CORE MATTERS

AI: Winning and losing countries

Vladimir Oleinikov / Martin Wolburg

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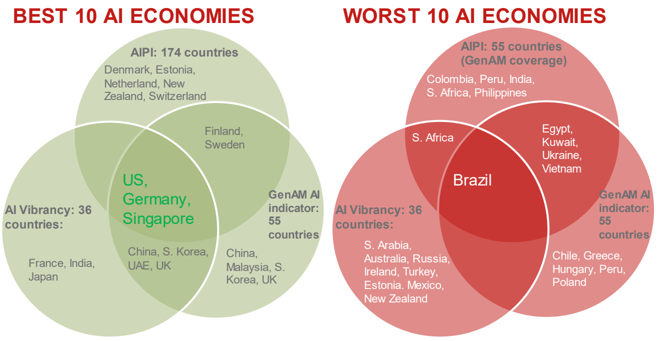
Artificial Intelligence (AI) is quickly making its way into the economy. It is rightly considered as a gamechanger and from an investor perspective, it is important to **identify potential winners and loser**s.



There is overall agreement on **positive productivity and growth effects**. However, empirical **estimates widely differ,** ranging from an 1.5% additional annual productivity growth to just 0.064%.

Countries are not equally prepared to reap the benefits from AI. To identify likely winners and losers we developed a proprietary **GenAM AI index** (55 countries) based on various categories: **innovation, adaption and diffusion, human capital, and regulation**.

There exist other such indicators. The IMF's AI Preparedness Index (AIPI) is a very broad indicator (covering 174 countries) while the Global AI Vibrancy tool (AIVT) from Stanford University has a deeper focus, containing 42 specific AI indicators but covering only 36 countries. Our indicator lies in between. The **US, Singapore** and (somewhat surprising) **Germany** are identified by all approaches as the economies best positioned to benefit, and **Brazil** the **least promising.**

We would also include China, the UK, South Korea, the United Arab Emirates, France, India, Japan, Malaysia, Sweden and Finland in the top group, but we are more sceptical regarding Kuwait, Vietnam, the Ukraine, Georgia, Hungary, Poland, Russia, Mexico, South Africa and Turkey.

A general shortcoming of all AI indicators is that they are based on data published with a substantial lag. The approach presented here can therefore only be a first screening. Our analysis also suggests that **investors should not simply rely on broad classifications like MSCI EM, EU or BRICS** when it comes to AI.

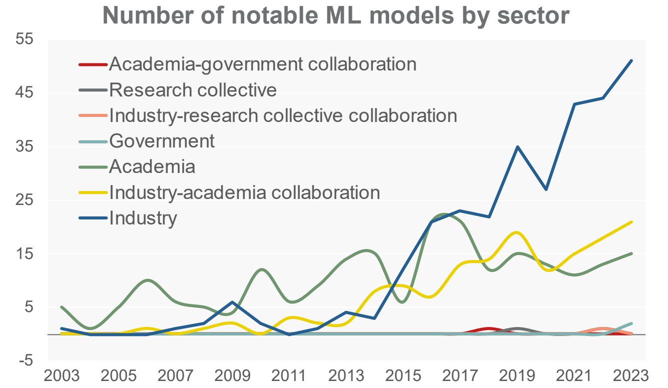
1. AI: a gamechanger

What is Artificial Intelligence (AI)? There is a common understanding that AI is related to the **ability of machines to perform tasks on their own**. It describes a wide range of technologies that power many of the services and goods we use every day which in former times required human intelligence, e.g. for identifying patterns. The current AI revolution is based on generative AI models and is no longer just an academic innovation but increasingly driven by the private sector.

One can differentiate among four types of AI technologies. First, LLMs (Large Language Models) are designed to understand and generate human language. These models are trained on vast amounts of text data to learn statistical patterns, semantic relationships, and contextual understanding of language and are focused on generating responses that mimic human speech (i.e., chatbots). Second, ML/PA (Machine Learning/Predictive Analytics) are quantitative, statistical models involving algorithms that make predictions or decisions learning from input data, updating in real time, and improving performance from feedback from objective functions. Third, Other Natural Language Processing unlike to LLMs deals with processing natural language produced by humans in order to extract meaning from the text. Fourth, speech recognition also known as ASR (automatic speech recognition), converts spoken language into written text or commands. It involves the process of transcribing spoken words or phrases into a textual form that can be processed, analysed, or acted upon by computers or applications.

