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The Macroeconomic effects of generative AI☆

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ABSTRACT

Our purpose is to estimate the macroeconomic impact of generative Artificial Intelligence (gen-AI). A theoretical model, based on a two-level CES production function, is developed to consider different elasticities of substitution between capital and labor, but differentiating between worker groups. Gen-AI is modeled as a potential enhancer of productivity for the different labor groups. We estimate the model for 67 countries over period 2022–2025. Results suggest that gen-AI contributed to increasing the productivity of most workers, regardless of their education, contract type, full or partial work time, and vulnerability level. This can be explained as, contrary to prior advances in this technology, gen-AI presents a wider range of uses, being easily accessible for most individuals. On the other hand, we were not able to find evidence of significant changes in the substitution dynamics across different groups of workers, while the overall macroeconomic impact has been modest so far.

1. Introduction

Artificial Intelligence (AI) is a disruptive technology undergoing initial adoption throughout systems of production.[1] The dynamics of disruptive technologies such as generative AI (gen-AI) can generate important technological, industrial, economic, and social changes (Coccia, 2025). Case studies and microeconomic research already indicate that gen-AI adoption can generate productivity improvements as well as labor disruption, such as substitution among worker categories.

At the highest level, impact estimations are polarized around two perspectives. One body of research suggests that the macroeconomic impact of AI will be modest, yielding limited productivity improvements over the next decade (Acemoglu, 2025). This perspective estimates that productivity will increase by substituting higher paid jobs (usually skilled) with AI capability enhanced less-skilled workers. That said, the ultimate impact on the labor demand will depend on wages and labor force availability. As argued by Acemoglu and Restrepo (2019a): "*When wages are low and labor is abundant, automation will bring only modest productivity benefits*." Case study evidence in support of skilled labor substitution and unskilled labor enhancement with AI has been generated by Brynjolfsson et al. (2025), Noy and Zhang (2023), and Peng et al. (2023), among others. Autor (2024) generalizes the effect of AI on unskilled labor, stating that the technology provides expertise to "*complement (workers') skills, and supplement their judgement*".

On the other hand, a far more optimistic vision estimates higher productivity growth than the first perspective (Aghion and Bune, 2024). By re-estimating the share of exposed tasks for which it will be economically profitable to use AI, and on the average costs savings from it, the authors derive a higher productivity impact.

In a different analytical dimension, some research tends to disagree with the labor effects of the "limited productivity effects" literature. In contrast to the enhancement of expertise of unskilled labor and the substitution of skilled workers mentioned above, this technology is expected to be a substitute for unskilled work and complementary to skilled work (Maswama, 2024). Furthermore, some initial analyses predict, in fact, significant capital labor substitution due to AI automation. It should be pointed out, however, that this perspective is not necessarily contradictory to that stated by the "limited productivity effects" paradigm since labor displacement effects can be affected by the evolution of wages, skills, and technology adoption.

Underlining the polarization of perspectives and driven by the paucity of actual macro data, most research is either based on the

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[1] For example, the OECD reports that for Germany, AI has been adopted by 25.97% of enterprises.

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historical impact of earlier technological developments, case studies or a task-based analysis of jobs complemented by theoretical models. In this context, the aim of this paper is to develop an alternative empirical strategy to estimate the macroeconomic impact of gen-AI based on actual data series such as the adoption of this technology as measured by gen-AI platform traffic by country. In doing so, our purpose is to generate evidence of the impact of gen-AI not only on labor productivity, but also the potential for derived labor substitution (in other words, whether gen-AI adoption at the enterprise level can also yield job displacement).

For that purpose, we implement a theoretical model that allows different elasticities of substitution between factors of production, based on a two-level Constant Elasticity of Substitution (CES) production function, which uses the stock of physical capital, and alternative types of workers (e.g.: more and less educated) as factors of production. In this production function, gen-AI is modeled as a potential enhancer of the productivity of workers. In doing so, the model tests productivity enhancement and labor substitution, meaning that we account for AI not being necessarily factor neutral. The model is empirically estimated for a sample of 67 countries for the period 2017–2025, covering before and after the 2022 launch of ChatGPT, the first gen-AI platform. In our understanding, this is the first research that relies on a macro indicator that is closely associated with adoption such as gen-AI platform traffic, rather than relying on indirect metrics, such as AI related patents or robots installed base.

The remaining of this paper is structured as follows. Section 2 presents the study theoretical framework and how it relates to the recent contributions regarding the economic impact of AI. In turn, Section 3 presents the study design, including the data samples, the models and data analysis procedure. Section 4 presents the empirical estimation of the model, under different specifications, and discusses the results. Section 5 implements an alternative methodology to test for robustness. Finally, Section 6 ends with conclusions and closing reflections on further research.

2. Theoretical framework

Among the most recent technological innovations, AI stands out as a powerful tool for organizations looking to execute significant changes in the production model, achieve their strategic goals, and remain competitive. The OECD defines AI technologies as *computer-based systems that are capable of influencing the environment by producing an outcome for a given set of objectives*.[2] This definition highlights that AI uses data and other inputs to assess the environmental conditions of production, perform analyses, and formulate its different outcomes. As defined by Coccia (2024), AI is based on complex software and algorithms for devices that foster learning processes from different sources to perform human-like tasks. Similarly, Syam and Sharma (2018) argue that AI can be interpreted as the ability of computers to mimic intelligent human behavior, which enhances the scope of technologies to a range including robotics, machine learning, computer vision, and generative AI.

Research on the economic impact of AI has been developing over the past decade, although the original contributions focused on robotics, and machine learning and only recently they have shifted to areas such as computer vision (Svanberg et al., 2024; Thompson, 2024) and generative AI (Cazzaniga et al., 2024; Brynjolfsson et al., 2025; Toner-Rodgers, 2024; Noy and Zhang, 2023; Handa et al., 2024; Acemoglu, 2025; Felten et al., 2023; and Frank et al., 2023).

As happened with prior automation technologies, innovation and adoption has triggered research aiming at estimating AI impact on productivity as well as its power to displace labor. Acemoglu and Restrepo (2019a, 2019b) state that, while AI and robotics adoption is at the heart of strong labor displacement effect, this is compensated by a series of effects, ranging from demand of nonautomated tasks stimulated by productivity growth, and capital accumulation. That being said, the authors do not ignore the potential for disruptions resulting from skills mismatching and even "excessive automation" (Hui, 2020).

Building on this original framework, Acemoglu (2025) develops a theoretical model based on workers' tasks to argue that the effects of AI will occur through cost savings and productivity improvements at the task level, meaning that the aggregate productivity gains are driven by the percentage of tasks impacted and the average cost reduction impact per task. More precisely, the author considers that expected productivity gains over 10 years are then estimated as the combination of four variables: the GDP share of tasks that are exposed to AI; the share of exposed tasks for which it will be economically profitable to use the technology; the average costs savings from technology adoption; and AI's exposure-adjusted labor share. Based on recent estimates of these indicators, Acemoglu's estimates suggest that the macroeconomic impact of AI will be modest, quantified as an increase in productivity of 0.71% over a 10-year period. The author even states that, depending on the circumstances, the effects could be even lower.

