Does AI Boost Firm Productivity? A Web Scraping and LLMs Approach

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Abstract

Artificial Intelligence (AI) is widely seen as a transformative technology with the potential to reshape firm productivity across sectors. However, empirical evidence on its actual impact at the firm level remains limited, mainly due to the lack of extensive firm-level data. Leveraging web scraping and Large Language Models (LLMs), this study develops a novel framework to detect and quantify AI adoption among 62,525 Spanish firms. The approach distinguishes between firms that adopt AI and those that integrate it intensively across business functions, constructing both binary and continuous measures of AI use. Using entropy-balanced instrumental variable estimations to address endogeneity, we find that AI-adopting firms exhibit approximately 53–55% higher sales and 48% higher value added than comparable non-adopters. Moreover, increasing the intensity of AI use is associated with an even larger productivity premium of 74–76% in sales and up to 67% in value added, highlighting the substantial returns from deeper AI integration. In dynamic terms, AI adoption is linked to 9–13% faster annual sales growth. These findings provide evidence that AI significantly enhances firm performance, underscoring its role as a key driver of productivity growth.

Keywords: Firm Productivity, Artificial Intelligence, Large Language Models, Web Scraping, Instrumental Variables

1 Introduction

Artificial Intelligence (AI) is widely recognized as a transformative force in business, reshaping operations, decision-making, and value creation across sectors (McAfee, 2017; Agrawal et al., 2019). However, the link between AI adoption and firm-level productivity remains elusive. Early evidence presents a mixed and sometimes contradictory picture: some firms report meaningful gains, while others show negligible or delayed effects (Bergeaud et al., 2025).

Empirical research shows that AI's productivity effects are heterogeneous and context-dependent. Gains tend to emerge when AI adoption is combined with complementary digital capabilities—such as IoT (Internet of Things), big data, or advanced analytics—while smaller or less digitally mature firms often experience limited short-term benefits (Czarnitzki et al., 2023; Ardito et al., 2024; Babina et al., 2024). Some studies even report null early effects, reflecting the adjustment costs, organizational changes, and workforce reskilling required for effective AI integration (Damioli et al., 2021). The emergence of generative AI, notably through tools such as ChatGPT, has further amplified expectations, yet systematic post-2023 evidence remains scarce and fragmented.

A key barrier to understanding AI's economic impact lies in data availability. Traditional sources—such as innovation or ICT (Information and Communication Technologies)—offer valuable insights but are costly, infrequent, and subject to reporting lags, making them ill-suited to capture fast-moving technological change. As a result, the diffusion of AI and its productivity effects are often undermeasured and poorly timed, reinforcing the "productivity paradox" (Brynjolfsson, 1993) associated with past general-purpose technologies.

This paper introduces a novel approach to measure AI adoption and its productivity effects that addresses these limitations. We combine web scraped corporate information with large language models (LLMs) to detect whether firms use AI and in what capacity, generating both a binary adoption indicator and a continuous intensity index. This method enables scalable, near real-time monitoring of AI adoption across thousands of firms, at a fraction of the cost of traditional surveys.

Our work builds on and extends recent studies such as Czarnitzki et al. (2023). While their analysis relies on structured survey data from German firms in 2018, we employ web-scraped corporate information combined with large language models to detect AI adoption. This approach enables more scalable and timely monitoring of AI use across firms. In addition, our focus on Spanish firms in 2023 captures a later stage of technological diffusion, shaped by the rise of generative AI tools such as ChatGPT. We share the same overarching goal—understanding how AI adoption translates into firm-level productivity—while following a methodologically similar framework to measure this relationship.

By providing a timely and scalable measurement of AI adoption and linking it to firm-level performance, this study helps to fill the persistent gap in evidence on AI's economic impact. Our approach delivers a novel perspective for both researchers and policymakers, enabling the assessment of how emerging technologies—particularly AI—translate into heterogeneous productivity outcomes across firms.

