Call for Research Proposals - July 2024

Quantitative empirical research on the economics of artificial intelligence in Latin America and the Caribbean

About this proposal

The Competitiveness, Technology and Innovation Division (IFD/CTI), part of the Vice Presidency of Sectors and Knowledge (VPS), in collaboration with the Vice Presidency of Countries (VPC) of the Inter-American Development Bank (IDB), invites individuals or teams of researchers to submit research proposals that study the economic impacts and determinants of Artificial Intelligence (AI) adoption and development in Latin America and the Caribbean (LAC). The objective is to generate new evidence relevant to innovation policy and private sector development. This is the first in a series of two calls aimed at generating evidence on the implications of AI adoption in economic growth[1].

Why are we launching this call?

Economic growth has been held back by weak productivity performance (Filippucci et al., 2024). The growth rate of labor productivity in OECD economies fell from around 2% per year between the 1970s and 1990s to 1% in the 2000s (Goldin et al., 2024). In the LAC region, low productivity has been the main factor behind the modest economic growth (Rodríguez-Apolinar & Fernández-Arias, 2016).

The diffusion of AI has widespread enthusiasm about its impact on productivity growth. Some studies show that, under the right conditions, AI could generate significant and sustained gains on the order of 1-1.5 percentage points to annual growth rates over the next 10-20 years (Baily et al., 2023; Briggs & Kodnani, 2023; McKinsey, 2023). Acemoglu (2024) argues that available evidence combined with aggregate economic theory supports only moderate impacts on total factor productivity and GDP growth, on the order of 0.1% annually.

AI can be the latest general-purpose technology (GPT) (Agrawal, Gans, et al., 2019b; Brynjolfsson et al., 2017; Francesco Filippucci et al., 2024; Nolan, 2020; Trajtenberg, 2018, 2019); similar to previous digital technologies such as computers and the internet or, going back further, to the steam engine and electricity. Agrawal, Gans, et al. (2019a) propose that AI algorithms are predictive machines that allow agents across the economy to better predict outcomes, thereby reducing uncertainty in a wide variety of economic tasks. Agrawal, McHale, and Oettl (2019) suggest an important application of this idea, as AI enables firms to find new productive combinations of existing technologies. Cockburn et al. (2019) suggest that AI is also a new technology for inventing.

The main feature of GPTs is to enable new and complementary production methods that may increase productivity over time. Czarnitzki et al. (2023) identify two distinctive characteristics of AI compared to other revolutionary inventions. The first of these is its intangible nature, which makes it difficult to measure its various forms and estimate its economic impact (Haskel & Westlake, 2017). The second feature is that AI allows machines to perform different cognitive tasks. As a result, several authors have argued that we are facing the first case in the history of a new immaterial technology

[1] The second call will focus on the public sector perspective of AI adoption and regulation, and its implications for public sector efficiency and private sector performance.

that displaces workers in the upper middle of the skill distribution (Brynjolfsson et al., 2017; Corrado et al., 2021).

As such, firms' adoption of AI technologies could be expected to enact new business opportunities and boost productivity (Brynjolfsson & McAfee, 2014). The literature shows two channels of how AI can positively impact firms' performance, especially productivity. One is that AI is an intangible capital asset. Firms can invest in AI and directly use it in production to generate output (Brynjolfsson et al., 2017). On the other hand, AI has the potential to enhance firms' innovation capabilities, affecting R&D investments, generate new marketable ideas, and thus improve firms' productivity (Aghion et al., 2017; Aghion et al., 2019; Cockburn et al., 2019).

Despite recent progress, the availability of empirical data comprehensively characterizing AI diffusion among firms is still in its incipient stages, especially outside the US (Calvino & Fontanelli, 2023). Empirical studies have relied mainly on the use of four data sources: Intellectual property records for AI-producing firms, investment announcements in AI-related technologies on stock markets, AI-related job offers, and firm-level microdata from specific surveys.

Empirical works using intellectual property records apply techniques related to natural language processing and machine learning (Alderucci et al., 2020) or keyword matching (Van Roy et al., 2020) to identify AI-related patents. The work of Alderucci et al. (2020) uses USPTO and US Census data and finds a positive effect of AI innovation (i.e., patents) on firm employment (+8.1%) and firm productivity considering sales per worker (+4.1%). Additionally, they find that the magnitude of the effect on employment and productivity increases over time considering the first AI-related patent. Yang (2022) combines data from the Taiwan Patent Office with a panel of electronics firms and finds a positive correlation between AI innovation and AI innovation intensity (i.e., the existence and quantity of patents) with the level of employment. However, these associations disappear when growth rates rather than levels are considered (especially for employment). Finally, Damioli et al. (2021, 2024) use PATSTAT and ORBIS data to obtain worldwide information on firms that patent inventions related to AI technologies. Their evidence shows a positive and significant impact of AI patent families on employment (+2.3%) but of small magnitude and concentrated in service sectors and younger firms.