That said, the importance of AI goes far beyond economics. A recent Brookings study focuses on the **fundamental impact on society**, warning that the concentration in the AI gains could increase economic inequality and ultimately lead to a vicious feedback loop of eroding democracy and rising inequality. There is also potential to create misinformation and to violate laws and regulation. Other concerns arise from biases and even potential discrimination from the dataset on which AI is trained, as well as cybersecurity issues. There is increasing political awareness about the potential benefits from AI and very recently US President Trump announced a $ 500 bn private AI infrastructure joint venture.

That said, in what follows we **restrict ourselves to the pure economic effects** and focus on the potential impact on productivity and growth. AI is currently fundamentally built on solving prediction problems; a large and growing number of tasks can be (re-)formulated as prediction problems, and thus solved effectively, ranging from image recognition to optimisation problems as well as to text and image generation.



Source: Artificial Intelligence Report 2024, GenAM

The ability of firms and countries to adapt to AI and reap its economic benefits will shape the future economic order. In what follows, we will briefly review the potential productivity gains from AI (chapter 2) and then outline some empirical evidence by countries (chapter 3). Thereafter, we will present our proprietary country rankings based on our AI indicator (chapter 4) and compare the results with those of other approaches (chapter 5) before concluding (chapter 6).

2. How big is the productivity potential?

AI has the potential to increase productivity in various economic activities. Recent estimates of potential productivity gains for specific tasks range from 10% to 56% (OECD 2024: 17). That said, an extension of these benefits to whole industries is not straightforward as there seems to be a productivity premium for large firms and higher gains for inexperienced workers. Yet these micro-level findings largely capture the short-term effects from early adapters. In contrast, the **long-run impact of AI on aggregate productivity growth will depend on the extent of its use and its permanent integration into business processes**.

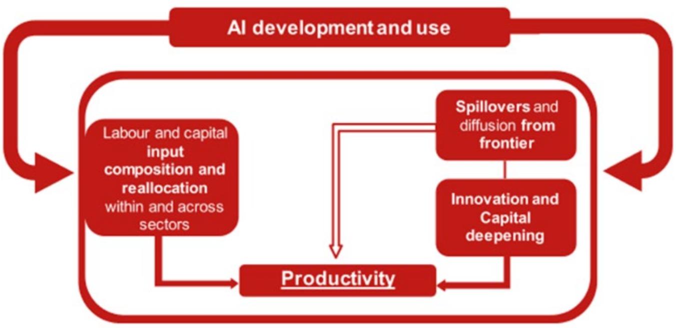
According to the literature (see OECD 2024 for an overview), the acceleration of AI development and diffusion **has not yet been associated with higher productivity growth at the**

macroeconomic level, and there are some important factors contributing to uncertainty about the timing and strength:

First, delayed aggregate productivity responses are common to so-called General-Purpose Technologies (GPTs), such as the steam engine, electricity, and the internet. GPTs initially require investment in complementary inputs – not well measured in National Accounts– before they can deliver productivity gains. This **leads to a Productivity J-curve**, characterising the adoption of a new GPT. In the first stage of adoption, both output and inputs are systematically underestimated due to unmeasured intangible investment. In a second stage there is an overestimation of total factor productivity (TFP) once the benefits of technological complementary intangible assets materialise. As much of the investment in AI is in intangible assets that are currently hardly measured and integrated into macroeconomic statistics, their overall aggregate effects may be difficult to capture.

Moreover, the increased use of proprietary **data** by firms might have reduced the potential for increasing returns to the extent that they **cannot be freely replicated by other firms** (the so-called appropriability effect).

AI and long-term productivity



Source: OECD 2024

Finally, demand growth for products from AI-boosted industries will most likely reach a limit, as **consumers might shift demand away towards other, less productive sectors,** as prices fall for these products and income rises. As a result, while overall productivity levels will be lifted through AI, productivity growth could be dampened by this so-called Baumol disease.

With these limitations in mind, there are **still huge gains to be made.** McKinsey estimates that generative AI could add the equivalent of $2.6 trillion to $4.4 trillion annually across the 63 use cases analysed. According to the study, this estimate would roughly double if the impact of embedding generative AI into software currently used for other tasks were taken into account. Generative AI could enable labour productivity growth of 0.1% to 0.6% annually by 2040, depending on the rate of technology adoption and redeployment of workers' time to other activities. Combining generative AI with all other technologies, work automation could add 0.5 to 3.4 percentage points to annual productivity growth thereby leaving potential for productivity growth to increase strongly.