The remainder of the paper is structured as follows: Section 2 reviews the literature on AI and productivity; Section 3 presents the data and empirical approach; Section 4 reports the main findings; Section 5 discusses the results; and Section 6 concludes.

2 Related work

This section reviews the relevant literature on AI adoption and its relationship with firm performance, organized into four thematic areas: (2.1) the impact of AI on productivity at the firm level; (2.2) insights from the literature on digitalization and general-purpose technologies, including the productivity paradox; (2.3) methodological approaches to measuring AI use in firms; and (2.4) the use of company websites and language models to detect AI adoption at scale.

2.1 AI and Productivity

The emergence of AI has generated considerable interest regarding its implications for firm performance and productivity. An expanding body of empirical research indicates that AI adoption can lead to productivity improvements at the firm level, although the magnitude and timing of these gains remain heterogeneous. For example, Marioni et al. (2024) find that firms across 15 European countries involved in AI-related innovation exhibit a 20–30% productivity premium, with laggard firms benefiting disproportionately through catch-up dynamics.

AI's impact appears particularly strong when combined with other digital technologies. Ardito et al. (2024) show that SMEs adopting AI, especially alongside Internet of Things (IoT) and big data analytics, exhibit significantly higher revenue growth. These results support the idea that AI's performance effects are amplified by complementary capabilities, as part of broader digital strategies.

Using German data, Czarnitzki et al. (2023) report that AI-adopting firms display higher total factor productivity (TFP), robust across multiple AI usage measures. Similarly, Damioli et al. (2021) find that AI adoption is associated with stronger labor productivity, especially in agile service firms. In the United States (U.S.), Babina et al. (2024) show that AI investments—proxied through hiring patterns—increase firms' growth in sales, employment, and market value, driven mainly by product innovation. However, these benefits materialize with a 2–3 year lag and are concentrated among large firms, raising concerns about uneven distribution.

Indeed, AI's productivity gains are not universal. According to Bergeaud et al. (2025), only large, digitally capable French firms have realized substantial improvements, while smaller firms lag behind. This reflects a "winner-takes-most" pattern, common with general-purpose technologies (Schwellnus et al., 2018). Moreover, some studies report null results in the short term, consistent with adjustment costs and implementation lags.

Overall, the literature offers a cautiously optimistic view: while many firms benefit from AI through innovation and complementary investments, the gains are heterogeneous and may take time to appear. Macro-level evidence remains inconclusive due to measurement challenges and uneven diffusion.

2.2 Digitalization, General-Purpose Technologies, and Productivity Paradoxes

The heterogeneous and sometimes delayed productivity effects of AI can be better understood through the lens of digitalization, intangible assets and general-purpose technologies. Historically, major general-purpose technologies—such as electricity, computing, and now AI—have followed a common pattern: they trigger initial disruptions and require

significant complementary investments before their benefits materialize in productivity statistics (Brynjolfsson et al., 2017, 2021).

AI, as a general-purpose technology, not only automates specific tasks but also enables broader innovations in products, services, and business models. However, these transformations demand substantial adaptation—such as workforce reskilling, data infrastructure, and organizational change—that may temporarily depress productivity as firms build intangible capital (Nakatani, 2021, 2023). This dynamic is captured by the "Productivity J-curve" model, which explains how early underinvestment in measurable capital can obscure future gains (Brynjolfsson et al., 2017). Once complementary assets are in place, productivity growth may accelerate, potentially overshooting as latent effects unfold. Nonetheless, some authors higlight that the impact of intangibles on productivity growth rapidly weakens, especially in sectors such as telecommunications (Nakatani, 2021, 2023).