The evidence from the literature that identifies AI activities from investment announcements of publicly traded firms is mixed. Lui et al. (2022) examine the AI investment announcements of 62 US-listed firms and find that stock prices fall on the day of the announcement (−1.77%). However, Fotheringham & Wiles (2023) show that AI investment announcements focused on customer service (e.g., AI customer service chatbots) generate a 0.22% abnormal stock return. Other scholars have used the COVID-19 pandemic as an exogenous shock to test whether AI adoption improves firms' stock market performance. Ho et al. (2022) found that the negative impact of COVID-19 on the AI stock market was less severe than on the conventional stock market during the first month of the pandemic and that the performance of the AI stock market recovered faster than that of the conventional stock market when the pandemic entered its third month. El Moujahid et al. (2023) use a panel of S&P 500 firms and find evidence that firms that adopted AI technology at least two years before the onset of the COVID-19 spread had better stock market performance during the crisis than firms that did not adopt AI (+0.4% daily return).

Another stream of literature uses the demand for AI-related jobs to identify the adoption of AI technology in firms. Some studies use data from online job postings and develop several proxies for AI-related skills or occupations. Alekseeva et al. (2021) find the existence of a positive and significant wage premium for AI skills. Controlling for occupation, job title, and firm fixed effects, the wage premium for AI skills is +5%. This premium is substantially higher than for other skills, for example, more than twice as high as for software skills. They also find a significant wage premium for non-AI positions in firms that search more intensively for AI skills. The positive association between firm-level AI share and non-AI wages could be a signal of firm quality and is also consistent with the view that AI technology can facilitate the creation of new tasks that increase the demand for high-skilled jobs complementing it. Acemoglu et al. (2022) find no significant employment effects, concluding that the impact of this new technology remains too small relative to the size of the US labor market to find first-order effects on employment. A second set of papers extends this strategy to measure the intensity of investment in AI. To do so, they augment online job demand data with a unique database of firms and workers constructed from resumes, which allows them to identify the composition of the workforce within the firm. On the one hand, their results suggest that AI investments are associated with important changes in the composition and organization of firms' workforces, leading to a broader shift toward younger workers with high levels of education and technical skills (Babina et al., 2023). On the other hand, firms that invest more in AI experience higher growth through increased product innovation, as evidenced by an increase in trademarks (+14.4%), product patents (+22.1%), and updates to firms' product portfolios (+14.9%). The results suggest that, so far, the first-order effect of AI is to increase growth through product innovation, which is consistent with reduced product development costs (Babina et al., 2024).

Another stream of literature has emerged in recent years that relies on microdata from firms, particularly innovation and ICT usage surveys from European countries, to study the impact of AI. Nucci et al. (2023) use data from a panel of Italian firms; their results show that firms that invested in at least one type of AI-related technology have a rate of change in productivity between 2015 and 2018 that is, on average, 1.59 percentage points higher than firms that did not invest in new technologies. Czarnitzki et al. (2023) use data from the German Community Innovation Survey and find positive and significant effects of AI adoption on firm productivity considering sales per worker (+4.4%). Calvino & Fontanelli (2023) analyze the relationship between AI use and productivity in several countries and find that the productivity premium tends to come from larger firms but does not seem exclusively due to AI adoption. On the contrary, it appears that additional resources, such as ICT skills and training, play a crucial role in increasing the productivity of AI users. Additionally, they distinguish between users who purchase AI from external providers and those who develop their AI. The evidence is mixed. Although the coefficients remain positive, AI use alone is not significantly associated with productivity in the case of buyers. Conversely, the relationship between AI use and productivity is significant for developers (+10.6%), even after controlling for initial productivity and complementary assets. Finally, Venturini et al. (2024) use firm-level data from 15 European countries and find a statistically significant and quantitatively important productivity premium associated with AI (+1.77% in the fifth year of adopting AI). Moreover, using a distance-to-frontier framework (Acemoglu et al., 2006), they provide evidence that productivity gains from AI may be proportional to the distance a firm is from the technological frontier. This suggests that by developing AI-related technologies, lagging firms acquire technological capabilities to reduce the productivity gap with the frontier.

Another group of papers employs simulation methodologies to explore the impact of AI, focusing on the possibilities identified in economic literature to study the predictions of various models. Trammell & Korinek (2023) outline mechanisms through which AI can overcome economic stagnation in industrialized economies, highlighting AI's potential to boost production by increasing capital-labor substitutability or automating tasks, which could accelerate growth and reduce labor share. Additionally, AI could enhance knowledge generation, further accelerating economic growth, with the authors concluding that advanced AI might produce both effects. Similarly, Korinek & Suh (2024) examine the economic implications of Artificial General Intelligence (AGI), arguing that technological advances could automate increasingly complex tasks, potentially leading to the automation of all tasks. They suggest that if automation progresses slowly, human work and wages can continue to rise, but wages may decline if full automation is achieved.