On the other hand, other researchers point out that AI productivity effect should be larger than the one estimated by the "limited effect" paradigm. Building on Acemoglu's model, Filippucci et al. (2025) calculates the labor productivity effect driven by a range of gen-AI impact adoption scenarios. According to the authors, a slow adoption pace would yield an annual productivity impact of 0.4%, while a rapid adoption curve results in a 1.28% increase in labor productivity. Another relevant academic contribution that shares an optimistic view is that of Aghion and Bune (2024). The authors use two alternative approaches to estimate the impact of AI on productivity growth over the next decade. The first one is based on the similarities between the AI revolution and past technological revolutions. The second follows Acemoglu (2025) task-based approach, but with different assumptions. In the first case, they argue that if the productivity gains enabled by the AI over the next decade can be comparable to those of the electricity wave of the 1920s in Europe, then productivity growth would increase by 1.3 percentage points per year. If the digital technology revolution of the late 1990s and early 2000s in the United States is taken as a reference, the increase in productivity growth should be around 0.8 percentage points per year. On the other hand, under the second approach, the authors find evidence to assume that some of Acemoglu (2025) assumptions were too conservative. By considering more optimistic estimations on the GDP share of tasks that are exposed to AI, on the share of exposed tasks for which it will be economically profitable to use the technology, and on the average costs savings from it, they obtain a median estimate of 0.68 percentage points of additional annual productivity growth. This annual growth rate compounded over a period of 10 years yields a much larger growth (7%) than the 0.71% over the complete period as argued by Acemoglu (2025).[3]

Along the lines of this body of research, some authors forecast a large economic contribution of AI over a limited period of time. Damioli et al. (2021), Bassetti et al. (2020), and Brynjolfsson et al. (2018b) argue that AI has the potential to disrupt almost every industry due to its numerous areas of application. In this sense, Brynjolfsson et al. (2018b) present some examples of possible gains in productivity, such as customer service centers, autonomous vehicles or a more efficient use of energy. Similarly, Hang and Chen (2022) argue that AI can increase revenue by improving employee productivity and understanding of consumer behavior, setting more competitive prices, and creating non-imitable skills and resources. More recently, a microeconomic study by Brynjolfsson et al. (2025) suggested significant productivity gains from

[2] Definition provided by the OECD AI Policy Observatory (https://oecd.ai/en/ai-principles).

[3] More optimistic effects, albeit less substantiated empirically can be found in Davidson (2021).

the use of generative AI assisting workers in a customer service firm in the United States. Interestingly enough, researchers within the “limited productivity” effect tradition reviewed above do not see this evidence as contradictory. As stated by Autor (2024), the evidence of positive productivity effects yielded by Brynjolfsson et al. (2025), Noy and Zhang (2023), and Peng et al. (2023) case studies factually support the productivity enhancement among unskilled workers in selected occupations.

Another important debate in academic literature concerns whether AI should be regarded as a general-purpose technology, with several authors supporting this classification, while others remain skeptical. General-purpose technologies are those with the potential to affect an entire economy, influencing societies through their impact on pre-existing economic and social structures.[4] As Bassetti et al. (2020) suggest, AI can be characterized as a general-purpose technology with the potential to become a major source of productivity gains, generating several economic effects that go beyond those of regular capital goods.

On the contrary, another body of research goes back to the Solow paradox original view of limited impact. Along these lines, Corrado et al. (2021) even cast doubt on whether AI should be considered a general-purpose technology, which would explain the vision that argues about its "low impact" on productivity. Likewise, Storm (2022) does not expect AI to generate greater productivity gains than previous general-purpose technologies. Moreover, Schmelzing (2020) predicts a future long-term decline in productivity, in which AI will only act as a palliative. As Trabelsi (2024) argues, the effects of AI on economic growth will not be uniform across sectors and regions. In this regard, some industries may experience more significant change and growth, while others may face greater challenges or complexities in the process.

Another dimension upon which there is a lack of consensus is the kind of jobs to be impacted by AI. Partly driven by the type of technology being assessed, the original analyses focused on robotics and machine learning tended to conclude that primary job substitution would focus on manufacturing and services of highly routinized occupations requiring moderate skills (Autor et al., 2003; Autor, 2022). Conversely, recent work focused on gen-AI appears to conclude that technology would contribute to the substitution of partially skilled labor in sectors such as data science (Felten et al., 2023; Frank et al., 2023), finance (Autor, 2022; Acemoglu and Restrepo, 2022; Felten et al., 2023; Zarifhonarvar, 2023), and the legal profession. In contrast, Maswana (2024) argues that AI is expected to be a substitute for unskilled work and complementary to skilled labor. This explains how AI can affect different countries or sectors very differently, favoring both economic growth and employment in those environments where the workforce is highly qualified. The complementarity between AI and skilled jobs can also be demonstrated in the study by Toner-Rodgers (2024), who analyzes the effects of this technology on innovation. Based on a sample of material discovery cases of 1018 scientists in an R+D laboratory of a US company, empirical research suggested that AI-assisted researchers discover 44% more materials, resulting in a 39% increase in patent applications and a 17% increase in downstream product innovation. In this way, the author proves that AI automates a significant percentage of the tasks linked to the generation of ideas, reassigning experts to other tasks.

A conclusion that can be gleaned also from the analysis of the available research on AI economic impact is that, based on the empirical strategies, most of it has been generated either through microeconomic case studies or theoretical modelling. As mentioned above, the absence of macroeconomic impact work is driven, in part, by the lack of long run time series typically used in these empirical strategies.

In this context, the following research is expected to address three research objectives: (i) shed some light on the debate of AI economic impact through an empirical strategy based on macroeconomic modelling of actual data series, including metrics of gen-AI adoption such as platform traffic, (ii) assess the relative impact on labor, highlighting the difference across kinds of jobs, and (iii) establish initial macroeconomic-based evidence of the overall effect from gen-AI.

Three research hypotheses have been stipulated:

- H1: Gen-AI induces productivity growth for most worker groups, regardless of their qualification or condition. This hypothesis comes from the fact that, contrary to previous advances, such as robotics and machine learning, where effects concentrated on routine and less cognitive-skill occupations with low qualifications, gen-AI can be easily adopted even by less-skilled workers, through support in basic tasks such as writing, coding, or gaining instant access to information and feedback. Along these lines, gen-AI should enable low-skilled workers to tackle complex tasks via productivity augmentation.
- H2: While most workers should experience productivity gains, the magnitude of these gains may diverge across labor groups, with some of them being relatively more benefited than others. This may lead to an increase in substitution dynamics across different workers’ groups (e.g., job displacement).
- H3: Based on international data analysis, gen-AI is expected to have generated, so far, limited macroeconomic impact on productivity growth. This modest impact can be explained by the fact that this technology is still in the initial stages of development and diffusion, although we expect that its contribution to productivity could increase over the long run. This hypothesis expands Acemoglu’s (2025) body of research on modelling production functions based on US data, bringing an international dimension.

In sum, our hypotheses are aligned with the view of gen-AI as a general-purpose technology that induces productivity gains for most workers’ groups, although some of them may be relatively more benefited than others, which can potentially give rise to job displacement effects. On an aggregate basis, the impact from 2022 to the present time should have been modest, given that it is still early days.

3. Study design

3.1. Models and empirical strategy

Our objective is to test the overall impact of gen-AI on output and the elasticity of substitution between factors, according to a production function. However, given that, as stated by Acemoglu and Restrepo (2019a, 2019b), displacement effects are not present in most production functions, we selected in accordance with hypothesis H2, an approach where different elasticity of substitution between any two factors (such as high and low educated workers) has to be accounted for. For this purpose, we used a two-level CES production function (Sato, 1967; Duffy et al., 2004). As its name implies, the CES production function exhibits constant elasticity of substitution among factors. This is a general framework that is conducive to estimating how the different factors of production are linked. In this sense, it is worth mentioning that the production functions of fixed proportions that denote perfect complementarity (Leontief), the linear function that denotes perfectly substitutive factors, and the Cobb-Douglas formulation are all particular cases of the CES production function.

The factors of production under consideration are the stock of physical capital (K), and at least two different groups of workers (namely L^1 and L^2), whose basic specification can be modeled as follows :[5]

[4] Previous examples are the steam engine, electricity, and information technology.