This framework also helps interpret the so-called "productivity paradox" in the AI era, echoing similar lags observed during the diffusion of computers in the 1980s and 1990s. Delayed adaptation and uneven uptake remain relevant explanations. Notably, the concentration of AI-driven performance gains in large firms (Babina et al., 2024) supports both the "superstar firm" hypothesis, where early adopters reap outsized benefits without lifting aggregate productivity, and the existence of economies of scale (Nakatani, 2024). Furthermore, these economies of scale would interact with the effects of intangible assets such as AI. As Nakatani (2024) notes, larger companies which already benefit from economies of scale have more resources to invest in intangible assets such as digitization and AI. Such investments would further enhance the exploitation of economies of scale and boost productivity growth. Then, a synergistic interaction would be taking place: intangible assets (AI in this case) create or reinforce network effects that enable greater economies of scale, and these economies of scale, in turn, enhance the impact of intangible investments on the company's productivity growth.

Other factors include mismeasurement—AI may improve product quality or create non-priced services not captured in general-purpose technologies—and inflated expectations. Critics argue that current AI tools focus on narrow tasks and may not yield transformative productivity effects without broader innovation and institutional support (Acemoglu & Restrepo, 2020). Still, the overall evidence suggests a cautiously optimistic outlook: like past general-purpose technologies, AI's full economic impact will likely emerge over time, conditioned by policy and complementary capabilities.

2.3 Measuring AI Use in Firms

A fundamental challenge for both researchers and policymakers is measuring AI use at the firm level. Unlike inputs such as labor or capital, AI adoption is typically intangible and software-based, making it hard to capture through conventional datasets. Consequently, multiple approaches have emerged in the literature, each offering partial insights into how AI diffuses across firms.

Surveys are the most widely used method. Official instruments such as the European Commission's Flash Eurobarometer 486 and Spain's Business Activity Survey provide representative, stratified insights. For example, around 20% of Spanish firms reported using AI in 2022, with adoption concentrated among large, young, and productive firms (Fernández Cerezo et al., 2025). Eurostat data show that under 12% of small EU firms used AI, compared to over 40% of large ones (Bergeaud et al., 2025). However, surveys

face known limitations: they rely on self-reporting, offer limited frequency, and often use binary indicators that obscure the intensity and function of AI deployment.

Beyond surveys, researchers have used alternative proxies. Patent data can indicate engagement with AI-related innovation but tend to capture frontier invention rather than widespread adoption of off-the-shelf tools. Likewise, R&D spending or venture capital investments are useful signals but often skew toward tech-heavy firms.

Labor market data provide more dynamic proxies. Babina et al. (2024) develop a firm-level AI measure by analyzing employee résumés and hiring patterns. The presence of AI-skilled staff or dedicated job postings strongly predicts firm growth and reflects internal capability building. Job postings near AI talent hubs or universities further correlate with AI adoption, illustrating the importance of human capital in technological diffusion.

No single method, however, can fully capture the complexity of AI adoption. Measuring it reliably requires combining diverse sources—each illuminating different dimensions of the phenomenon. Surveys provide representative but limited snapshots; patents and R&D data capture innovation efforts; labor market signals reflect capability building; and digital traces offer scalable, real-time insights. A particularly promising line of work in this last category draws on firms' online presence: by analyzing public-facing content such as product descriptions or strategic messaging, researchers can infer AI use even when not formally reported, as detailed in the next section.

2.4 Company Websites and AI Adoption

Company websites have become a valuable source of information for analyzing firm characteristics, including innovation activity, digital maturity, and technology adoption. Compared to traditional datasets, websites offer more timely, granular, and firm-specific data—particularly useful for capturing signals from SMEs that are often underrepresented in official registries (Blazquez & Domenech, 2018; Rammer et al., 2022; Mazzoni et al., 2024). These digital footprints complement standard indicators such as patents or surveys and provide forward-looking insights into corporate strategy and technological positioning (Crosato et al., 2024).

