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Artificial Intelligence and the Clustering of Human Capital: The Risks for Europe

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EXECUTIVE SUMMARY

• Europe trails the global frontier of productivity growth and the region's trend is sluggish.

• Much prospective economic growth for Europe is likely to come from AI and its adoption by European firms which is projected to shoot up the productivity trend.

• For such AI-generated growth to work, high levels of human capital need to be available for firms, in particular Science, Technology, Engineering, and Mathematics (STEM) graduates.

• However, much of this human capital for AI is leaving Europe and the region experiences a net outflow when it comes to the skills required to make AI work.

• Moreover, the spread of both human capital and AI is very uneven within Europe, with some in the West spearheading whilst others in the East are trailing.

• This paper shows that those regions in Europe that successfully have invested in human capital in the past explain more than one-third of AI adoption by their firms a decade later.

• Furthermore, this persistent trend is driven by the most human capital-intense firms as they explain more than 50 percent of the observed adoption of AI across Europe.

• The clustering of human capital is very persistent over time and those that lag in human capital now will weigh down Europe's ability in generating AI-related growth in the future.

• This will likely have long-lasting effects for Europe as a whole, defining its capacity to catch up to the global frontier or amplifying the region's slow-moving growth and productivity trend.

• Policy makers who are serious about creating growth in the future on the back of AI should therefore invest in human capital now, or else Europe will further fall behind.

1. INTRODUCTION

Will Artificial Intelligence (AI) be a game-changer for future economic growth? It could certainly have a very strong impact on the economy – also in Europe. But for European economies to get a substantial boost from AI, they need to reverse the trend of a growing distance to the AI frontier and become far more attractive for AI human capital.

AI is no different from other major technological developments in history. New technology will reshape the success of countries and regions, and new technology will especially impact economies at different times. A country that starts out as a laggard can catch-up on the developments in the frontier economies. However, that process will take time to be completed – and, unfortunately, that period can be very long.

History is an abundant source of examples of long and technological catch-up cycles. For instance, economic analysis of the introduction of electricity as a breakthrough technology in Switzerland in the 19th century shows a stubborn persistence over time in the regional dispersion of innovation and eventually growth.[1] Regions in Switzerland that were quick to invest in the adoption of electricity grew richer faster than those regions who were slower to roll out electricity. Obviously, the slower regions have caught up on the quicker regions in terms of electricity access, but the difference in regional output generated by earlier electricity adoption have persisted – not fully but substantially. The key factor making these differences persistent over time is human capital.

Regions or countries that are at the frontier of technological change often get a head start also in the development of human capital.[2] They also attract the type of human capital that is high-skilled and good at working with and diffusing the new technology. Often, they attract human capital from other regions and economies that want to be at the central places of new and path-breaking technological change – leading to a larger pattern of clustering. In essence, human capital flock to regions where other human capital is already located.

Countries that are behind or catching up often develop a big handicap: its schools and universities can still educate the human capital that is needed, but parts of it will leave for work in the regions where human capital agglomerate and have a higher return. Ultimately, this hurts their growth prospects and prolong the productivity gap.

Is it likely that AI development and adoption will follow the same historic pattern? This paper outlines where and how AI adoption takes place in Europe, and how these two factors are linked to the accumulation of human capital. Europe is a diverse economic and technological region – also in matters of AI-related human capital. We show that current human capital trends will likely have a long-lasting impact on who will be successful in using AI in the future – both within the EU and when the EU is compared to the global AI frontier, namely the U.S.

1 Brey (2021).
2 Acemoglu (1998).

Specifically, those regions in Europe that successfully have invested in human capital in the past explain more than one-third of AI adoption by their firms a decade later. Therefore, the early adoption of AI technologies, using the supply of high-skilled human capital, explains to a large extent the long-run success in reaping the benefits of this technology. Especially high-skill firms play a crucial role as this persistent trend is driven by the most human capital-intense firms given that, as this paper also shows, they explain more than 50 percent of the observed adoption of AI across Europe.

This puts Europe at a serious risk: with current human capital unequally spread across EU countries, and between the EU and the global frontier, Europe's AI uptake will likely be slower than at the frontier. Indeed, current trends in human capital will probably make many EU members to fall behind even more in AI-generated long-run economic growth.

The policy message of our outcome is clear: if European leaders are serious about reaping bigger growth benefits from AI developments, it needs to focus on policies that attracts and builds up more AI human capital.

2. EUROPE'S HUMAN CAPITAL PROBLEM FOR AI

AI human capital in Europe is growing, but the region still struggles to develop a skilled workforce that could create and work with AI technologies.

Figure 1 (left-panel) shows that Europe's trend in human capital is approaching the one of the U.S., which is generally considered as the global frontier when it comes to skills and growth. Similarly, compared to the U.S. and several other leading economies such as Switzerland, Korea and Australia, Europe produces a high level of STEM graduates, skills related to natural sciences, mathematics, ICT, and engineering (all subject fields that are crucial for new technologies like AI). Only Korea appears to bypass Europe with a share of almost 30 percent in total graduates of these skills, with Europe having a corresponding share of 25 percent, whereas the U.S. having a much lower share of almost 19 percent.[3]

However, something is missing in this portrait of Europe's human capital. One indication is Europe's level of Total Factor Productivity (TFP), the key factor for creating long-term economic growth resulting from new technologies. The trend has been regressing for almost 20 years when compared to the U.S. Productivity levels are of course determined by many factors, but human capital and how effective it works with new technologies are together nonetheless a major one.

