-0.097	-0.102	-0.107	-0.110*	-0.114**	-0.117**	-0.121*	-0.125	-0.129
	(0.111)	(0.087)	(0.071)	(0.060)	(0.055)	(0.056)	(0.064)	(0.077)	(0.096)
Ln(GDPpc)	-5.898***	-6.205***	-6.438***	-6.647***	-6.845***	-7.049***	-7.250***	-7.475***	-7.731***
	(1.961)	(1.533)	(1.252)	(1.065)	(0.975)	(0.998)	(1.127)	(1.361)	(1.692)
Ln(Ageing)	7.684*	7.568**	7.480***	7.401***	7.327***	7.249***	7.174***	7.089***	6.992**
	(3.947)	(3.084)	(2.520)	(2.142)	(1.961)	(2.007)	(2.268)	(2.740)	(3.405)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016	2,016
N(regions)	224	224	224	224	224	224	224	224	224

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Source: Authors' construction

Appendix F. Robustness checks: Endogeneity issues

Table F1: System-GMM: AI and economic growth and employment growth
Rendszerszintű GMM: AI, gazdasági növekedés és foglalkoztatásbővülés

	GDPpc growth	*Employment growth*
	(1)	(2)
AI	0.0357***	0.0428**
	(0.0137)	(0.0191)
Ln(Physical capital)	-0.765	-1.866*
	(0.838)	(1.124)
Ln(Educational attainment)	0.461	3.762
	(1.128)	(5.372)
R&D intensity	0.0916	-0.0416
	(0.110)	(0.327)
Ln(GDPpc)	-1.081*	-1.106
	(0.640)	(2.638)
Ln(Ageing)	-4.536	-0.557
	(3.397)	(3.347)
L1.GDPpc growth/Employment growth	0.341***	0.216
	(0.126)	(0.236)
N(IVs)	47	23
AR (1)	-4.22***	-2.64***
AR (2)	0.8	2.33*
Hansen test	36.75	4.54
Region fixed-effects	NO	YES
Year fixed-effects	YES	YES
Region*Year	NO	NO
Observations	224	224
N(regions)	1,792	1,792

*Notes: In column 1, two endogenous variables including AI and R&D intensity are lagged by one year, the instrumental variables are physical capital and GDP per capita, both lagged by one year. In column 2, only AI is treated as endogenous and is lagged by two years, the instrumental variables include one-year lagged physical capital and GDPpc as well. Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01. Source: Authors' construction*

Appendix G. Robustness checks: more controls

Table G1: AI and economic growth and employment growth
AI, gazdasági növekedés és foglalkoztatásbővülés

	GDPpc growth			*Employment growth*		
	Random-effect	*Fixed-effect*	*Fixed-effect*	*Random-effect*	*Fixed-effect*	*Fixed-effect*
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.188***	0.137*	0.136*	0.0758***	0.120**	0.147**
	(0.0511)	(0.0781)	(0.0824)	(0.0169)	(0.0552)	(0.0585)
Ln(Physical capital)	-0.865	-2.718***	-2.856***	-0.391*	-0.920**	-1.052**
	(0.568)	(0.776)	(0.749)	(0.233)	(0.459)	(0.469)
Ln(Educational attainment)	0.897**	1.664*	1.653**	0.0317	0.0975	0.240
	(0.407)	(0.850)	(0.780)	(0.169)	(0.586)	(0.572)
R&D intensity	0.0736	0.0474	0.0327	0.0378	-0.0398	-0.0130
	(0.0813)	(0.124)	(0.120)	(0.0285)	(0.0671)	(0.0642)
Ln(GDPpc)	-2.514***	-11.11***	-12.43***	0.235	-4.218***	-5.343***
	(0.466)	(2.360)	(2.371)	(0.230)	(1.104)	(1.182)
Ln(Ageing)	-1.971***	16.44***	19.56***	-1.373***	8.036***	11.06***
	(0.503)	(3.033)	(3.370)	(0.229)	(2.426)	(2.586)
High-tech rate	33.40***	29.24**	17.46	13.50***	20.34**	14.69
	(7.367)	(14.61)	(15.74)	(3.811)	(9.636)	(9.898)

	GDPpc growth			*Employment growth*		
	Random-effect	*Fixed-effect*	*Fixed-effect*	*Random-effect*	*Fixed-effect*	*Fixed-effect*
	(1)	(2)	(3)	(4)	(5)	(6)
EQI	-0.214	-1.564***	-1.425***	0.0350	-1.187***	-1.087***
	(0.189)	(0.335)	(0.354)	(0.0604)	(0.296)	(0.300)
Ln(population density)	-0.0922	-0.966***	-1.139***	-0.0370	-0.0326	-0.0640
	(0.0943)	(0.226)	(0.146)	(0.0436)	(0.130)	(0.106)
Constant	32.09***	62.80**	-190.3	3.087	16.59	-231.3***
	(5.667)	(24.34)	(115.8)	(2.126)	(12.395)	(86.191)
Region fixed-effects	NO	YES	YES	NO	YES	YES
Year fixed-effects	YES	YES	YES	YES	YES	YES
Region*Year	NO	NO	YES	NO	NO	YES
Observations	1,932	1,932	1,932	1,932	1,932	1,932
N(regions)	215	215	215	215	215	215

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.*
Source: Authors' construction

Table G2: Fixed-effect quantile regression: AI and territorial polarisation
Fix hatású kvantilis regresszió: AI és területi polarizáció