Initial research in this area employed keyword-based methods to detect innovation-related content, often relying on frequency counts of terms linked to R&D or product development (Gök et al., 2015). Subsequent approaches combined lexical features with machine learning to improve predictive accuracy (Axenbeck & Breithaupt, 2021; Kinne & Axenbeck, 2020). More recent work demonstrates that structural and semantic cues—such as HTML layout or page volume—can also signal innovation capabilities (Bottai et al., 2024). In the case of AI, large-scale studies have scraped and classified firm websites to build adoption indicators and trace diffusion patterns across business networks (Dahlke et al., 2024). These methods reveal that AI adoption often follows networked spillovers and competitive dynamics, and that website-derived indicators can approximate traditional survey metrics (Kinne & Axenbeck, 2020; Ashouri et al., 2024).

Despite their promise, website data present well-known challenges: content is unstructured and heterogeneous, firms may strategically under- or over-disclose, and extraction pipelines must handle issues like dynamic rendering, language diversity, and inconsistent update frequency (Blazquez & Domenech, 2018). These limitations make it difficult to assess not just whether a firm uses AI, but how and to what extent.

To overcome such constraints, researchers are increasingly turning to large language models. LLMs excel in extracting meaning from unstructured text and enable tasks such

as classification, topic detection, and semantic matching with high contextual sensitivity (Porter et al., 2024; Huang et al., 2024). In fields like education, healthcare, and business analytics, LLMs have matched or surpassed human evaluators on complex labeling tasks (Savelka & Ashley, 2023; Chang et al., 2024). They are also adaptable to user-defined scoring criteria when guided by rubrics or structured prompts, improving consistency in outputs (Jonsson & Svingby, 2007; Panadero & Jonsson, 2013; Chiang et al., 2024).

Recent tech mining studies have begun using LLMs to identify emerging technologies, map innovation patterns, and classify firms based on website content (Bouschery et al., 2023). Applied to AI adoption, this approach allows the detection of nuanced signals—such as business functions using AI, product mentions, or implementation depth—beyond binary classification. Hybrid architectures like retrieval-augmented generation (RAG) further enhance reliability by narrowing the model's focus to the most relevant text segments (Gao et al., 2023).

Our study contributes to this literature by combining large-scale web scraping with LLMs to construct detailed firm-level indicators of AI use and intensity (Pastor-Merino et al., 2025). This enables empirical analysis of AI's role in productivity with greater precision and coverage than prior methods—positioning LLM-based web mining as a scalable tool for tracking general-purpose technologies in the digital economy.

3 Methodology

This section outlines the empirical strategy used to estimate the causal effect of artificial intelligence on firm performance. The analysis combines a structural production function framework with an identification approach that integrates entropy balancing and instrumental variable (IV) estimation. The approach accounts for endogeneity, and unobserved heterogeneity in the relationship between AI and firm outcomes.

3.1 Empirical Framework

To estimate the effect of AI on firm-level productivity, we adopt a production function approach in which AI enters as an additional productivity-enhancing factor. This framework builds on standard microeconometric models of production and follows a broadly similar methodology to the one proposed in Czarnitzki et al. (2023), where AI is treated as either an explicit input or as a determinant of total factor productivity (TFP).

We start from a Cobb-Douglas production function where firm output Y_i depends on capital K_i, labor L_i, material inputs M_i, and potentially AI use:

$$Y_i = A_i \cdot K_i^{\alpha} \cdot L_i^{\beta} \cdot M_i^{\gamma} \cdot e^{\delta \cdot AI_i} \cdot e^{\varepsilon_i}, \tag{1}$$

where A_i denotes firm-specific TFP and ε_i is a stochastic error term. The term AI_i captures either a binary indicator of AI adoption or an index reflecting the breadth of AI use across business areas.

Taking logarithms, the equation becomes linear and estimable:

$$\ln Y_i = \alpha \ln K_i + \beta \ln L_i + \gamma \ln M_i + \delta AI_i + \ln A_i + \varepsilon_i. \tag{2}$$

In this formulation, AI can be viewed either as a direct input in the production function or as a determinant of TFP. Following Czarnitzki et al. (2023), both interpretations are valid and equivalent under log-linearity, and we proceed with the reduced-form equation where AI is included explicitly.