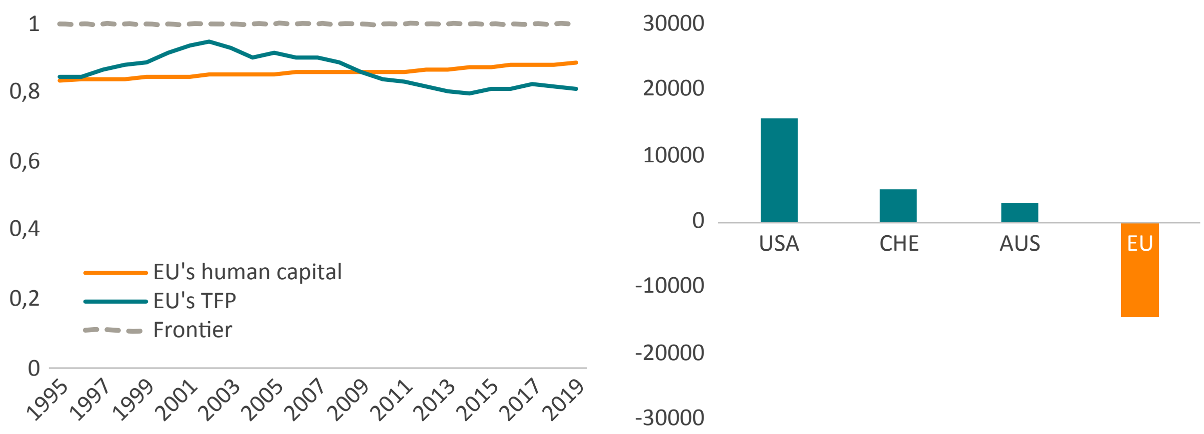
Figure 1 (right panel) points to one explanation: STEM human capital is also leaving Europe. Importantly, even if Europe fosters a reasonable share of STEM graduates to develop AI, the region has difficulties retaining them. Recent work by the OECD shows the EU suffers from a net outflow of scientists needed to develop successful new technologies, resulting in a large gap in

[3] OECD (2022). Recent studies have shown that demand for AI-related skills reflected in online vacancies are growing in Europe and other OECD countries, as well as the US, even though the share of online job postings requiring specific AI-related skills are still small (Borgonovi et al., 2023; Restrepo et al, 2021).

accumulating AI skills employed in businesses between the EU and the frontier (U.S.) or other countries that are otherwise closer to the global frontier such as Switzerland.

The adverse development of human capital flows for Europe reinforces its laggard status. It will take a longer time and more cost more for the region to adopt AI technologies and get to a point where it equals frontier regions in AI research and development (R&D). Ultimately, this will translate into a loss of global competitiveness, which is already reflected in Europe's long-term trend of declining productivity. Given the persistence of human capital dispersion and its effect on economic growth through new technologies over time, countries that lag in human capital trends right now will have slower economic growth in the future. Ultimately, this trend is likely to weigh down on long-term economic growth for the entire region, further deteriorating the region's capacity to create and work with AI.

FIGURE 1: EU'S HUMAN CAPITAL AND TFP DEVELOPMENTS AGAINST THE US (FRONTIER) AND SCIENCE HUMAN CAPITAL NET FLOWS



Source: author's calculations using Penn World Tables (PWT) & OECD. US is the frontier, set at 1. The right-panel shows the cumulative absolute number of the annual net flow (which is the difference between inflow and outflow) of scientific authors between 2015-2020 following OECD (2022).

Given these profound risks to the long-term health of Europe's economy, EU policymakers should take a new approach to building an AI environment that retains and attracts AI human capital. It is crucial for creating long-term economic growth. As this paper shows, those countries which will be successful in employing and maintaining human capital graduates are a strong predictor for deploying digital technologies like AI in the future. Those who do that successfully now will yield the higher productivity levels needed for Europe to sustain future long-term economic growth.[4]

[4] Academic research also shows the crucial link between AI adoption and the firms' investments in human capital to generate long-term economic growth, such as Aghion, et al. (2017). suggest that human capital will play an important role on the effect of AI adoption within firms, mainly in the form of replacing low-skilled workers or requiring them to obtain specific new knowledge. However, the role of human capital in the endogenous decision to adopt AI is little discussed.

3. EUROPE'S AI PERFORMANCE

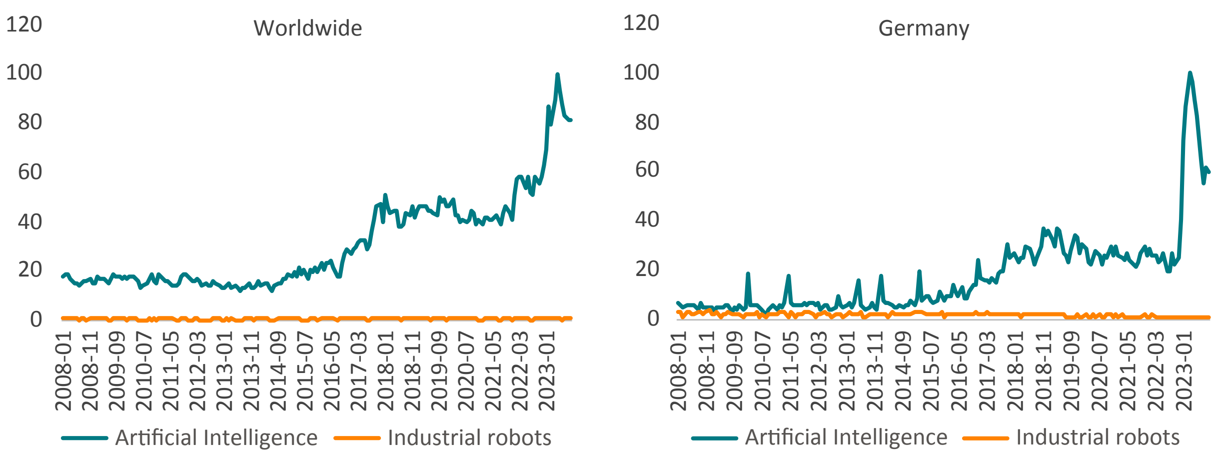
As elsewhere in the world, Europe is expanding its capacity to work with AI. However, EU countries do not capitalize equally on these AI developments. In fact, there are substantial differences across the European economy.

AI is a general-purpose technology (GPT), which means that the technology has a wide range of applications across many activities int the economy. AI is used in obvious technology areas like cloud computing, the Internet-of-things (IoT), and the Metaverse. Most people will already have heard of applied AI forms like ChatGPT and other equivalent chat robots using large language models. But AI is much more than that and is increasingly powering industry-led data models and the way organisations produce tasks and other activities in a wide variety of different sectors.

In this study, we define AI as the adoption of one of the following technologies, as measured by Eurostat: text mining, speech recognition, natural language generation, image recognition, machine learning, decision making, and autonomous decision making. See Table A1 for details. What all these AI technologies have in common is that they are based on huge amounts of data that have trained machines that will be able to predict future outcomes using an algorithm.