Goldman Sachs predicts an annual 1.5 pp boost to US labour productivity over the next decade if widespread adoption of AI is achieved which compares to recent productivity growth of about 1%. The major drivers of growth are assumed to be faster rates of innovation, which in turn are driven by higher efficiency of researchers.

However, some academic studies are **less optimistic.** Acemoglu for instance estimates that TFP will be higher by 0.66pp in 10 years, or annual TFP growth will be higher by around 0.064%. The author even argues that the encouraging empirical **evidence so far is based on easy-to-learn tasks; applying AI to harder tasks may not be straightforward**. Many specific, context-dependent factors are at work reducing the predicted TFP gains over the next decade to 0.53%. The key to reaping all the benefits from AI is continued improvement in AI capabilities and fast widespread adoption to engineer complementarities with human skills and other technologies. This is where public policy also comes into play.

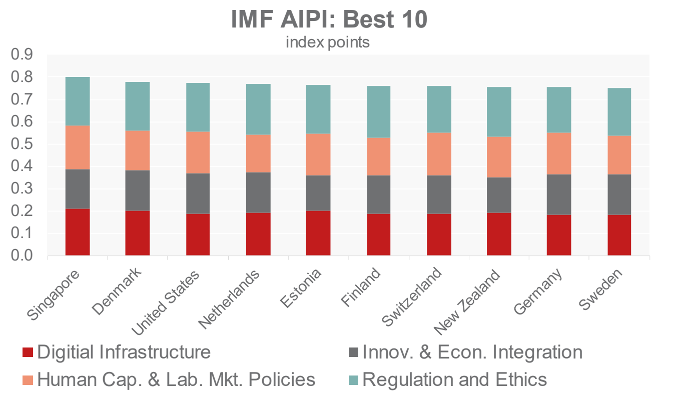
3. Which countries will benefit most from AI?

Notwithstanding the uncertainties about the AI-induced productivity boost, there is no doubt that countries need to adapt to the new technology and that the timing and penetration of AI will be key to reaping its growth potential. How well prepared are individual economies to adapt to AI, and which countries are likely to benefit most?

The **IMF recently developed an** AI Preparedness Index (AIPI) which assesses the level of AI preparedness across 174 countries, based on a rich set of macro-structural indicators. It is the sum of four key dimensions: **digital infrastructure, human capital, technological innovation, and legal frameworks** which are seen as relevant for smooth AI adoption. The resulting scores in the graph below show, not surprisingly, that the advanced economies are generally better equipped than the developing ones. However, according to the AIPI, Singapore and Denmark are ahead of the US that ranks only 3rd. Moreover, there is only little variation among the advanced economies. However, China– generally perceived as very vibrant AI developing – economy only ranks 31st.

The reason for this is that the "*Foundational AI Preparedness*" which in the AIPI captures the dimensions Digital Infrastructure and Human Capital and Labor Market Policies does not differ too much among advanced economies, e.g. sub-indicators like estimated internet users per 100 inhabitants. But when it comes to innovation and economic integration and Regulation and Ethics – that shall capture the "*Second-generation AI Preparedness*" – there is much more variation between developing economies and advanced ones than within advanced economies. The **upshot from AIPI is that the US is very well prepared to adapt to AI but that it is not the top country as other advanced economies are in a similarly good position**.

That said, from an investor's perspective it is more important to assess **which countries are likely to benefit most from AI in terms of productivity enhancement and growth**. In the above citied OECD study, it is pointed out that for the adaption and diffusion of AI an exposure to knowledge-intensive services (e.g. ICT, telecommunications, finance and professional services) is helpful. Also, high-skilled occupations are significantly more prone to be complemented than other