[5] In Duffy et al. (2004), the selected production function groups capital and skilled labor as a composite factor in their relationship with unskilled labor. In our case, we group both worker’s kinds as a composite labor factor as we intend to understand how the substitution dynamics evolve within the labor input.

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(A_{it}^{L^1}L_{it}^1\right)^{\theta} + (1-\beta)\left(A_{it}^{L^2}L_{it}^2\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \tag{1}$$

In the equation (1), Y represents the gross domestic product (GDP), and the subscripts i and t indicate country and time-period, respectively. The term A_{it} represents Total Factor Productivity (TFP). On the other hand, α and β are parameters constrained between zero and one, reflecting the relative importance of the different factors of production. A key element of the proposed production function is the interpretation of the parameters θ and ρ, which, depending on the value they take, will allow us to evaluate to what extent the different factors of production are complementary or substitutive.[6]

Starting with θ, this parameter allows us to identify the relationship between the different types of workers. The elasticity of substitution between L^1 and L^2 can be approximated as $\sigma_{L^1-L^2} = \frac{1}{1-\theta}$, so it can be stated that:

$$\sigma_{L^1-L^2} = \begin{cases} 0 \ \textit{if} \ \theta \to -\infty \\ 1 \ \textit{if} \ \theta = 0 \\ \infty \ \textit{if} \ \theta = 1 \end{cases}$$

From this, it can be deducted that the respective group of workers will be:

$$\begin{cases} \textit{perfect complementary}, \ \textit{if} \ \theta \to -\infty \\ \textit{gross complementary}, \ \textit{if} \ \theta < 0 \\ \textit{independent}, \ \textit{if} \ \theta = 0 \\ \textit{gross substitutes}, \ \textit{if} \ 0 < \theta < 1 \\ \textit{perfect substitutes}, \ \textit{if} \ \theta = 1 \end{cases}$$

Therefore, a positive value of θ would indicate a substitutability relationship, while a negative one would indicate complementarity. On the other hand, if such a parameter were zero, both labor factors would be independent (as reflected, for example, in the Cobb-Douglas production functions). Following hypothesis H2, we expect some degree of substitution within worker groups, so we hypothesize $\theta > 0$.

On the other hand, we assume that both labor groups act as a composite factor in their relationship with capital. In this way, the link between the two is interpreted from the parameter ρ. Therefore, the elasticity of substitution between the compound labor and capital is represented as $\sigma_{L-K} = \frac{1}{1-\rho}$, so it can be stated that:

$$\sigma_{L-K} = \begin{cases} 0 \ \textit{if} \ \rho \to -\infty \\ 1 \ \textit{if} \ \rho = 0 \\ \infty \ \textit{if} \ \rho = 1 \end{cases}$$

From which it can be deduced that the labor compound factor and capital will be:

$$\begin{cases} \textit{perfect complementary}, \ \textit{if} \ \rho \to -\infty \\ \textit{gross complementary}, \ \textit{if} \ \rho < 0 \\ \textit{independent}, \ \textit{if} \ \rho = 0 \\ \textit{gross substitutes}, \ \textit{if} \ 0 < \rho < 1 \\ \textit{perfect substitutes}, \ \textit{if} \ \rho = 1 \end{cases}$$

Thus, ρ will take a positive value in the case of substitutability and a negative value in the case of complementarity (and zero in the case of the composite factor and the capital being independent of each other). Considering previous evidence from the literature (Duffy et al., 2004), the link between physical capital and labor may be complementary, which in that case results in $\rho < 0$.

A relevant aspect in the analysis will depend on the treatment to be given to $A_{it}^{L^1}$ and $A_{it}^{L^2}$, that is, the productivity term associated with both labor groups. Given that the objective of this work is to analyze the role of gen-AI in this matter, we model these elements as follows:

$$A_{it}^{L^1} = e^{\delta_{L^1}AI_{it}}$$

$$A_{it}^{L^2} = e^{\delta_{L^2}AI_{it}}$$

In other words, the idea is to verify to what extent gen-AI contributes to increasing the productivity of the different kinds of workers under consideration. In this sense, if $\delta_{L^i} > 0$ is verified, this would imply that gen-AI increases the marginal productivity of labor group i. Similarly, if $\delta_{L^i} = 0$, this would imply that gen-AI plays no role in increasing the marginal productivity of these workers. This approach challenges perspectives that argue that the effect of technology is factor-neutral, aiming for differences in their contribution to the different worker's groups.

Substituting the terms associated with the productivity of both labor measures in the production function represented in Eq. (1), we obtain:

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_{L^1}AI_{it}}L_{it}^1\right)^{\theta} + (1-\beta)\left(e^{\delta_{L^2}AI_{it}}L_{it}^2\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \tag{2}$$

Applying logs to the Eq. (2), the following expression is obtained:

$$\ln Y_{it} = \ln A_{it} + \frac{1}{\rho}\ln\left[\alpha\left[\beta\left(e^{\delta_{L^1}AI_{it}}L_{it}^1\right)^{\theta} + (1-\beta)\left(e^{\delta_{L^2}AI_{it}}L_{it}^2\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right] \tag{3}$$

This final empirical specification will be estimated for different and alternative working groups.

3.2. Sample and data

The analysis is based on a panel of 67 countries covering the period 2017–2025 with quarterly data. Estimates will be done by splitting the panel into two periods: 2017Q1–2022Q3 (period without availability of generative AI), and 2022Q4–2025Q2 (period in which gen-AI tools became available).[7]

The countries included are all the ones for which the International Monetary Fund (IMF) reports quarterly GDP data. The full list is shown in Table 1, consisting of both advanced and emerging economies.

The variables to be used in the empirical estimation of the model are detailed in Table 2. The dependent variable will be the quarterly gross domestic product (GDP), obtained from the IMF database. For the capital stock, the 2016 value reported in the Penn World Tables (PWT) is taken as starting point, and it is projected to 2025 by taking the quarterly investment in capital formation according to the IMF and the capital depreciation rate per country according to PWT.[8] Both GDP and capital stock are expressed in constant prices and converted into dollars.

With respect to gen-AI adoption, we built a variable that quantifies the traffic on gen-AI platforms. This was done by compiling from Semrush the monthly visits to the main AI tools that have been launched worldwide since the end of 2022: ChatGPT, Gemini, Deepseek, Copilot, Claude and Perplexity.[9] The monthly data was added by quarters as this is the temporal breakdown of our panel. The use of traffic data to

[6] Following the conventional specification of CES functions, it is assumed that $\theta \leq 1$ and $\rho \leq 1$.

[7] ChatGPT, the first generative AI tool to be diffused, was launched in October 2022, although its availability by country might have somewhat shifted.

[8] For China, Kenya and North Macedonia we used capital formation levels reported by the World Bank (converted into quarterly levels) as the IMF does not report data for these countries.

[9] Semrush is a search engine marketing platform developed by the American company Semrush Holdings, Inc. It is used for keyword research, competitive analysis, site audits, backlink tracking, domain authority tracking, and online visibility insights. The platform also collects information about online keywords gathered from Google and Bing search engines. Across the information it offers it includes estimations of any website's desktop and mobile traffic. Among other information, for any website it tracks the number of visits, of unique visitors and average time that users spend on them.

Table 1
Countries included in the sample.