Global interest in AI has been increasing over the last decade and has generated more attraction in recent years, most likely reflecting the large promise of AI. Figure 2 (left panel) plots the worldwide monthly Google searches since the start of the Global Financial Crisis (GFC) in 2008 till 2023. What becomes immediately clear is that the interest increased considerably between 2016 and 2018. Many AI developments emerged in this period – such as the invention of image recognition, the development of text able to speak (called realist speech synthesisers), and many other applications used for instance in robots. In 2018 the first automatic shuttle was introduced in the U.S. carrying 32,000 passengers. In recent years, global interest in AI has escalated, most likely due to the introduction of more powerful versions of general AI applications like ChatGPT.

FIGURE 2: MONTHLY GOOGLE SEARCHES ON AI RELATED TERMS FOR WORLD AND GERMANY (2008-2023)



Source: authors' calculations using Google-trends.

Global interest in AI is mirrored in Europe, albeit at lower levels. For instance, in Germany the interest in this technology got a boost in 2015-2019. Compared with other digital technologies such as industrial robots – a natural comparator in a manufacturing powerhouse like Germany – interest in AI technology has been much stronger. But Germany's interest has been waning in more recent time, and the interest in the country was until recently not as high as in the world – a trend that was also reflected in the rest of Europe. In fact, Google searches in Europe for AI were about half than observed globally. However, in Germany too that changed considerably with the new version of ChatGPT launched in early 2023, as shown in the right panel.

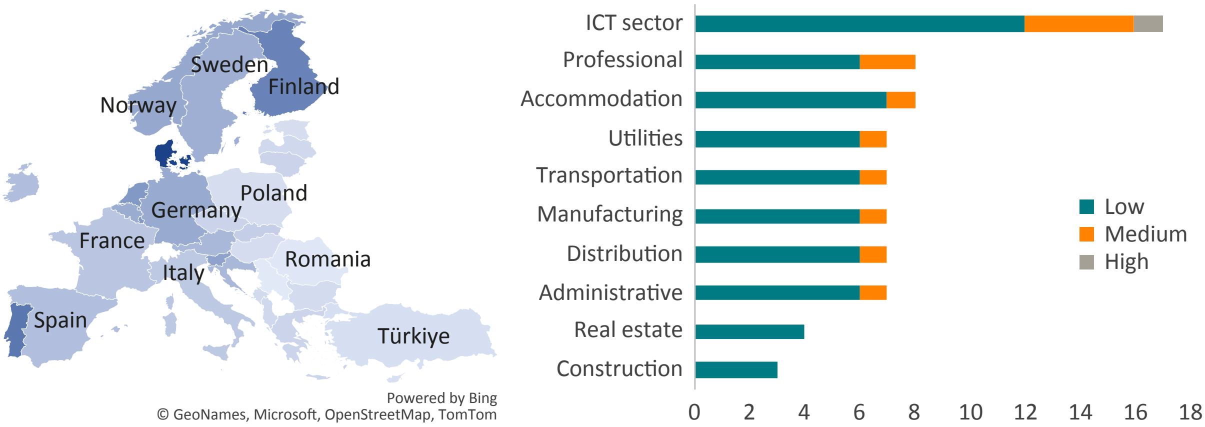
Obviously, Germany's search interest in AI is not a reliable barometer for the country's success in taking up the technology. However, more structured data measuring the uptake of AI in Europe show that Germany, together with other European countries, is performing worse than expected given the varying levels of AI adoption in the European region. Figure 3 (left panel) shows the extent to which firms in EU member states (plus other affiliated countries) have adopted at least one AI technology (plotted as share of all firms in the country).[5] All types of firms are covered, ranging from small firms with about 25 employees, to large ones with more than 250 persons employed.

The EU's performance in AI adoption is not equally distributed: the region has leaders and laggards. Nordic countries such as Finland and especially Denmark show a much higher share of firms deploying at least one AI technology. One interesting data point in Figure 3 is Portugal, which unlike most of its Mediterranean peers has a high rate of firms using AI technology. The Netherlands shows a higher rate than Germany, which in turn has a higher rate than France. The picture in Europe looks similar if the metric is based on two or more AI technologies instead of one. In other words, there is high variability in AI use among EU members.

Interestingly, the map does not confirm standard patterns of a so-called "North-South" divide. If anything, one could see a split between East and West. Countries in Central and Eastern Europe (CEE) are generally less frequent users of AI than most other European countries, which probably reflects in large part their lower levels of economic development and as we will see their lower levels of human capital. Yet in this region there are outliers such as Slovenia and, to a lesser extent, Croatia, with much greater users of AI than in other CEE countries. These two countries show an adoption rate of AI that is higher than the EU average. Poland, Hungary, Romania, and – surprisingly – Estonia are the lowest adopters of AI.

[5] As stated above, AI adoption refers to whether a firm has adopted one of the following technologies: text mining, speech recognition, natural language generation, image recognition, machine learning, decision making, and autonomous decision making. These are the AI technologies as measured by Eurostat.

FIGURE 3: EU'S AI ADOPTION PERFORMANCE BY MEMBER STATE AND SECTOR (2021)



Source: authors' calculations using Eurostat. Note: both panels show the share enterprises that use at least one of the AI technologies in the total number of firms for each country. The right-panel breaks up AI adoption between low, medium, and high, which denotes firms' adoption of at least one, two and three AI technologies, respectively. Numbers refer to 2020 in right panel.

Similar pattens appear when analysing small and big firms separately, even if some differences also emerge. Spain, France, Sweden, Ireland, and Norway reveal much lower pick up of AI by small firms. One big exception is again Portugal where smaller firms have a higher propensity to absorb AI than in most other countries, which probably explains its overall rate (as shown in Figure 3). And even though Germany is above the mean, other bigger markets like France and Spain are below Europe's average in the adoption rate of AI in small firms.

Adoption rates also vary across sectors, as reported in Figure 3 (right panel). In the figure, AI adoption is broken down by firms that use only one AI technology in their operations (low), two types of AI technology (medium), and three or more types of AI technology (high). Sectors where the AI adoption rate of firms are highest are expectedly in the ICT industry, which is a "provider" of this technology.[6] The ICT sector covers broad industries such as telecom, computer, and information services. The second biggest adopter in Europe is professional services, followed by accommodation services.