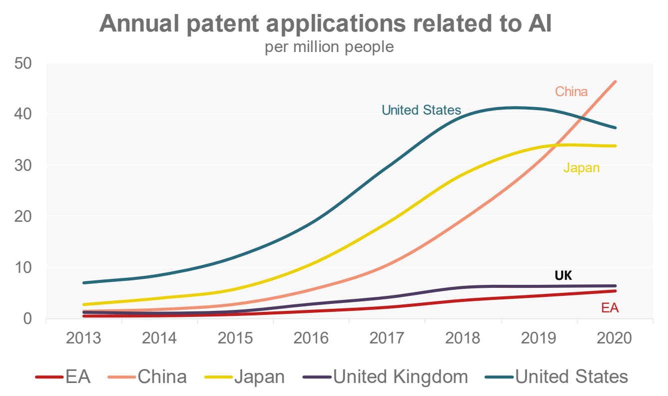


Source: IMF, GenAM

sectors, so growth will be stronger in this case (OECD: 4.2.1). To reap as much as possible economic benefits from AI, it is crucial for a country to innovate and be able to implement those innovations quickly and broadly. Against this backdrop, AI patents are key. A look at their development across economies shows a quite different picture: **China and the US by far outpace the rest of the world.** More recently, China even became the most AI innovative economy according to this indicator.

4. Our AI Competitiveness Indicator

To address the shortcomings, we have constructed a proprietary AI competitiveness indicator based on the equally weighted dimensions of a. innovation, b. adaption and diffusion, c. human capital and d. regulation (see box below for



Source: Artificial Intelligence Report 2024, GenAM

details). The intention is to shift the focus from AI preparedness more towards expected future growth and productivity gains. The aim of covering a broad range of countries comes at the cost of a more limited availability of indicators. Still, **our country sample includes both key advanced economies and all the MSCI Emerging Market economies,** which we deem very useful from an investor perspective. In total, our sample contains 55 countries.

A/ Innovation in general and in AI specifically is key for economies to gain competitive advantage over others. Innovative countries should be characterised by a high share of R&D expenditures in GDP amid a high patent activity in general as well as in AI.

B/ For these **innovations to translate quickly into economic gains, preparedness is for sure needed.** But in contrast to the broad scope of the IMF's AIPI, we prefer to use a narrower definition. To fully capture the infrastructure dimension, we use the International Telecommunication Union's ICT Development Index. It provides a high-level, partial view of the state of digital connectivity. It is complemented by the UNCTAD's Frontier technology readiness index consisting of the categories ICT deployment, skill, R&D activity, industry activity and access to finance. Additionally, we have chosen Scholarly articles on AI (covering English- and Chinese-language scholarly publications related to the development and application of AI including journal articles, conference papers, repository publications, books, and theses) as a proxy for the speed at which new AI knowledge spills over from academia into the broader economy. A potential tailwind for the adoption of AI is, in our view, the average age of the population, as the ability and willingness to use new technologies decreases with age.

Metrics used in the GenAM AI Competitiveness Indicator

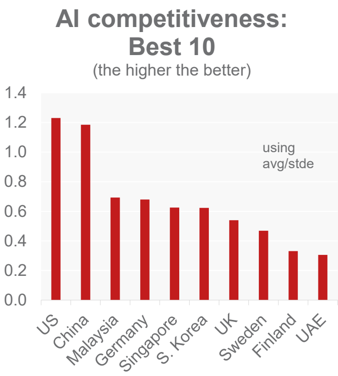
(weights in brackets)

Catego-ries	Indicators	Sources
Innova-tion (25%)	R&D expenditure share in GDP (60%)	https://data.worldbank.org/indica-tor/GB.XPD.RSDV.GD.ZS
	Patent applications per mln people (20%)	https://ourworldindata.org
	AI patents per 1 mln people (20%)	https://ourworldindata.org
Adaption & Diffu-sion (25%)	Scholarly articles on AI per mln people (20%)	https://ourworldindata.org
	Frontier technology readiness index (20%)	https://unctad-stat.unctad.org/datacen-tre/dataviewer/US.FTRI
	ICT Development In-dex (20%)	https://datahub.itu.int/dash-boards/idi/?e=DEU&y=2024
	Average age (40%)	https://our-worldindata.org/population-growth
Human capital & labour market (25%)	STEM graduates share (50%)	https://data-bank.worldbank.org/US-STEM-(ISCED-and-Ter-tiary)/id/cd77ac48#
	Internal labour market mobility (50%)	https://prosperi-tydata360.worldbank.org/en/indica-tor/WEF+GCI+EOSQ499
Regula-tion/legal frame-work (25%)	Cumulative number of AI-related bills passed into law since 2016 (25%)	https://our-worldindata.org/grapher/cu-mulative-number-artificial-in-telligence-bills-passed
	Government effective-ness (25%)	https://www.worldbank.org/en/publication/worldwide-gov-ernance-indicators
	Government voice and accountability (25%)	https://www.worldbank.org/en/publication/worldwide-gov-ernance-indicators
	Legal framework's adaptability to digital business models (25%)	https://prosperi-tydata360.worldbank.org/en/indica-tor/WEF+GCI+EOSQ509