Albania	France	North Macedonia
Armenia	Georgia	Norway
Austria	Germany	Poland
Belarus	Greece	Portugal
Belgium	Guatemala	Romania
Bolivia	Hungary	Russia
Bosnia and Herzegovina	India	Saudi Arabia
Botswana	Indonesia	Serbia
Brazil	Ireland	Singapore
Brunei Darussalam	Italy	Slovak Republic
Bulgaria	Kenya	Slovenia
Chile	Korea	South Africa
China	Latvia	Spain
Colombia	Lithuania	Sri Lanka
Costa Rica	Luxembourg	Sweden
Croatia	Malaysia	Switzerland
Cyprus	Malta	Thailand
Czech Republic	Mauritius	Türkiye
Denmark	Mexico	Ukraine
Egypt	Moldova	United Kingdom
El Salvador	Montenegro	United States
Estonia	Netherlands	Uruguay
Finland		

Source: authors' own elaboration.

Table 2
Variables to be used in econometric regressions.

Group	Variable	Description	Source
Outcome	Y	Real Gross Domestic Product (In billion dollars at constant prices).	IMF
Capital	K	Real physical capital stock (In billion dollars at constant prices).	PWT/IMF
Gen. AI indicator	AI	Total visits to ChatGPT, Gemini, Deepseek, Copilot, Claude and Perplexity websites (in millions)	Semrush
Workers by education	Primary	Workers with primary education as their highest educational attainment (in millions)	IMF/ TCB/WB
	Secondary	Workers with secondary education as their highest educational attainment (in millions)	IMF/ TCB/WB
	Tertiary	Workers with at least a bachelor's degree (in millions)	IMF/ TCB/WB
Workers by working hours	Part-time	Part-time workers (in millions)	IMF/ TCB/WB
	Full-time	Full-time workers (in millions)	IMF/ TCB/WB
Workers by contract condition	Self-employed	Self-employed workers (in millions)	IMF/ TCB/WB
	Hired	Hired workers (in millions)	IMF/ TCB/WB
Workers by vulnerability	Vulnerable	Vulnerable workers (in millions)	IMF/ TCB/WB
	Not vulnerable	Not-vulnerable workers (in millions)	IMF/ TCB/WB
Workers by sector	Agriculture	Agriculture workers (in millions)	IMF/ TCB/WB
	Industry	Industry workers (in millions)	IMF/ TCB/WB
	Services	Service workers (in millions)	IMF/ TCB/WB

Source: authors' own elaboration.

measure gen-AI adoption needs to be justified further. By definition, gen-AI adoption is fulfilled by three different segments: individual consumers relying on the technology as an enhancement of information search, individual users within private and public sectors organizations that rely on gen-AI to complement/enhance individual tasks (write a memo, produce a presentation), and organizations that rely on gen-AI to enhance operational processes (e.g. agents in support of customer care operations). In this context, aggregate traffic data, such as visits to ChatGPT site, is capturing adoption across all three segments, although it is assumed that all three are correlated over time. Thus, for purposes of this analysis it is considered that traffic data is an adequate gen-AI adoption metric.[10]

The variables for the five groups of workers were built by relying on different sources to have the possibility of breaking down workers by education level, by their working hours, by their contract conditions, by their degree of vulnerability and by the economic sector they work in.

First, we built a series of quarterly employment by country. For this purpose, we started by compiling the quarterly employment data as reported by the IMF. Missing data was filled with employment data from The Conference Board (TCB), and when a country was not covered by TCB, by the World Bank (WB).[11] As both TCB and WB report only annual data, these imputations required conversion into quarterly levels.[12]

Once the data of quarterly employment for each country was obtained, the next step consisted in compiling series that allowed us to split the employment values by specific worker's groups. First, we compiled the workforce percent distribution by educational attainment. To do this, the percentage of the population over 25 years of age with primary, secondary and tertiary (bachelor's or equivalent) education according to the WB is taken as a reference, which is then multiplied by the number of workers to make the distinction between educational group.[13] Data reported from the WB is collected from the UNESCO Institute for Statistics which compiles data mainly from national population census, household surveys, and labor force surveys.

Second, we segmented workers according to their working hours, distinguishing between part-time and full-time employees. We split the workforce data by relying on the series of part-time employment (as % of total employment) compiled from the WB. Part-time employment is based on the definition of <35 actual weekly hours worked, which the WB collects from the International Labor Organization (ILO) statistics, compiled from labor force surveys designed to cover virtually the entire non-institutional population of a given country, all branches of economic activity, all sectors of the economy and all categories of workers.

Third, we segmented workers according to their contract conditions (self-employed versus hired ones). The split is made through the variable self-employed (as % of total employment) as reported by the WB, compiled from ILO surveys. Self-employed workers are those individuals who work on their own account or with one or a few partners or in cooperation. They include sub-categories of (i) self-employed workers with employees (employers), (ii) self-employed workers without

[10] Ideally, one might want to measure adoption by considering the percent of enterprises using the technology. However, data in this case is fairly scarce. For example, the OECD reports annual adoption statistics for 28 countries between 2022 and 2025, which at 84 observations limits the statistical significance of results. In other work, Katz et al. (2025) relied on AI spending as a measure of adoption. However, as pointed out by an anonymous referee, spending levels may not accurately capture the effectiveness or depth of AI integration through business process. However, data traffic is available for all countries, being this an accurate proxy of both adoption and usage intensity. Contrary to the other measures, it refers exclusively to gen-AI, being this the sole focus of this study. In addition, we found gen-AI traffic to present a high correlation with enterprise AI adoption (0.7) for the cases in which both variables are available for OECD reported countries.

[11] The WB reports the labor force by country, which was used in conjunction with the unemployment rate to calculate the employment level.

[12] Conversion from annual to quarter data was done by assuming that for each country, the compound average growth rate of employment remained constant across the different quarters of a given year. Employment series from IMF, TCB and WB were assumed to be consistent among them.

[13] For missing values in the World Bank reported data of percentage of the population over 25 years of age by educational attainment, we made an imputation based on the remaining years and existing variation rate on such ratio by country. The dataset is available upon request.

employees (own-account workers), and (iii) members of producers' co-operatives and contributing family workers (also known as unpaid family workers).

Fourth, we classified employees according to their vulnerability level, using the variable of vulnerable employment (as % of total employment), as reported by the WB and collected from the ILO. Vulnerable employment corresponds to contributing family workers and own-account workers; thus, this is effectively a subgroup of the self-employment category. These individuals are vulnerable because they lack formal work arrangements, often lack social protection, and face high economic risks, frequently reaching low earnings.

Finally, we also considered jobs broken down by their economic sector. For this purpose, we relied on the WB variables of employment in agriculture, industry, and services (in all cases as % of total employment), which were sourced from the ILO.[14]

With the overall employment series and the shares of workers in the categories described above, we were able to effectively create several series of workers by group type.

4. Results and discussion

4.1. Descriptive statistics

Table 3 presents the main descriptive statistics for the variables to be used in the empirical analysis. We conducted skewness–kurtosis test for all variables, with the hypothesis of normality rejected in all cases, providing support for the application of logarithms in the final empirical specification presented in Eq. (3).

Across the sample, on average the most common workers are those with primary education. On the other hand, full-time workers prevail over part-time ones. Hired workers are much more than self-employed ones, although the latter represent an important portion of the workforce. In addition, most of the workers are classified as not vulnerable. When split by sector, most of the workers belong to services, followed by industry and lastly by agriculture.

Table 3
Descriptive statistics.

Group	Variable	Mean	Std. Dv.
Outcome	Y	258.1332	817.3074
Capital	K	4078.9860	11,196.8600
Gen. AI indicator	AI	19.2433	122.3267
Workers by education	Primary	12.8633	59.0479
	Secondary	10.4133	27.1580
	Tertiary	5.4539	12.6377
Workers by working hours	Part-time	5.6810	13.5268
	Full-time	16.4890	44.8791
Workers by contract condition	Self-employed	13.8642	56.7297
	Hired	19.0038	53.2943
Workers by vulnerability	Vulnerable	12.7048	53.1518
	Not vulnerable	20.1631	57.0972
Workers by sector	Agriculture	7.1312	30.5339
	Industry	8.5553	30.9868
	Services	17.1864	46.3701

Source: authors' own elaboration.