To estimate equation (2), we use a cross-sectional specification with additional controls:

$$\ln Y_i = \alpha \ln K_i + \beta \ln L_i + \gamma \ln M_i + \delta AI_i + X_i'\theta + \varepsilon_i, \tag{3}$$

where X_i includes firm age (in logs), patent ownership, and sector dummies to account for structural heterogeneity. Output Y_i is measured alternatively as total sales or value added.

Before estimation, we apply entropy balancing (Hainmueller, 2012) to reweight observations and ensure that observable characteristics—such as firm size, age, and input structure—are statistically equivalent between AI and non-AI firms. This procedure mitigates selection bias arising from non-random AI adoption and produces a balanced pseudo-population suitable for causal inference.

While the Cobb-Douglas specification is the standard in the literature, it might suffer from the simultaneity input choices as early indicated by Olley & Pakes (1996). Consequently, OLS estimates of input elasticities might be biased. Later papers have proposed different methods to address this issue (Levinsohn & Petrin, 2003; Ackerberg et al., 2015; Gandhi et al., 2020). Nonetheless, the use of such methods is limited in the present analysis due to the cross-sectional nature of the data. Accordingly, less complex methodologies

are employed, and the analysis is strengthened through several robustness checks. Despite balancing observables, endogeneity may persist if unobserved factors simultaneously influence AI adoption and productivity. To address this, we estimate the model using instrumental variables with both two-stage least squares (IV–2SLS) and the generalized method of moments (IV–GMM) estimators, each weighted by the entropy balancing factors. We consider the two following instrumental variables:

- `lnDistanceDIH`, the natural logarithm of the geographical distance in kilometers between each firm and the nearest European Digital Innovation Hub (DIH)[1] within its Autonomous Community (NUTS 2 level). This variable captures firms' spatial proximity to regional innovation infrastructure and potential access to digital support networks. A shorter distance may indicate stronger exposure to innovation ecosystems, knowledge spillovers, and policy-driven technological diffusion.

- `GoogleTrends`, the normalized search intensity for the term *"AI"* in 2022 by Autonomous Community, scaled from 0 to 100 based on relative regional interest. This variable reflects societal and institutional awareness of artificial intelligence and serves as a proxy for the regional diffusion of digital culture and demand-driven innovation dynamics.

Both instruments are assumed to be relevant and influence AI adoption without directly affecting current productivity, conditional on controls. Then, they will fulfill the relevance and exclusion restrictions required by the IV approach.

In this sense, it is worth noting that research consistently finds that greater distance from innovation hubs is a barrier to adopting new technologies. For example, Hunt et al. (2024) show that in the U.S., regions 200 km away from an AI innovation hotspot experienced 17% lower growth in AI-related job postings, indicating significantly slower AI uptake. Distance-based instruments have a long tradition in technology-adoption studies, with geographical distance to infrastructure or innovation sources being considered as an exogenous driver of technology availability. For instance, Stockinger (2019) used distance to telephone network nodes as an instrument for broadband adoption. In addition, a firm's distance to the nearest DIH affects its productivity only through AI adoption (and not through other direct channels). Two main arguments support this. On the one hand, DIH placement is largely driven by policy factors rather than by the productivity of nearby firms. On the other hand, distance to a DIH is not inherently a production input – if a firm does not utilize the hub's services or adopt AI, merely being physically closer doesn't automatically increase output.

As regards our second IV, the Google Trends AI-related searches are considered as a proxy for regional interest and awareness of AI. High search volumes may correspond to greater media coverage, public discourse, or consumer interest in AI, which can create a favorable environment for firms to use AI technologies. Thus, a higher Google Trends index for AI should correlate with a higher probability of AI adoption by firms in that region. Only through this channel would it influence firm productivity. The Google Trends index might be considered an information climate indicator. If higher search intensity leads to higher productivity, it would likely be because it led the firm to adopt

[1]European Digital Innovation Hubs (EDIH) are regional one-stop center that help firms become more competitive through digital technologies. They provide access to technical expertise, testing, training, and innovation ecosystems across the EU. See the official catalogue at (*EDIH Catalogue | European Digital Innovation Hubs Network*, 2025).