Overall, the panel shows that AI adoption is so far largely a services sector phenomenon as the uptake of this technology in Europe's manufacturing sector is smaller compared with the ICT and business services sectors. Interestingly, the sector of administrative services does not have (as of yet) a very high adoption of AI technologies; the sector is sometimes referred to as "intermediate" services and is thought to be sensitive to AI adoption with large consequences for globalization.[7] The low adoption rate of AI for this sector are also visible in the U.S.

[6] This result is also found by Restrepo et al. (2021) in the U.S.

[7] See Baldwin (2022). At the same time, a separate strand of the AI and trade literature provides research on the question to what extent to which AI technologies are complementing or substituting for international trade in intermediate services with countries in which wages are of lower levels, such as Stapleton and O'Kane (2021).

These patterns of European AI adoption broadly resemble the ones found in the U.S. In a recent research paper, the authors found that AI adoption by U.S. firms was highest in the ICT sector such as software publishers, data processing services and other information sectors.[8] A recent OECD study for the UK confirms the pattern.[9] However, the manufacturing sector also scores high in AI adoption in the U.S. whereas it does not in the EU.[10] This presents an interesting reversal compared to industrial robot adoption in manufacturing, where European countries mostly were ahead of US adoption in the 2000s.[11] The lowest score of AI adoption is similarly found in Europe and across the Atlantic in construction, transport, and distribution services. Interestingly, high AI adoption is also found in healthcare in the U.S., which European data prevents us from assessing given the lack of data.

4. EUROPE'S HUMAN CAPITAL PERFORMANCE

The EU is adding more AI human capital to its economy. Measured in graduates from universities, it is also closing the gap with the U.S., as shown in Figure 1 (left panel).

However, the U.S. is the de facto global leader when it comes to attracting the most talented skills for its technology industries and the country's wider knowledge economy. The country has the world's best universities when it comes to STEM education and is immensely successful in attracting migrants and retaining foreign students to work in knowledge and technology industries. Human capital will also be a determining factor in the development of AI technology. For instance, an Infosys survey in 2021 showed how companies are best preparing for AI deployment: besides investing in basic infrastructure, the best strategy is to develop knowledge and skills. If the U.S. will be able to keep on attracting human capital, firms in the country are likely to retain its lead in AI development.

Where does Europe stand with its human capital developments? And which are the type of firms that are most likely to invest in the human capital needed for AI technology? As with AI adoption, the situation in Europe today is mixed, and the services sector is again in the lead.

Figure 4 (left panel) shows that it's not always the Nordic countries that have greatest skill levels. Germany together with the Czech Republic, Slovakia, Norway, and Estonia have the highest accumulation of human capital per capita. Sweden, Finland, and Denmark are not far off from the top five countries. Surprisingly, Portugal with its high rate of AI adoption has one of the lowest human capital levels in Europe.[12] This mixed pattern paints a somewhat different picture than the figure showing Europe's AI adoption by firms. Yet even though overall levels

[8] McElheran et al. (2023).

[9] Calvino et al. (2022).

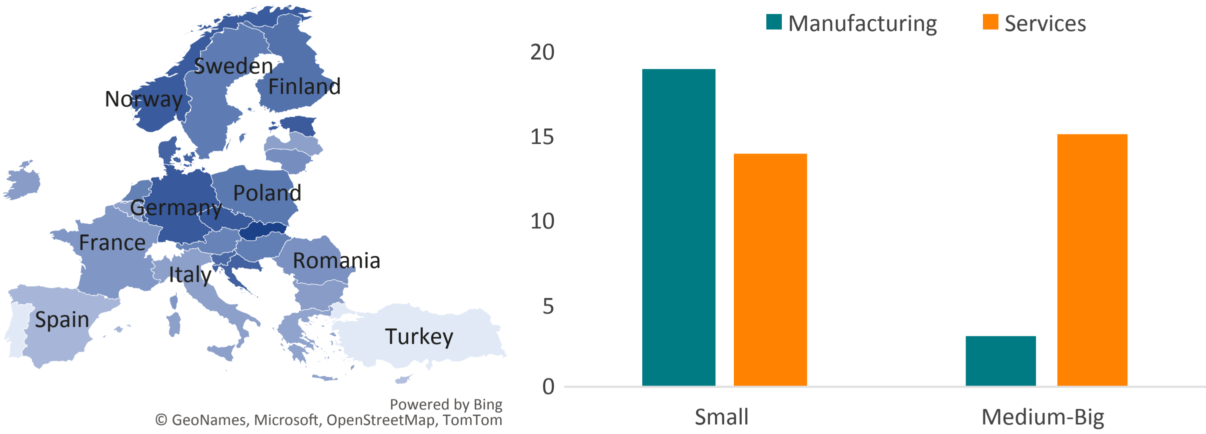
[10] McElheran et al. (2023) assesses whether U.S. firms have adopted at least one of the following AI technologies, namely Automated guided vehicles (AGV) systems, Machine learning, Machine vision, Natural language processing, and Voice recognition software. Their list therefore differs somewhat than the Eurostat list of AI technologies this paper uses. Yet, interestingly, the share of firms in the baseline sample that adopt at least one AI-related technology in 2017 was about 6 percent according to their study. The corresponding share for the EU that we measure based on Eurostat's list of AI technologies is about 7-8 percent.

[11] Acemoglu & Restrepo (2020).

[12] One factor that might explain the Portuguese puzzle is the country's unique immigration policies (e.g. the Digital Nomad Visa and specific tax breaks) that are aimed at attracting IT talents and workers, which might not be captured well in the 2012 education statistics, but generate positive spillovers for Portuguese firms in AI adoption.

of human capital may give some indication, it's ultimately firms that need to attract and invest in human capital for AI adoption.

FIGURE 4: ENTERPRISES BY PERCENTAGE OF EMPLOYEES WITH UNIVERSITY EDUCATION (2019-2020)



Source: authors' calculations using Penn World Tables and Eurostat. Business services includes figures as outlined in Figure 3, excluding utilities and construction. Small firms are defined as having up to 49 employees, whilst medium and big firms above 50 employees, in line with Eurostat. The business services sector includes which includes the above-mentioned administrative and support services. Excluding the latter sector holds a similar pattern.