4.2. Estimation approach

The empirical specification presented in Eq. (3) presents important nonlinearities, coming from the nature of the CES function. This implies that the econometric analysis cannot be performed through Ordinary Least Squares (OLS), but through Non-linear Least Squares (NLS). In a further robustness' analysis, we will conduct estimates using different functional specifications and empirical methodologies.[15]

NLS routines require form assigning initial values to the parameters to begin the estimation. All estimates to be conducted will use the same set of feasible initial values.[16] In addition, all estimates will incorporate fixed effects by country, year, and quarter.[17] Country fixed effects absorb unobservable aspects that can make some countries more productive than others because of industrial organization, cultural, idiosyncratic, or institutional reasons, as long as they are invariant over time. The addition of fixed effects per year and quarters, on the other hand, allows us to contemplate exogenous technological growth, as well as absorb any cyclical shock that affects all economies (for example, the effects of COVID-19 in 2020).

4.3. Model results when classifying workers by their educational attainment

This section reports the econometric results when classifying workers by their educational group. It is important to consider that more education is not synonymous with more skills, as some university graduates can lack practical abilities, while many non-tertiary workers can be highly skilled tradespeople.[18] However, it can be argued that both aspects should be positively correlated, as a part of the skills depends on knowledge. As argued by the WB in the variable definition, the classification of workers by educational attainment can be considered as a measure of knowledge skill level,[19] as certain competencies are typically associated with the completion of each educational level.

Table 4 presents the estimates. In columns (i), (ii) and (iii) we split the workers into two groups: on the one hand those with primary education only (therefore we assume they lack important skills) and on the other hand those with either secondary or tertiary education (we assume this group to be more skilled than the first one). Therefore, the production function to be estimated takes this form:

[14] The agriculture sector consists of activities in agriculture, hunting, forestry and fishing, in accordance with division 1 (ISIC 2) or categories A-B (ISIC 3) or category A (ISIC 4). The industry sector consists of mining and quarrying, manufacturing, construction, and public utilities (electricity, gas, and water), in accordance with divisions 2-5 (ISIC 2) or categories C-F (ISIC 3) or categories B-F (ISIC 4). The services sector consists of wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social, and personal services, in accordance with divisions 6-9 (ISIC 2) or categories G-Q (ISIC 3) or categories G-U (ISIC 4).

[15] We thank three anonymous referees for suggesting this.

[16] The set of initial parameters is consistent with the economic theory: $\alpha = 0.6, \beta = 0.4, \rho = -0.8, \theta = 0.8$. In situation in which a third group of workers is added, the corresponding relative initial value will be $\gamma = 0.2$. In addition, productivity enhancing coefficient will take initial values of $\delta_i = 0.2$ for every working group i. We conducted checks by running again the estimations using as initial values the ones that arise from the respective estimates, with results being almost unchanged.

[17] Estimation of NLS models with multiple parameters can be highly demanding from a computational point of view. For this reason, in situations in which the estimation had difficulties to converge into an optimum, we relaxed the default convergence criterion for successive parameter estimates and for the residual sum of squares, to improve the computational performance process.

[18] We thank an anonymous referee for pointing this.

[19] We follow Acemoglu and Autor (2011) who stipulate that the distinction between "skilled" and "unskilled" workers, identified as those endowed with college and high school degrees respectively, are useful categories to understand the labor market's valuation of skills and the impact of technology. We remain cognizant that the level of a tertiary degree as a differentiating factor might be somewhat arbitrary given that it does not establish the discipline attached to the degree, whether it is STEM or the Humanities. However, the experience in human resources regarding AI implementation indicates that even Humanities degrees are conducive to result in the critical thinking capability required for a successful AI case implementation.

Table 4
NLS estimates classifying workers by education.

	(i)	(ii)	(iii)	(iv)
Constant	10.1748***	10.2862***	10.6694***	10.6640***
	[0.0850]	[0.0933]	[0.0227]	[0.0308]
ρ	−0.5630***	−0.5767**	−0.7121***	−0.7342***
	[0.2116]	[0.2532]	[0.0598]	[0.0462]
θ	4.6835**	1.0000	0.8783	0.6619**
	[2.1654]	(set)	[0.6319]	[0.3006]
α	0.6006***	0.5565***	0.3802***	0.4658***
	[0.0832]	[0.0883]	[0.0299]	[0.0163]
β	0.6645***	0.3515***	0.4202***	0.3844***
	[0.1726]	[0.1171]	[0.1471]	[0.0321]
γ				0.2054***
				[0.0430]
δ_P			0.2516***	0.2119***
			[0.0530]	[0.0424]
$\delta_{S\&T}$			0.1897***	
			[0.0264]	
δ_S				0.2506***
				[0.0460]
δ_T				0.1574***
				[0.0489]
Country FE	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Z-test θ=1	1.70*		−0.19	−1.13
Z-test $\delta_P=\delta_{S\&T}$			0.88	
Z-test $\delta_P=\delta_S$				0.50
Z-test $\delta_P=\delta_T$				0.84
Z-test $\delta_S=\delta_T$				1.08
R-squared	0.997	0.997	0.949	0.914
Period	2017–2022	2017–2022	2022–2025	2022–2025
Observations	1518	1518	685	685

Note: *** $p < 1$, ** $p < 5\%$, * $p < 10\%$. Robust standard errors in brackets.
Source: authors' own elaboration.

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_P AI_{it}}L_{it}^{P}\right)^{\theta} + (1-\beta)\left(e^{\delta_{S\&T}AI_{it}}L_{it}^{S\&T}\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \tag{4}$$

In Eq. (4), P denotes primary education, while $S\&T$ denotes secondary and tertiary education.

In columns (i) and (ii) we cover the period 2017Q1 to 2022Q3, therefore before the diffusion of gen-AI. This means that the estimation is done by imposing $\delta_P = \delta_{S\&T} = 0$ in Eq. (4). The result from column (i) cannot be considered valid as it reflects a very high θ, beyond the accepted range by the theoretical model where $\theta = 1$ at most. The z-test conducted to θ after the estimation confirmed that its value can be considered to be above 1 with a significant level of 10%. While this suggests a very high substitution level between workers, we choose to re-estimate the model to make it consistent with the theory. Therefore, in column (ii) we present the estimated model when setting $\theta = 1$, this is imposing the corner solution after making the restriction stipulated by the theory to be binding. This new estimation shows that, in the pre-generative AI era, there was some complementarity between labor and capital (denoted by $\rho = -0.577$, significant at 5%), in a context of high substitutability between workers by their education level.

Next, in column (iii) we estimate the model for the gen-AI period, 2022Q4–2025Q2, now allowing the identification of the δ_P and $\delta_{S\&T}$ parameters. The comparison between the estimated coefficients from column (ii) and those in column (iii) allow us to understand some of the economic dynamics taking place after the diffusion of gen-AI. First, there seems to be an increase in the absolute value of ρ (from -0.577 to -0.712), suggesting that the complementarity between labor and capital has increased. This can be explained as gen-AI augments human capabilities rather than merely automating routine tasks, increasing the workers' productive use of capital.

In addition, we can see that β, that measures the relative importance of the less educated workers in the labor composite input has increased as well, suggesting that these workers, now using generative AI, can become more important for economic activity. In addition, θ has been reduced (now reaching 0.878 but not being significantly different from zero). This is consistent with the increase in relevance of lower educated individuals, making them less substitutable than before.