Herrera Giraldo et al. (2024) is one of the few empirical papers to study AI adoption in the LAC region empirically. Combining microdata from the Annual Manufacturing Survey, the Survey of Technological Development and Innovation, and the Survey of Information and Communication Technologies, they build a unique database with information on the adoption of AI by firms in Colombia's manufacturing sector. The evidence suggests two salient findings. On the one hand, the rate of AI adoption reaches only 6.09% of industrial firms, only 2.24% are AI-producing firms, and the rest use AI developed by third parties. On the other hand, in line with evidence from developed countries, AI adoption rates show a skewed distribution according to sector, size, firm age, and technological intensity.

This background points out a notorious lack of studies on AI's impact on firms' performance in LAC. One of the main reasons is that, at least until the COVID-19 pandemic, technological adoption in LAC countries has been relatively slow (Ripani et al., 2020). The lack of studies on the particularities of AI development and adoption in the LAC undermines the quality of AI policy in the region. This CFP aims to start filling this gap, answering pressuring questions while setting a regional research agenda.

What are we looking for and who can apply?

Individual researchers or teams are invited to submit their proposals. Research proposals should meet the following eligibility criteria:

1) The individual researcher or the team leader must be a citizen of one of the IDB's 48 member countries and have no family members currently working at the IDB Group.
2) The research proposal should be quantitative in nature and prioritize the study of determinants or economic impacts of AI adoption and development at the firm or industry level in one or several countries of Latin America and the Caribbean.
3) Possible research topics to be addressed include (the list of topics is meant to be suggestive and by no means exclusive):

    - Making vs buying AI
    - Obstacles to AI adoption
    - AI adoption and job creation and wage structure
    - AI as an input to innovation
    - AI development and firm performance
    - AI adoption and firm productivity

- Factors related to AI startup creation
- Evaluation of policies promoting AI adoption
- AI and competition
- AI and scientific production

How to apply

Interested researchers should submit a research proposal that shall not exceed 2,500 words (excluding CVs, budgets, and references). The proposal shall follow the naming convention *LeadResearcherLastName*_AI_2024_Proposal and should include:

- An abstract posing the research question, a sound justification of why the proposed study is relevant, and the likely implications in policymaking.
- Relevant literature with a standard citation style (e.g., APA, MLA).
- A description and justification of the proposed methodology.
- A work plan for the project that does not exceed six months.
- A description of what data will be used in the study and how it will be obtained/generated.
- Background of the researcher(s) (indicating the team leader). Please attach CVs indicating current affiliation and publication record, highlighting any relevant publications to this Call. Maximum two pages per researcher.
- In a separate file with naming convention (*LeadResearcherLastName*_IA_2024_Budget), the researcher(s) should indicate the resources that will be necessary to undertake this research.

All proposals should be submitted in English.

Evaluation Criteria

This Call will select a minimum of two research proposals. The evaluation team will be coordinated by Fernando Vargas (IFD/CTI). A selection panel will review the applications and evaluate them based on the following criteria:

- Technical (80% of Overall Score)

i. Strength of the proposed methodology (30% of technical score).
This criterion evaluates the proposed research methodology's robustness, rigor, and appropriateness. Consider the use of advanced analytical tools and techniques, the theoretical framework's soundness, and the research design's clarity.

ii. Relevance and significance of the expected results (20% of technical score).
This criterion assesses the potential impact of the research findings on the field of AI economics. Consider how the expected results can contribute to this developing field.

iii. Novelty and feasibility of access to or generation of data (25% of technical score).
This criterion considers the originality of the data sources and the practicality of obtaining or generating the data. Assess the innovative use of data and the potential for new insights.

iv. Relevance to the LAC region and policy implications (25% of technical score)
This criterion evaluates the extent to which the research addresses issues pertinent to LAC, including specific regional challenges and opportunities, and the potential for the study to inform policymaking in the region.

- Financial (20% of Overall Score)

i. Reasonableness and Level of Detail Provided on the Key Assumptions and Their Compatibility with the Technical Proposal (100% of Financial Score).
This criterion evaluates the clarity and comprehensiveness of the budget details, ensuring they align with the technical aspects of the proposal.

Deadline for submission of proposals

September 20, 2024. 23:59:59 pm (Eastern Time Zone). Proposals should be emailed to fvargas@iadb.org with copy to ladyl@iadb.org with the following subject line: IA CFP: "Proposal's title."

Funding Information

The IDB will contribute up to US$18,000 for each selected study proposal. The payment schedule will be structured as follows:

- 10% at the signature of the formal agreement between the IDB and the researcher or team leader.
- 50% upon approval by the IDB of the first draft of the research paper.
- 40% upon approval by the IDB of the final research paper.

1. References

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