Moreover, not all firms equally employ high skills in their business practises. There is a huge variety in the type of firms, and in which sector or industry that firms are active, that explains the broader employment of human capital. That becomes visible in the right panel of Figure 4. The figure plots on the horizontal axis the size of the firm based on their number of employees, split between small and medium-to-big firms, and broken down by manufacturing and the business services sector. The figure measures the percentage of employees with a university education which are employed by these firm categories.

The figure shows that, in large part, services firms employ high skilled workers, which is in line with the fact that these are also the ones that adopt AI technologies more intensively than manufacturing, as illustrated above. Moreover, the size of firms matters too: bigger services firms are much more likely to employ high skilled workers than big manufacturing firms. To a great extent, this pattern is reversed for small firms active in manufacturing: smaller manufacturing firms tend to recruit more skilled workers relative to services. Therefore, based on firm size, the combination of human capital and AI adoption in Europe is led by services sectors.

It's worth noticing that larger firms are typically more productive than smaller firms, which in turn correlates with the share of high-skilled workers that companies employ and the level of R&D they perform. These empirical facts have to a large extent been traditionally associated with the manufacturing sector and not so much with services.

However, these patterns have started to change in recent years. New research shows that services, in particular firms in the business and ICT sector, can be at least as productive as manufacturing firms. Therefore, insofar as larger firms in Europe drive country-wide productivity thanks to their adoption of R&D, new technologies, and human capital, it's very likely that these are the services firms which will be in the lead to generate growth on the back of AI in the future.

One caveat to this conclusion is that the manufacturing sector in Europe may simply be lagging behind services and that it is catching up, also compared to the U.S. If this is the case, it would be consistent with the fact that, compared to its human capital development, Europe's industrial powerhouse – Germany – is currently lagging in AI adoption. The view is also in line with the fact that some Nordic countries – generally considered as services economies – are now leading in AI adoption. But, this picture may reverse at some point in the future once AI adoption becomes more widespread in manufacturing.[13]

5. LASTING EFFECTS OF HUMAN CAPITAL ON TECHNOLOGY ADOPTION

While patterns of human capital endowments will change over time – as do country and sector trends – it is uncommon that these changes happen rapidly and that they change how different economies prosper on the back of accumulated human capital. Most likely, this pattern holds for investment in AI human capital too, and how that human capital fuels economic behaviour.

As this section will show, there is a strong persistence of human capital investments and AI adoption over a long period of time. In other words, the countries and regions where firms invest in human capital today are likely to become the biggest winners of AI deployment tomorrow. They will be reaping the greatest economic gains for a long period to come.

More generally, history matters when looking at the links between human capital developments and new technology adoption. One of the authors has shown that the regions in Switzerland in the 19th century that adopted new technologies early on to produce electricity from the rapid changes in waterpower generation, were the ones that saw most rapid income growth.[14] This result in output persisted even after these new technologies became widely spread in the entire country. Moreover, the regions that invested in the new technology at an early phase experienced a rapid shift to a new type of economy: the production and employment of these regions shifted earlier from agriculture to manufacturing, which persisted a century later with long-lasting effects of higher income for the "early adopters".

These long-run income gains were almost entirely stemming from the use of electricity by downstream industries as these new technologies became available in the regions. For instance, it is estimated that for the chemical industry, where electricity was a crucial input in novel production processes, the early adopters of the new technology at the end of the 19th

13 As similarly suggested by Calvino and Fontanelli (2023).

14 Brey (2021).

century could explain more than 70 percent of the spatial distribution of the chemical industry across Switzerland today. This is a key factor in the lasting income divergence across regions as chemicals and pharmaceuticals remain some of Switzerland's leading and most productive industries.[15] It shows that this pattern of technology adoption, in this case electricity, is extremely persistent over time.

But the most interesting aspect of the analysis is that the channel through which this transformation happened was human capital accumulation. Those regions that did adopt electricity early had an incentive to invest in human capital, resulting in an almost immediate improvement in necessary knowledge and specific skills, such as math, for the new industries. The number of students expanded more quickly in these areas, too. Incidentally, these areas also experience more innovative output, which is still observable with, for instance, their higher rates of patenting nowadays. This emphasizes the close relation between human capital and technology adoption.

Early adopters of AI today

The waterpower generation example is comparable to the growth of new digital technologies such as AI; they are the "new electricity" that is powering much of new business and economic output. Using algorithms, AI builds on vast quantities of data pushed through online networks that facilitate the production and innovation in all sorts of downstream sectors in the economy, ranging from computer electronics over car production to business services and health care. Without good data, there is no digitalisation nor the emergence of machine learning or other forms of AI.

Therefore, just like electricity generated by hydropower was needed to produce and innovate in the Swiss chemical industry in the 19th century, data is driving AI and other downstream innovations today, leading to new forms of production and new types of products and services. However, how successful AI will be to generate new economic output in the long run depends crucially on investments in human capital.

The link between human capital investments and early adoption of new technologies looks equally persistent for AI adoption in European countries in current times. Using the human capital investments about 10 years before the AI adoption rates of European firms, we have studied econometrically the impact of this relationship between human capital investments and AI technology adoption within country-industry cells using novel data released by Eurostat. In doing so, we regressed the following empirical model:

$$AI_{sc} = HC_{sc} + \delta_s + \delta_c + \varepsilon_{sc} \tag{1}$$

where AI_{sc} denotes the share of firms that adopt one of the AI technologies as described above for each country c and sector s. It is defined as the share of total firms active in the country and

[15] Indeed, many current and former Swiss national champions trace their origins back to being set up as small companies exploiting advantages in early access to cheaper electricity, just naming some: Lonza, Ems-Chemie (initially Hovag), Alusuisse/AIAG (now Rio Tinto Aluminium), etc. See Lunge (1901).

sector. The term HC_{sc} denotes the extent to which human capital is employed. We use two types of human capital variables, namely the share of workers active in each country and sector that has a university degree; and the share of firms of which more than half of their workers have a university degree. Both variables are measured for the year 2012, whereas the dependent variable of AI is measured for the year 2021, almost a decade later.