It is important to notice that both δ_P and $\delta_{S\&T}$ parameters are positive and statistically different from zero. This indicates that both low and highly educated workers benefit from the use of generative AI to enhance their productivity. This can reflect the general-purpose condition of gen-AI, as argued by some authors (Bassetti et al., 2020). However, the magnitude of the coefficient seems to be larger for the less educated ones, although it is worth considering that the difference between them is not significant from a statistical standpoint, as the z-test for $\delta_P = \delta_{S\&T}$ yields a not significant result. Again, this is consistent with the previous comparison between the pre- and post-gen-AI estimations.

Finally, we further split the workers into three groups: those having primary education only, those having only completed secondary education, and finally those with tertiary education. Therefore, the production function to be estimated takes this form:

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_P AI_{it}}L_{it}^{P}\right)^{\theta} + \gamma\left(e^{\delta_S AI_{it}}L_{it}^{S}\right)^{\theta} + (1-\beta-\gamma)\left(e^{\delta_T AI_{it}}L_{it}^{T}\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \tag{5}$$

Where P denotes primary education, while S and T denote respectively secondary and tertiary education. Results for Eq. (5) in column (iv) of Table 4 suggest some substitutability between workers, although lower than before the gen-AI period. Also, the increased complementarity between labor and capital is verified. As can be appreciated, AI enhances the productivity of all types of workers. While not statistically different among them, the coefficient appears to be larger for primary and secondary workers than for tertiary ones.

Overall, these results are consistent with H1, as they seem to verify that AI induces productivity growth for most workers' groups, even unskilled and less prepared ones. However, these results are not able to identify differences in the gains by education level, while there seems to be reduction in the substitution dynamics across different worker's groups, so H2 cannot be proven. This can be explained by the fact that it is still early days for this technology, with the substitution constrained only to specific sectors, as certain literature suggests being the case for data science (Felten et al., 2023; Frank et al., 2023) and finance (Autor, 2022; Acemoglu and Restrepo, 2022; Felten et al., 2023; Zarifhonarvar, 2023).

4.4. Model results when classifying workers by part-time and full-time

In this section we estimate our model now splitting workers not by education level, but according to their working hours, differentiating between part- or full-time conditions.

According to the WB, part-time employment has often been regarded as a tool for expanding labor supply. Considering that it can provide a better balance between professional and family life and appeal to individuals who prefer shorter hours and more personal time, part-time work may encourage a larger share of working-age people to participate in the labor market. Additionally, policymakers have supported part-time arrangements as a means to redistribute available work in economies struggling with high unemployment, thereby reducing politically sensitive unemployment rates without necessarily increasing the total volume of hours worked.

Part-time work, however, is not always the result of personal choice. While flexibility is often cited as one of its main advantages, part-time employment can also entail disadvantages compared to full-time positions. Many countries have adopted policies aimed at enhancing the quality of part-time jobs. Yet occupational segregation between part-time and full-time roles continues to persist in most nations, restricting the range of opportunities available to part-time workers.

By splitting workers by their part- and full-time conditions, the production function to be estimated takes the following form:

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_{PT}AI_{it}}L_{it}^{PT}\right)^{\theta} + (1-\beta)\left(e^{\delta_{FT}AI_{it}}L_{it}^{FT}\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \quad (6)$$

Where *PT* denotes part-time jobs, while *FT* denotes full time ones.

Results for the estimation of Eq. (6) are presented in Table 5. In column (i) we present the results for the period before gen-AI diffusion, while in column (ii) we present the results for the period after gen-AI launch identifying in this latest case the parameters δ_{PT} and δ_{FT}.

Results from column (i) suggest some complementarity between capital and labor, and high substitutability between part- and full-time jobs. The estimated θ is slightly above 1, although according to the z-test we can consider it to be one, therefore consistent with the economic theory that stipulates $\theta \leq 1$. This suggests very high substitution between part- and full-time jobs.

The comparison between both results, in this case, reflects low differences. Again, the results confirm that during the gen-AI diffusion period the complementarity between labor and capital rose considerably (as ρ evolved from -0.357 to -0.737). However, the degree of substitution between both kinds of workers remains the same, with both θ reach similar values and neither of them is statistically different from one.

Finally, it is important to note that gen-AI presents a significant effect in enhancing the productivity of both types of workers, again proving it to be transversal technology with a wider range of uses than previous AI generations. Comparatively, the effect seems to be larger in the case of full-time workers, although the difference is not statistically significant. Full-time workers may benefit slightly more from generative AI due to greater exposure and learning effects from sustained use, as productivity gains may scale with usage intensity and duration.

Again, these results seem to validate H1 but not to reach the expected results according to H2.

4.5. Model results when classifying workers by their contract condition

Now, we test the model by different groups of workers according to their contractual condition (self-employed and hired ones).

As reported by the WB, disaggregating employment data by contract status provides a basis for understanding workers' behavior, working conditions, and their placement within socio-economic groups. A large share of salaried employees in a country typically reflects a higher level of economic development. Conversely, when the proportion of own-account workers is relatively high, it often suggests a significant agricultural sector and limited growth of the formal economy. Likewise, a high percentage of contributing family workers tends to signal weaker economic development, limited job creation, and a predominately rural labor market. Self-employed individuals are the least likely to have formal employment arrangements, often lack access to social protection and safety nets that cushion economic shocks, and generally have limited capacity to accumulate savings to cope with such disruptions.

In this case, the production function to be estimated takes this form:

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_{SE}AI_{it}}L_{it}^{SE}\right)^{\theta} + (1-\beta)\left(e^{\delta_{H}AI_{it}}L_{it}^{H}\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \quad (7)$$

Where *SE* denotes self-employed jobs, while *H* denotes hired or salaried employees.

Results for the estimation of Eq. (7) are presented in Table 6. In column (i) we present the results for the period before gen-AI diffusion, while in column (ii) we present the results for the period after gen-AI launch identifying in this last case the parameters both δ_{SE} and δ_{H}.

Results from column (i) suggest some complementarity between capital and labor, while no substitutability between self-employed and hired jobs (the estimated θ is not different than zero, therefore both labor inputs are independent).

The comparison between both results confirms that during the gen-AI period the complementarity between labor and capital increased (as ρ evolved from -0.561 to -0.780). However, these types of jobs remain not substitutable, with θ now positive but still insignificant.

A relevant result in this estimation is that the β parameter that measures the relative importance of self-employed jobs over the total employment, evolves from being not significant before gen-AI was launched, to being positive and significant ($\beta = 0.383$) once the technology is available.

Finally, it is verified again that gen-AI presents a significant effect in enhancing the productivity of both types of workers, self-employed and contracted. Comparatively, the effect seems to be slightly larger in the case of self-employed workers, although the difference is not statistically significant. Self-employed workers may benefit more from gen-AI than hired employees due to their greater flexibility in tool adoption and customization, allowing rapid integration into diverse workflows

Table 5
NLS estimates classifying workers by working hours.

	(i)	(ii)
Constant	10.2230***	10.6710***
	[0.1191]	[0.0210]
ρ	−0.3568**	−0.7372***
	[0.1456]	[0.0540]
θ	1.1352*	1.1764*
	[0.6512]	[0.6541]
α	0.5498***	0.4217***
	[0.0910]	[0.0223]
β	0.4636***	0.4661***
	[0.1706]	[0.0863]
δ_{PT}		0.1668**
		[0.0742]
δ_{FT}		0.2126***
		[0.0232]
Country FE	YES	YES
Quarter FE	YES	YES
Year FE	YES	YES
Z-test θ=1	0.21	0.27
Z-test $\delta_{PT}=\delta_{FT}$		−0.50
R-squared	0.997	0.931
Period	2017–2022	2022–2025
Observations	1472	671

Note: *** $p < 1$, ** $p < 5\%$, * $p < 10\%$. Robust standard errors in brackets.
Source: authors' own elaboration.