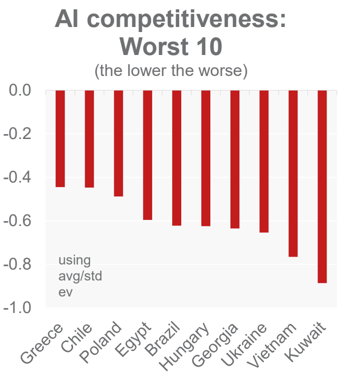
C/ Elevated human capital is of the essence for spreading and applying AI. Especially STEM (science, technology, engineering, and mathematics) graduates will be needed. To ensure diffusion among firms and sectors internal labour market mobility is also included here.

D/ Finally, legislation should neither hinder AI nor allow the negative aspects of AI to gain the upper hand. We follow the World Bank's approach and try to capture this **regulatory and legal dimension** by looking at the AI bills passed. Admittedly, this sub-category is the weakest exhibits the loosest relation to AI innovation on theoretical grounds. But together with the view about the legal adaptability to the digital business model it should provide some indication of whether the legislative or regulatory environment is conducive to AI. Additionally, we incorporate an indicator for government effectiveness and accountability in this category.

When constructing AI competitiveness indicators, it is important to bear in mind that the outcome is potentially sensitive to two dimensions: **First, the operationalisation of critical variables in absolute terms or per capita numbers**. The per capita (mln persons) approach emphasises the positive spillover effects from agglomeration via density while the absolute number emphasises the mere scale. We find both approaches viable on theoretical grounds; it is in the end an empirical question whether positive externalities arise from a high density of patent applications, AI patents and Scholarly articles on AI, or their sheer number. **Second, when ranking the economies, this can be done by means of the min/max-method or z-scores**[1]. The IMF's AIPI indicator fol-



Source: Worldbank, Ourworldindata, Unctadstat, GenAM calculations

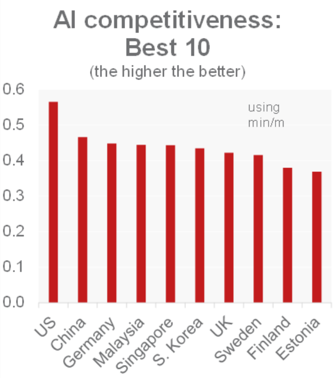


Source: Worldbank, Ourworldindata, Unctadstat, GenAM calculations

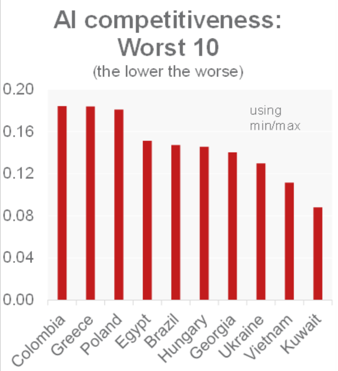
lows other international organisations (e.g. the World Bank) and uses the first approach. However, to detect the potential technological leadership of a country, its distance from the average might be more telling.

[1] The z-score approach or standardization subtracts from a point the average of this variables and adjusts it by the corresponding standard deviation. The min-max approach normalizes a data point by subtracting the min/max of the sample and dividing the result by the difference between the max and min value.

With these considerations in mind, we decided to **analyse using per capita as well absolute variables and adjusting them by means of the z-score as well as min-max approach**. From an investor perspective it may be useful to detect the economies best suited for adaption of AI and with a high probability to reap its potential economic gains while one should be cautious about investing in the laggards. We therefore **focus on the best 10 and the worst 10**.



Source: Worldbank, Ourworldindata, Unctadstat, GenAM calculations



Source: Worldbank, Ourworldindata, Unctadstat, GenAM calculations

Based on **absolute numbers** we find that the identified economies belonging to the **best 10** are – in slightly different order - in case of min/max or z-score the **US, China, Germany, Malaysia, Singapore, South Korea, the UK, Sweden and Finland.** The only economy included in case of the z-score approach is **United Arab Emirates** which is replaced by **Estonia** in the min-max approach.