All data is sourced from Eurostat. Our measure of AI adoption is based on the novel 'Community survey on ICT usage and e-commerce in enterprises' dataset. As listed in Table A1, the variable measures the share of firms that adopted at least one of the following AI technologies: (i) text mining, (ii) speech recognition, (iii) natural language generation, (iv) image recognition, (v) deep/machine learning, (vi) automating decision making, and (vii) physical movement of machines via autonomous decisions based on observation of surroundings.

The variables of human capital are also sourced from Eurostat. The first variable denoting the share of workers with a university degree is measured by educational attainment and reports how many employees have up to a university education degree. The second variable measures the share of firms that have at least 50 percent of their workforce comprised of workers with university education. As such, this latter variable represents a measure of knowledge clustering.

Finally, the terms δ_s and δ_c are fixed effects for sector and country, respectively. They control for any other factors that may influence firms to adopt AI in a country and sector. For instance, some sectors such as digital services are more likely to adopt digital technologies, because of the way their production structure has evolved as well as that they are in general very knowledge intensive even before AI emerged. The fixed effects take care of these sector specific factors and cancels out these potential unobserved reasons that jointly drive human capital and AI adoption. Similarly, some countries might have long-standing policies aimed to increase human capital and AI adoption in distinct ways. Again, any correlation between country specific policies would not be driving our estimated relationship after accounting for the country fixed effects. Our econometric analysis covers 9 sectors and 32 European countries. As stated, all data is from Eurostat.

The results of our regressions are reported in Table 1. Column 1-3 shows that the coefficient results of our first human capital variable, namely the share of university education, comes out positive and significant across all entries. It confirms the persistent relationship between human capital accumulation and the early adoption of AI technologies: countries that had invested in human capital more intensively, and which were being used in sectors that needed them, explain AI adoption about a decade later. The sizable R2 highlights that the regression predictions approximate well the real data points, in simple terms predicted AI adoption based on human capital alone forecasts 27.7 percent of the variation in observed AI adoption in column 1. This significant outcome remains robust when including country and sector fixed effects as reported in column 3. However, the coefficient size in this column is reduced by more than half after accounting for country and industry specificities.

Column 4-6 repeats this exercise for the share of firm whose tertiary employment is above 50 percent, even though Eurostat unfortunately provides this data only from 2021. Doing so is nonetheless useful. Namely, it focusses more on the upper-tail of firms in terms of human-capital, which as we expect are the drivers of AI adoption. Results are positive and significant, similar to our findings in columns 1-3. Moreover, the effect in column 6 is even more robust in magnitude.

TABLE 1: EDUCATION AND AI ADOPTION

	(1)	(2)	(3)	(4)	(5)	(6)
University education 2012	0.185***	0.222***	0.084**			
	(0.024)	(0.022)	(0.042)			
Firms >50% university 2021				0.103***	0.130***	0.124*
				(0.028)	(0.021)	(0.062)
N	267	267	267	88	88	88
R2	0.277	0.681	0.830	0.215	0.723	0.872
FE Country		yes	yes		yes	yes
FE Sector			yes			yes

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

On the basis of these results, basic calculations using the most conservative results (i.e. lower in coefficient size) suggest a sizable influence of human capital for AI adoption. Taking the mean of 26.7 percentage points for university education and 6.5 percentage points for AI adoption, the coefficient suggests that human capital explains about 34.5 percent of AI adoption (calculated using the estimated AI adoption explained by human capital, 2.2 percentage points, divided by the observed average AI adoption). The equivalent calculation for firms with more than half of their workforce having a university degree, results suggest human capital explains 50.2 percent of the observed adoption of AI across firms.

We further explore the role of human capital in Table 2. In this table, we use the extent to which different levels of human capital between the share of secondary and university education determine the outcome of firms to adopt AI. First, columns 1-2 show the results when using both secondary and tertiary education of 2012, which are similarly defined as a share of total. The results suggest that the effect on AI adoption is indeed driven by university education only, as found above. There is no corresponding effect of secondary education observable.

Second, columns 3-4 further report the results when looking at firms within the country and sector that have a lower share of high-skilled work force than initially measured in Table 1. That is, firms with a lower share of workers that have a university degree. As the results show, there appears to be a critical mass of clustered human capital that explains the adoption of AI consistent with the effects that we found in Table 1. In other words, AI adoption is driven by a high share of firms with more than 50 percent of university education. There is no corresponding effect from firms with lower levels of university education in their workforce.