Table 6
NLS estimates classifying workers by contract condition.

	(i)	(ii)
Constant	9.9585***	10.6067***
	[0.1357]	[0.0835]
ρ	−0.5608***	−0.7797***
	[0.2056]	[0.0474]
θ	−1.7806	0.7872
	[1.8167]	[0.4961]
α	0.6347***	0.5447***
	[0.0973]	[0.0418]
β	0.0011	0.3830**
	[0.0064]	[0.1911]
δ_{SE}		0.2514***
		[0.0901]
δ_{H}		0.1915***
		[0.0238]
Country FE	YES	YES
Quarter FE	YES	YES
Year FE	YES	YES
Z-test θ=1	−1.53	−0.43
Z-test $\delta_{SE}=\delta_{H}$		0.54
R-squared	0.997	0.881
Period	2017–2022	2022–2025
Observations	1518	685

Note: *** $p < 1$, ** $p < 5\%$, * $p < 10\%$. Robust standard errors in brackets.
Source: authors' own elaboration.

without bureaucratic delays or managerial approvals often faced in firms. They may also be more exposed to gen-AI related tasks due to the different nature of their work.

As in the previous cases, these results seem to validate H1 but not H2.

4.6. Model results when classifying workers by their degree of vulnerability

In this section, we test the model by workers group according to their degree of vulnerability. To reiterate, vulnerable jobs are those contributing to the family and own-account workers, being the most disadvantaged ones and the most likely to fall into poverty. Vulnerable jobs are, effectively, a subgroup of self-employed jobs (the most vulnerable part of that group). The vulnerable employment rate, which is the share of vulnerable employment in total employment, was an indicator targeted in the Millennium Development Goals, under the employment target on decent work.

The production function to be estimated takes this form:

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_V AI_{it}}L_{it}^{V}\right)^{\theta} + (1-\beta)\left(e^{\delta_{NV} AI_{it}}L_{it}^{NV}\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \quad (8)$$

Where V denotes vulnerable jobs, while NV denotes non-vulnerable ones.

Results for Eq. (8) are presented in Table 7. In column (i) we present the results for the period before gen-AI diffusion, while in column (ii) we present the results for the period after gen-AI launch identifying in this latest case the parameters both δ_V and δ_{NV}.

Results from column (i) suggest some complementarity between capital and labor, while no substitutability between vulnerable and non-vulnerable jobs (the estimated θ is not different than zero).

The comparison between both results confirms that during the gen-AI period the complementarity between labor and capital increased (as ρ evolved from −0.598 to −0.780). However, these types of jobs are now partial substituted, as θ now positive and significant at a 10% level.

As in the self-employed case, a relevant result in this estimation is that the β parameter, that measures the relative importance of vulnerable jobs over the total employment for the economy evolves from being not significant before generative AI was launched, to being positive and significant ($\beta = 0.372$) once gen-AI is available.

Finally, again it is verified that gen-AI presents a significant effect in enhancing the productivity of both kinds of workers. This, again, seems to be consistent with the condition of general-purpose technology. Comparatively, the effect seems to be slightly larger in the case of vulnerable workers, although the difference is not statistically significant.

These results again seem to validate H1, while at the same time they provide some limited support to H2.

4.7. Model results when classifying workers by economic sector

Finally, we distinguish the labor force according to the sector they work in agriculture, industry or services. In this section, the interest is not to see the evolution of substitutability patterns, but to find out if the productivity enhancing effect of generative AI varies by economic sector.

The production function to be estimated takes this form:

$$Y_{it} = A_{it}\left[\alpha\left[\beta\left(e^{\delta_{SER} AI_{it}}L_{it}^{SER}\right)^{\theta} + \gamma\left(e^{\delta_{AGR} AI_{it}}L_{it}^{AGR}\right)^{\theta} + (1-\beta-\gamma)\left(e^{\delta_{IND} AI_{it}}L_{it}^{IND}\right)^{\theta}\right]^{\frac{\rho}{\theta}} + (1-\alpha)(K_{it})^{\rho}\right]^{\frac{1}{\rho}} \quad (9)$$

Results for Eq. (9) presented in Table 8 verify that generative AI presents a significant effect in enhancing the productivity of industry

Table 7
NLS estimates classifying workers by vulnerability.

	(i)	(ii)
Constant	9.8849***	10.6012***
	[0.1421]	[0.1072]
ρ	−0.5983***	−0.7797***
	[0.2170]	[0.0485]
θ	−1.5894	0.7622*
	[10.1429]	[0.4485]
α	0.6710***	0.5454***
	[0.0994]	[0.0511]
β	0.0001	0.3718*
	[0.0041]	[0.2124]
δ_V		0.2516**
		[0.1011]
δ_{NV}		0.1934***
		[0.0214]
Country FE	YES	YES
Quarter FE	YES	YES
Year FE	YES	YES
Z-test θ=1	−0.26	−0.53
Z-test $\delta_V=\delta_{NV}$		−0.49
R-squared	0.997	0.882
Period	2017–2022	2022–2025
Observations	1518	685

Note: *** $p < 1$, ** $p < 5\%$, * $p < 10\%$. Robust standard errors in brackets.
Source: authors' own elaboration.

Table 8
NLS estimates classifying workers by sector.

Constant	10.6258***
	[0.1315]
ρ	−0.7648***
	[0.0473]
θ	0.7626
	[0.4716]
α	0.5315***
	[0.0594]
β	0.4080*
	[0.2161]
γ	0.1926
	[0.1695]
δ_{SER}	0.1859***
	[0.0261]
δ_{AGR}	0.2519
	[0.1804]
δ_{IND}	0.2363***
	[0.0493]
Country FE	YES
Quarter FE	YES
Year FE	YES
Z-test θ=1	−0.50
Z-test $\delta_{SER}=\delta_{IND}$	−0.71
R-squared	0.886
Period	2022–2025
Observations	685

Note: *** $p < 1$, ** $p < 5\%$, * $p < 10\%$. Robust standard errors in brackets.
Source: authors' own elaboration.

and service workers, but not for those of agriculture.

Services and manufacturing workers can benefit from gen-AI due to its applicability to cognitive, data-intensive, and design-oriented tasks central to these sectors, while agriculture workers should see limited gains because the sector relies primarily on physical, environmental, and manual processes less exposed to current gen-AI capabilities. This is consistent with some authors, such as Trabelsi (2024), who argue about the effects of AI not being uniform across sectors.

4.8. Overall effects during the period of analysis

From the generic Eq. (3), we can calculate the following derivative:

$$\frac{\partial \ln Y_{it}}{\partial AI_{it}} = \frac{\alpha\left[\beta\left(e^{\delta_1 AI_{it}}L_{it}^1\right)^\theta + (1-\beta)\left(e^{\delta_2 AI_{it}}L_{it}^2\right)^\theta\right]^{\rho/\theta-1}\left[\beta\delta_1\left(e^{\delta_1 AI_{it}}L_{it}^1\right)^\theta + (1-\beta)\delta_2\left(e^{\delta_2 AI_{it}}L_{it}^2\right)^\theta\right]}{\alpha\left[\beta\left(e^{\delta_1 AI_{it}}L_{it}^1\right)^\theta + (1-\beta)\left(e^{\delta_2 AI_{it}}L_{it}^2\right)^\theta\right]^{\rho/\theta-1} + (1-\alpha)K_{it}^\rho}$$

Now we will apply actual values to calculate the average contribution of gen-AI during the period. Using the coefficients of the two-labor model presented in column (iii) of Table 4, taking the mean values of the model variables for the gen-AI period (2022-Q4–2025Q2), and considering the average increase in AI traffic, we can conclude that, for the mean country between 2022Q4 and 2025Q2, the GDP increased 0.008% due to gen-AI. This modest increase is in line with our hypothesis H3. This is also consistent with the limited economic gains argued by Acemoglu (2025), or the visions in the same direction pointed out by Storm (2022) and Schmelzing (2020).