GenAM AI country heatmap

country ranking under various standarisation approaches

absolute number		per capita	
zscore	min-max	zscore	min-max
best 10			
US	US	S. Korea	US
China	China	US	S. Korea
Malaysia	Germany	Singapore	Singapore
Germany	Malaysia	Germany	Germany
Singapore	Singapore	Malaysia	Malaysia
S. Korea	S. Korea	UK	Sweden
UK	UK	Sweden	UK
Sweden	Sweden	Finland	Finland
Finland	Finland	Switzerland	Luxembourg
UAE	Estonia	China	Switzerland
worst 10			
Greece	Colombia	Colombia	Chile
Chile	Greece	Chile	Poland
Poland	Poland	Poland	Colombia
Egypt	Egypt	Hungary	Hungary
Brazil	Brazil	Egypt	Egypt
Hungary	Hungary	Brazil	Brazil
Georgia	Georgia	Georgia	Georgia
Ukraine	Ukraine	Ukraine	Ukraine
Vietnam	Vietnam	Vietnam	Vietnam
Kuwait	Kuwait	Kuwait	Kuwait

Note: highlighted countries are those that come up consistently in tops/flops irrespective of the standardization approach taken

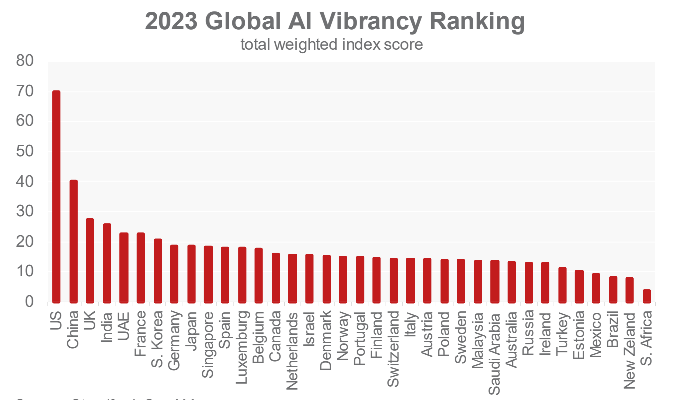
Source: GenAM calculations

Likewise, in both cases – in slightly different order – Greece, Poland, Brazil, Egypt, Hungary, Georgia, the Ukraine, Vietnam and Kuwait belong to the worst 10 group, while Chile does so only when using z-scores and Columbia only in case of the min-max approach.

We do the same in case of the per capita approach. Overall, **our approach identifies eight economies which are robustly in the best 10 or worst 10** (see table above). It is a bit surprising that China does relatively poor in the per capita specification. The key reason is that, given its huge population size of 1.4 bn people, it scores poorly in the category adaption and diffusion. On the other hand, small countries with some AI focus benefit, e.g. Switzerland.

5. AI Vibrancy Ranking

Even more narrowly focused on AI is the Global AI Vibrancy Tool from the Stanford University. It is much more detailed than our proprietary indicator using 42 indicators organized into 8 pillars. These are R&D, Responsible AI, economy, education, diversity policy and governance, public opinion, and infrastructure. For instance, it contains variables such as newly funded AI companies and net migration flows of AI skills. However, this comes at the cost of covering only 36 countries. while our proprietary indicatory covers 55 countries and the IMF's AIPI even 174.

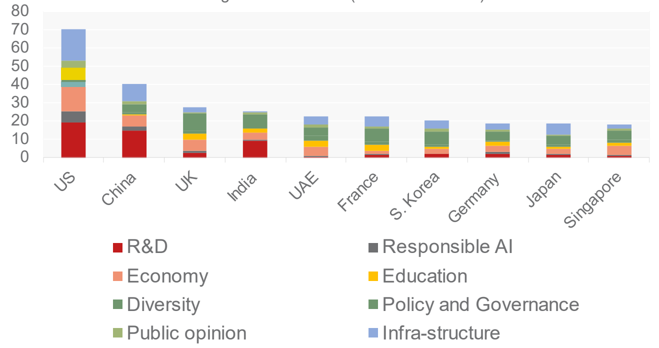


Source: Standford, GenAM

Despite the lower number of economies included and the greater focus on AI only, this indicator **also shows that the US, Germany, and Singapore are in the best 10** group. It is important to keep in mind that the AI Vibrancy Ranking (see graph below) can among others also be calculated based on absolute numbers or per capita basis. In the chosen absolute number approach, there is a big overlap with the outcome of our proprietary approach: both consistently place **China** number two after the US. However, **India, France and Japan** did not appear in our best 10.