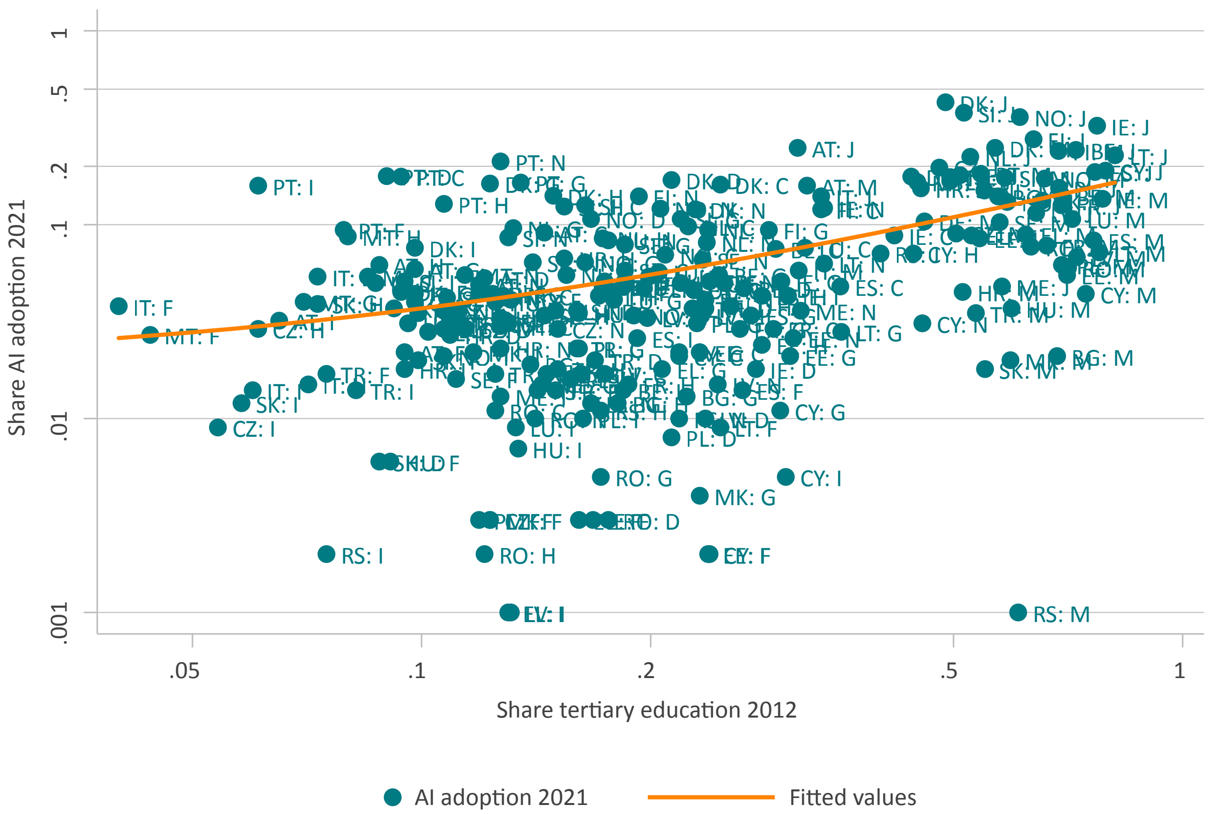
TABLE 2: EDUCATION INTENSITY AND AI ADOPTION

	(1)	(2)	(3)	(4)
Secondary education 2012	-0.090***	0.016		
	(0.021)	(0.030)		
University education 2012	0.137***	0.0970**		
	(0.028)	(0.047)		
Firms >10% university			-0.063	-0.074
			(0.066)	(0.059)
Firms >25% university			0.006	0.005
			(0.077)	(0.058)
Firms >50% university			0.145***	0.132*
			(0.049)	(0.068)
N	267	267	88	88
R2	0.315	0.830	0.237	0.879
FE Country		yes		yes
FE Sector		yes		yes

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5 graphically summarizes the relationship for Europe we found in our empirical assessment. The figure plots the level of tertiary education in each European country and industry in 2012 on the horizontal axis, whereas on the vertical axis the extent to which firms adopt AI technologies about a decade later is plotted. An upward trend is visible, similar to our findings in Table 1 and 2. It means that higher levels of human capital is positively associated with a higher share of firms adopting AI technologies 10 years later with this relationship incredibly clearly visible even in our raw data. Thus, where there is more human capital, persistent patterns arise in that firms use that human capital to adopt greater levels AI adoption a decade later.

FIGURE 5: TERTIARY EDUCATION IN 2012 AND AI ADOPTION IN 2021



Source: authors' calculations using Eurostat. Notes: The figure depicts share of university education 2012 in a country and industry and the share of firms adopting AI technologies in 2021 with a quadratic fit depicted by the red line. Log-scale used on both axis for better readability. Markers report 2-letter country code and 1-letter NACE industrial sector as defined by Eurostat.

Moreover, the increasing trend on the right-hand half of the figure suggests that the effect of human capital on AI adoption is stronger where human capital is particularly intensive, consistent with our findings that firms whose university employment is above 50 percent is driving this significant relationship.

Furthermore, this relationship also appears to hold within each industry: no matter whether one looks inside the chemical industry, the services sector, or the retail sector, firms that operate in countries where there is a higher levels of human capital available exhibit higher rates of AI adoption later on.[16] This confirms our main message: human capital plays a crucial role in the adoption of AI technologies by firms.

As in the 19th Century, the relationship between human capital and new technologies in Europe is furthermore important for two fundamental reasons. One is that its reinforcing role has a long-

[16] There are two more economic reasons for using historic human capital levels. One is that it highlights that the investments in human capital might take time to reap the benefits of adoption AI technologies. Second, is related to potential endogeneity between human capital and technology adoption as the latter could lead to the former. To avoid reversed causality issues that AI adoption affects the composition of human capital across country-industry cells, a time-lag of 10 years rules out this reversed causal impact.

lasting effect over time. Even though the time-line is only a decade in our regressions, due to the availability of data, the economic returns from AI technologies in the long run cannot do without the constant investments in human capital at the beginning when new technologies start to become available. Second, those firms that capitalize on new technologies first by investing in human capital right from the start are the ones that reap most of the welfare gains in the distant future, ahead of others that will invest in human capital at a later stage and might never catch up.

Firm adoption of AI today

Importantly, it is not only what happens in human capital investments in countries that matters. Ultimately, firms who move towards AI will have to build up their human capital levels either by recruiting more skilled workers or investing in their current workforce. This is also what we find in our research. European firms which have a greater pool of highly skilled workers, for instance by more than half of their workforce being employees that have a university degree, are significantly more likely to adopt digital technologies 10 years later. In short, firms in Europe successfully using AI technology are actually the ones that already have very high levels of human capital in their workforce.

Again, this outcome is regardless in which country the firm is placed or in which sector it is active. For sure, industries that were already known for being very innovative or having high technology adoption and a high skill-intensive business activity in the first place are faster in adopting AI than other industries. However, the differences between sectors do not seem to matter. Firms within the same industry with higher shares of university-degree workforce are driving AI adoption.

Similarly, countries which have active policies in place to expand higher education are not driving this relationship of firms adopting AI due to human capital in our estimates. This relationship holds within all countries no matter their human capital policies. This, of course, does not mean that higher education policies do not matter, rather it means that successful education policies increase AI adoption across all sectors in a country.

Moreover, it matters in which type of AI and where in the business line high-skilled firms adopt these AI technologies. Further econometric analysis as provided in the Annex B reveals that higher adoption rates of AI driven by high human capital levels appear to occur in the most advanced variants of AI, namely for the purpose of automation (i.e. through automating different workflows and assisting in decision making, and for enabling physical movement of machines via autonomous decision). Our analysis also reveals that the use of AI is particularly high in the production and administration process, as well as related to logistic functions of the high-skilled firm and not so much for marketing, management, or human resources of firms.