5. Robustness' analysis using differences-in-differences estimator

To further validate our conclusion, we conduct a robust analysis regarding the positive effect that we found of gen-AI on productivity. Its purpose is to test whether, using different functional specifications and advanced techniques of causal analysis, we are able to confirm that the diffusion of gen-AI led to the worker's productivity increases for the countries of our sample.

The empirical approach in this section uses the differences-in-differences methodology, that consists in comparing a specific outcome between treated and control groups. Naturally, treated observations in our case should be countries with positive gen-AI traffic, while controls are the countries without it. This raises a methodological problem, since almost all the observations began to be treated in the same period (2022Q4, when ChatGPT was launched), leaving no representative control group. To overcome this problem, we developed a series of AI binary indicators accounting for certain traffic thresholds. This is justified as some critical mass is needed for technology to deliver substantial gains.

For this purpose, four different treatment variables were defined. First, we consider treated observations that reach at least 50 gen-AI visits every 100 inhabitants. This threshold was defined by considering that this is equivalent to 10% of the population using gen-AI, a critical mass that ensures certain degree of diffusion and use of the tool within the country.[20] We will also test further alternatives of higher critical mass thresholds, such as 75, 100 and 125 visits for every 100 inhabitants as treatment variables. Using these definitions, we can test a differences-in-differences model with staggered treatment ensuring a representative control group.

We will use the estimator developed recently by De Chaisemartin and d'Haultfoeuille (2020), specifically useful for panel settings such as ours. The proposed estimator is designed to be valid for situations where the treatment effect is heterogeneous over time and across groups. The functional form will be a simple linear regression in which the dependent variable is the log of labor productivity (GDP per worker), with fixed effects by country and time periods, using the aforementioned AI indicators as treatment, and capital per worker as control. This specification is consistent with a Cobb-Douglas production function with two factor inputs with constant returns to scale (capital and labor) and gen-AI as the technological factor embedded in the TFP.

The results for the differences-in-differences estimator following the De Chaisemartin and d'Haultfoeuille (2020) methodology are reported in Table 9.

When using the first proposed treatment definition (50 visits for every 100 inhabitants), we found that the average treatment effect on the treated (ATT) is positive, although not significant. This suggests that this critical mass threshold was too low to trigger significant productivity gains at a macro level. When using the treatment defined as 75 for every 100 inhabitants, the ATT is positive and statistically significant (0.057). Further, the effect reaches the positive and significant value of 0.049 when using the 100 visits for every 100 inhabitants' treatment. Finally, under the definition of 125 visits per 100 inhabitants, the ATT is still positive and significant, reaching 0.025. Overall, these results suggest that, once a critical mass of AI diffusion is reached, labor productivity experienced on average an increase ranging from 2.5% to 5.7%.

An important assumption of differences-in-differences models is that, in the absence of treatment, variations over time in the outcome variable between observations that received the treatment and those that remain without it would have remained constant. This parallel trend assumption is tested through a placebo test reported by De Chaisemartin and d'Haultfoeuille (2020) estimator. In all the estimates conducted and presented in Table 9 we were not able to reject the null hypothesis of parallel trends and no anticipation assumptions based on the first and second pre-trends, providing validity to the results presented.

Table 9
Differences-in-differences estimates for labor productivity.

Dep. Var: Log(Y/L)	(i)	(ii)	(iii)	(iv)
Treatment: gen-AI visits/100 inhab.	> 50	> 75	> 100	> 125
ATT	0.090	0.057**	0.049**	0.025*
	[0.070]	[0.023]	[0.025]	[0.015]
Pre-trends (*p*-value)	0.624	0.121	0.993	0.326
Country Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES
Observations	189	239	289	289

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in brackets. All estimates incorporate capital per worker as control.
Source: authors' analysis.

[20] This calculation responds to the fact that, on average, every ChatGPT user made approximately 5 visits to the platform during year during 2023, according to data reported by Semrush for a sample of 26 countries. More details available upon request.

6. Conclusion

The purpose of this research was to develop a model that allows estimating empirically through macroeconomic modelling the economic impact that gen-AI has had in recent years. To do this, we have taken as reference the traffic to AI platforms data covering a sample of 67 countries for the period 2022–2025. The model developed allows different elasticities of substitution between any two factors, based on a two-level CES production function, which uses the stock of physical capital and different types of labor as factors of production. In this production function, gen-AI traffic is modeled as potential to expand the productivity of different worker groups.

The contribution of this research to the literature can be summarized as follows:

- In support of H1, we verified that gen-AI has indeed contributed to increasing the productivity of a wide variety of workers: those with primary, secondary and tertiary education, part time and full time, self-employed and hired, vulnerable and not vulnerable. Considering that these impacts were not addressed before in a macroeconomic framework, this represents a novel research contribution.
- Contradicting H2, we could not find significant disparities in gen-AI associated productivity gains across different labor segments. Based on this, we found no evidence regarding increases in the substitution dynamics across different worker groups. This contradicts, at least so far, those perspectives warning of important job displacements effects.
- Confirming H3, the overall macroeconomic impact generated by gen-AI induced productivity gains has been modest so far, accounting for a GDP increase of only 0.008% for the mean country in the sample. This result is in line with the body of research that forecasts a limited macroeconomic effect, although the situation may change in future periods.

From the perspective of the theoretical implications, this evidence adds a new layer of understanding to the conventional view that technological change fulfills a key role beyond the accumulation of capital and labor in driving economic growth. In particular, the fact that AI induces productivity growth for most workers' groups provides support to the consideration of this technology as a general-purpose technology. The wider impact of generative AI across different workers groups can be explained as, contrary to the pre-generative AI period (when the technology was dominated by robotics and machine learning tools that require highly skilled workers to implement and make use of it), gen-AI offers a wider range of users, including those unskilled individuals who can easily access and use this tool.

From a policy perspective, the results suggest that policymakers should view gen-AI as a productivity-enhancing complement to a broad range of workers. Given the modest aggregate impact observed so far, policy efforts should prioritize fostering AI diffusion across sectors -particularly among small and medium-sized enterprises, that typically lag in technological adoption- through incentives for digital transformation, infrastructure investment, and training programs. At the same time, to ensure equitable access to gen-AI benefits, education and labor policies should focus on developing digital literacy and adaptive skills across all demographic and contractual groups. Because substitution effects remain limited at the current stage of adoption, early and inclusive policy design can help maximize the technology's aggregate contribution while minimizing potential inequalities as gen-AI matures and integrates with other digital tools.

For future research, the lack of change in the substitution dynamics and the modest macroeconomic impact experienced so far should be further analyzed in forthcoming empirical studies. The possibility is that the results found in this paper can be attributed to the fact that this technology is still at an early diffusion point, with workers still learning how to make the most of these tools, while at the same time the gen-AI platforms are still in phase of improvement. Future research will be key to find out if economic growth will accelerate in the forthcoming years, and if some job displacement effects arise. Finally, future research will have to contemplate the interdependencies and interactions that arise from the convergence of AI with other advanced technologies (such as cloud computing, big data or IoT), given that data limitations prevented us to provide a contribution in this field.

CRediT authorship contribution statement

Raúl Katz: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Juan Jung:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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