The only country that is also included in our sample and among the worst ten is Brazil. Quite surprisingly, Estonia ranks only 32 in the AI Vibrancy Ranking, as it ranks poorly in AI-related R&D, responsible AI and the economy. In contrast, it does relatively well on the more general measurement human capital endowment and the labour market that is included in our proprietary indicator. The breakdown of this indicator shows that the sheer size of R&D and the huge infrastructure endowment are major drivers in making the US and China the two leading AI economies.

2023 Global AI Vibrancy Ranking: Best 10
total weighted index score (absolute numbers)

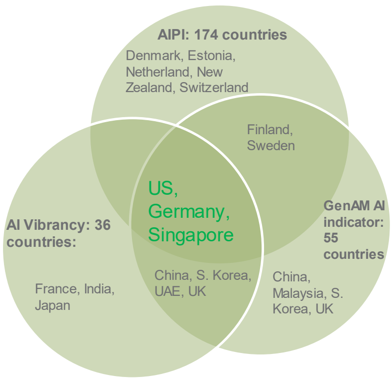


Source: Stanford, GenAM

6. Conclusions

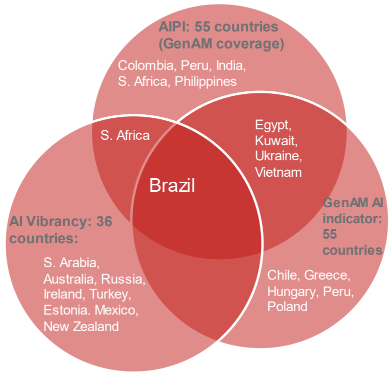
AI is spreading more and more into economic activity. While it is not clear how strong the related growth and productivity gains will be, they will undoubtedly be positive. From an investor perspective, it is crucial to identify in a first step the most promising markets. To do so, we constructed a proprietary AI indicator that captures key dimensions (innovation, diffusion, human capital and regulatory framework) required for exploiting the benefits of AI. Unlike to the IMF's AIPI broad indicator (covering 174 countries), we focused more narrowly on the AI dimension (at the cost of a smaller country sample), if not as much as the Global AI Vibrancy tool (AIVT) from Stanford University (covering only 36 countries). Our sample of 55 economies contains all MSCI Emerging Markets members. Still the **US, Germany, and Singapore** are consistently identified as belonging to the best 10 group by either indicator. When building the analysis on absolute numbers (like the AIVT does), **China** gets included too, as are **South Korea, the UK and the United Arab Emirates**. However, there are also countries that are not in the best 10 of either our AI indicator or the AIVT: **France, India, United Arab Emirates, Japan, Malaysia, Sweden and Finland**.

BEST 10 AI ECONOMIES



All the indicators considered identify **Brazil** as being very **poorly prepared** for AI. Not so clear are the signals for other countries but our upshot is that **Kuwait, Vietnam, the Ukraine, Georgia, Hungary, Poland, Russia, Mexico, South Africa, and Turkey** are not in a position of strength.

WORST 10 AI ECONOMIES



A shortcoming of all AI indicators is that data are available only with a substantial time lag and can hence serve only be a first screening. More detailed information should be gathered, e.g. from the European Commission in case of regulation by EU countries. The latest Trump initiative to launch a $ 500 bn investment in AI infrastructure reminds us that the AI environment might change quickly and substantially. Disruptive innovations might suddenly alter the AI country ranking. The appearance of DeepSeek, for instance, put Chinese AI models (almost) at par with the top Silicon Valley products reminding us about the non-linear nature of AI innovations and inventions, thereby challenging the ability of the discussed AI indicators to predict future economic success.

Nevertheless, our study suggests that **investors should not rely on broad classifications like MISCI EM, EU or BRICS**. Within the MSCI EM, only South Korea belongs to the most promising AI economies, and Mexico and South Africa belong to the least promising. Likewise, within the euro area France and Germany belong to the leading economies; Ireland, according to the AIVT, to the laggards. Within the BRICS, China undoubtedly has a huge potential while Russia and South Africa have only a very small one.

Imprint

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