6. CONCLUSION

This paper argues the crucial role that human capital plays if Europe wants to benefit from AI technologies. The spread of both human capital and the adoption of AI in Europe are uneven. Given that higher human capital levels and the successful up-take of AI across countries are crucially intertwined, there is a serious risk for many EU members that lag the human capital to fall behind even more in AI-generated economic growth. This will likely weigh down Europe's ability as a whole in generating continued and equal growth on the back of AI.

Moreover, these effects are likely to be long-lasting. Existing investments in human capital that take considerable time to accumulate are a strong predictor of future success in picking up AI technologies. Indeed, we show that available human capital explains about one third of AI adoption by firms 10 years later. Moreover, this result is driven by firms where human capital for AI cluster together: firms of which the majority of their workforce is comprised of university graduates explain more than 50 percent of AI adoption within countries and industries today.

In short, the ones that invest in human capital now are the ones that reap most of the benefits in the distant future from AI technologies. But that also means that there's a great risk of those countries that don't invest in human capital (or are unable to retain it) to fall further behind in the future. Already now Europe experiences difficulties to catch up with the global frontier (i.e. U.S.) and countries lagging in both generating human capital and the firm-adoption of AI will make it more difficult to close that gap.

These findings have straightforward policy implications. Given Europe's net outflow of high-skilled graduates that are needed to invent and deploy new technologies, there is an urgent need for the region to retain its human capital. Moreover, as we have seen, European countries show varying degrees of human capital levels. Given that digital technologies such as AI often display a high rate of agglomeration forces because of the associated spill-over effects, it would be economically beneficial to encourage human capital to flow to places where AI is most deployed alongside the investments in human capital made.

AI technologies are, for now at least, more often deployed in the services sector than in manufacturing. That too has policy implications. Many services sectors are intense users of human capital with often very specific expert knowledge required to perform their tasks. Yet some of these services industries in Europe are still restricted. Previous research by ECIPE & Bertelsmann (2018) shows that restricted services markets in Europe often prevent digital technologies from being deployed. Reforming services markets would likely stimulate the AI adoption in these sectors.

Overall, the policy message of our paper is clear: if European leaders are serious about reaping bigger growth benefits from AI developments, Europe needs to focus on policies that attracts and builds up more human capital needed for AI adoption.

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ANNEX A

TABLE A1: TYPES OF AI TECHNOLOGIES AS MEASURED BY EUROSTAT.

Type of AI technology	**Description**
Text mining	Technologies analysing written language
Speech recognition	Technologies converting spoken language into a machine-readable format
Natural language generation	Technologies generating written or spoken language
Image recognition	Technologies identifying objects or people based on images, covering both image recognition and processing
Machine learning	Machine learning (e.g. deep learning) for data analysis
Automating decision making	Technologies automating different workflows or assisting in decision-making (AI based software robotic process automation)
Autonomous decisions	Physical movement of machines via autonomous decisions based on observation of surroundings

ANNEX B

We also assess for what purposes and where in the business process high-skilled firms adopt AI technology. Not all AI technologies are the same, given that there is a large variation of how AI is used. Similarly, not in every step of the production process of a firm AI is being used. The data allows us to make that distinction by separating the type of AI technology and for what purpose firms are adopt AI technology. In doing so, we regress the same empirical model:

$$AI_{sc} = HC_{sc} + \delta_s + \delta_c + \varepsilon_{sc} \quad (1)$$

where AI_{sc} denotes again the share of firms that adopts one of the AI technologies, but this time split up over the 14 types of these technologies individually, for each country c and sector s. The term HC_{sc} denotes the extent to which human capital is employed, namely the share of tertiary education levels in 2012. Here we use one human capital variables, namely the share of workers active in each country and sector that has a tertiary degree.

Results are reported in panel A and B respectively in Table 4. In Table 4, the results shows that higher adoption rates of AI appear to occur in the most advanced variants of AI, namely for purpose of automating different workflows or assisting in decision making (PA) as reported by the significant coefficient sign in column 6, as well as for enabling physical movement of machines via autonomous decisions based on observation of surroundings (AD) as reported in column 7 in panel A.

In panel B the results shows that highlights that the use of AI is particularly high in the production process of the firm (column 9), in addition in the administration process (column 11) and logistics (column 12). We find similar positive effects on the basis of the share of firms with more than 50 percent of their workforce having tertiary education.

TABLE B1 HUMAN CAPITAL AND AI TYPE AND USAGE

A. Type AI	(1) TM	(2) SR	(3) LG	(4) IR	(5) ML	(6) PA	(7) AD
Tertiary 2012	0.020	-0.013	-0.008	0.021	0.009	0.089**	0.024**
	(0.035)	(0.022)	(0.019)	(0.023)	(0.040)	(0.037)	(0.012)
N	259	259	261	263	260	265	254
R2	0.789	0.754	0.720	0.738	0.808	0.771	0.630

B. Use AI	(8) MKT	(9) PRD	(10) ADM	(11) MNG	(12) LOG	(13) HR	(14) ITS
Tertiary 2012	-0.001	0.046**	0.047*	0.024	0.029***	0.009	0.030
	(0.026)	(0.019)	(0.026)	(0.022)	(0.011)	(0.012)	(0.024)
N	263	261	261	260	255	254	259
R2	0.737	0.710	0.714	0.711	0.575	0.642	0.749
Country FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Notes: In panel A and B, column titles refer to for what purpose the firm is using AI technologies, namely (1) for performing analysis of written language (TM: text mining); (2) for converting spoken language into machine-readable format (SR: speech recognition); (3) for generating written or spoken language (LG: natural language generation); (4) for identifying objects or persons based on images (IR: image recognition, image processing); (5) for machine learning (e.g. deep learning) for data analysis (ML: machine learning); (6) for automating different workflows or assisting in decision making (PA: AI based software robotic process automation); (7) for enabling physical movement of machines via autonomous decisions based on observation of surroundings (AD: autonomous robots, self-driving vehicles, autonomous); (8) for marketing or sales (MKT); (9) for production processes (PRD); (10) for organization of business administration processes (ADM); (11) for management of enterprises (MNG); (12) for logistics (LOG); (13) for human resources (HR); (14) for IT security (ITS).