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP per capita growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.049	0.076	0.097	0.118	0.139*	0.157**	0.175**	0.195*	0.221*
	(0.145)	(0.116)	(0.095)	(0.080)	(0.073)	(0.075)	(0.084)	(0.100)	(0.128)
Ln(Physical capital)	-2.755**	-2.743***	-2.734***	-2.726***	-2.717***	-2.710***	-2.702***	-2.694***	-2.683**
	(1.212)	(0.966)	(0.793)	(0.669)	(0.609)	(0.626)	(0.704)	(0.837)	(1.065)
Ln(Educational attainment)	1.631	1.641	1.649*	1.657**	1.665**	1.672**	1.678**	1.686*	1.696
	(1.308)	(1.042)	(0.856)	(0.722)	(0.657)	(0.675)	(0.760)	(0.903)	(1.149)
R&D intensity	0.039	0.041	0.043	0.045	0.048	0.049	0.051	0.053	0.056
	(0.182)	(0.145)	(0.119)	(0.100)	(0.091)	(0.094)	(0.106)	(0.126)	(0.160)
Ln(GDPpc)	-13.774***	-12.967***	-12.315***	-11.694***	-11.065***	-10.526***	-9.968***	-9.373***	-8.565***
	(3.287)	(2.619)	(2.152)	(1.816)	(1.655)	(1.699)	(1.911)	(2.270)	(2.888)
Ln(Ageing)	20.290***	19.126***	18.184***	17.287***	16.379***	15.600***	14.794***	13.936***	12.768***
	(4.756)	(3.790)	(3.114)	(2.628)	(2.394)	(2.458)	(2.765)	(3.285)	(4.179)
High-tech rate	20.183	22.920	25.133	27.242*	29.377**	31.207**	33.100**	35.118**	37.863*
	(25.414)	(20.251)	(16.632)	(14.030)	(12.775)	(13.120)	(14.767)	(17.552)	(22.330)
EQI	-1.879***	-1.784***	-1.707***	-1.633***	-1.559***	-1.496***	-1.430***	-1.359***	-1.264***
	(0.543)	(0.433)	(0.356)	(0.300)	(0.273)	(0.280)	(0.316)	(0.375)	(0.477)
Ln(population density)	-0.563	-0.685	-0.783	-0.877**	-0.972***	-1.054***	-1.138***	-1.228**	-1.350**
	(0.729)	(0.581)	(0.477)	(0.402)	(0.367)	(0.376)	(0.424)	(0.503)	(0.640)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employment growth	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
AI	0.133	0.129	0.126	0.124	0.121	0.117	0.115	0.112	0.109
	(0.274)	(0.110)	(0.092)	(0.200)	(0.331)	(0.481)	(0.596)	(0.718)	(0.880)
Ln(Physical capital)	-0.745	-0.797	-0.838	-0.874	-0.913	-0.957	-0.990	-1.025	-1.072
	(2.439)	(0.983)	(0.814)	(1.780)	(2.945)	(4.276)	(5.301)	(6.387)	(7.826)
Ln(Educational attainment)	-0.401	-0.254	-0.137	-0.031	0.080	0.204	0.299	0.399	0.532
	(2.502)	(1.008)	(0.835)	(1.826)	(3.021)	(4.387)	(5.438)	(6.553)	(8.029)
R&D intensity	-0.118	-0.095	-0.077	-0.060	-0.043	-0.023	-0.008	0.008	0.029
	(0.323)	(0.130)	(0.108)	(0.236)	(0.390)	(0.566)	(0.702)	(0.846)	(1.036)
Ln(GDPpc)	-3.456	-3.680*	-3.859**	-4.021	-4.191	-4.381	-4.526	-4.679	-4.882
	(5.331)	(2.148)	(1.780)	(3.890)	(6.436)	(9.347)	(11.586)	(13.961)	(17.107)
Ln(Ageing)	6.889	7.228*	7.497**	7.739	7.995	8.281	8.500	8.731	9.036
	(10.581)	(4.263)	(3.532)	(7.722)	(12.776)	(18.552)	(22.998)	(27.712)	(33.955)
High-tech rate	14.059	15.913	17.388	18.716	20.118	21.685	22.881	24.147	25.819
	(49.412)	(19.911)	(16.497)	(36.062)	(59.662)	(86.638)	(107.399)	(129.414)	(158.570)
EQI	-1.224	-1.213**	-1.204***	-1.197	-1.189	-1.180	-1.173	-1.165	-1.156
	(1.272)	(0.513)	(0.425)	(0.928)	(1.536)	(2.230)	(2.765)	(3.331)	(4.082)
Ln(population density)	0.487	0.334	0.212	0.102	-0.014	-0.144	-0.243	-0.347	-0.486
	(1.421)	(0.573)	(0.475)	(1.037)	(1.715)	(2.491)	(3.088)	(3.721)	(4.559)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time fixed-effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,932	1,932	1,932	1,932	1,932	1,932	1,932	1,932	1,932
N(regions)	215	215	215	215	215	215	215	215	215

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Source: Authors' construction

Appendix H. Robustness checks: country by year fixed effect

Table H1: AI and economic growth and employment growth
AI, gazdasági növekedés és foglalkoztatásbővülés

	GDPpc growth	*Employment growth*
AI	0.140***	0.065***
	(0.016)	(0.019)
Physical capital	-2.948***	-1.258***
	(0.905)	(0.482)
Educational attainment	2.599***	1.048*
	(0.849)	(0.597)
R&D intensity	0.019	-0.066
	(0.128)	(0.070)
GDPpc	-12.683***	-4.524***
	(2.497)	(1.146)
Aging	16.673***	8.706***
	(3.594)	(2.739)
Country*year	0.001	-0.002
	(0.003)	(0.002)
Observations	2,016	2,016
N(regions)	224	224
Region fixed-effects	YES	YES
Time fixed-effects	YES	YES

*Notes: Robust standard errors in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01*
Source: Authors' construction