AI. In addition, using 2022 search data to instrument adoption by 2023 means that we capture a pre-existing interest level leading into the adoption decision, rather than a response to the firm's 2023 performance. It could also be argued that the Google Trends index might correlate with regional features that influence firms' productivity. In this sense, it is important to highlight that Google Trends captures interest in AI, which is a leading indicator of adoption, not a direct productivity driver. Furthermore, regional productivity changes are slow-moving, while search intensity is highly volatile and driven by global tech news, making direct correlation unlikely.

NACE 2-digit fixed effects are included in all main estimations presented in the paper, while additional robustness checks using NACE 1-digit fixed effects are reported in the Appendix 7. Standard errors are computed using a robust estimator and, in alternative specifications, clustered at the NACE 2-digit industry level to account for within-sector correlation. This multi-level approach ensures that both fine and coarse sectoral heterogeneity are properly controlled for. The inclusion of sector fixed effects is particularly relevant when analysing AI effects, given the significant industry-based heterogeneity reported by early papers on firms' AI adoption (McElheran et al., 2024).

To complement the cross-sectional analysis, we also estimate a first-difference version of the model using firm-level data for 2022–2023. This specification controls for time-invariant unobserved heterogeneity by modelling changes in output as a function of changes in inputs, with AI adoption included as a level variable rather than a change. Following Czarnitzki et al. (2023), this choice reflects that AI adoption is a relatively persistent investment decision that does not vary substantially within short time spans. In our case, firm-level data do not capture variations in the degree of AI use over time but rather indicate whether the firm has adopted AI during the observed period. The estimated coefficient on AI_i therefore represents the average short-term productivity effect of introducing AI between 2022 and 2023, conditional on changes in conventional inputs.

Overall, robustness is assessed across different dimensions: (i) alternative output measures (sales, growth, value added), (ii) alternative AI indicators (binary adoption versus intensity index), (iii) estimation methods (2SLS versus GMM), and (iv) alternative standard error structures (robust versus clustered). A translog production function is also estimated as an additional check on functional form assumptions.

3.2 Data

Our empirical analysis combines structured firm-level data with web-based indicators of AI adoption. The dataset is constructed by merging three main sources: (i) financial data from the *Sistema de Análisis de Balances Ibéricos (SABI)* provided by Bureau van Dijk (BvD), (ii) external indicators capturing firms' exposure to AI-related innovation environments—including the distance to the nearest Digital Innovation Hub (DIH) and regional AI search intensity from Google Trends—and (iii) firm-level AI adoption measures obtained through web scraping and LLMs.

The structured data from SABI provide firm-level information on turnover, employment, capital, material costs, and patent ownership for 2023, along with historical R&D activity and founding year to construct controls such as firm age and innovation history.

The key novelty of this study lies in the measurement of AI adoption through web-based content. We follow the methodology explained in Pastor-Merino et al. (2025), which applies web scraping and LLMs to identify whether firms use AI technologies based on their websites. First, websites are crawled using an ethical, bounded crawler and converted

into plain text. Then, the content is segmented into 1000-byte chunks and converted to embeddings using the `text-embedding-3-small` model. Each chunk's semantic similarity to the concept of "Artificial Intelligence" is computed using cosine similarity, and the top 10 relevant fragments are selected for further analysis (Pastor-Merino et al., 2025).

The filtered text fragments are then passed to an LLM-based classification system (GPT-4o-mini), which evaluates whether they indicate AI adoption using a structured rubric based on the Oslo Manual innovation definitions. Specifically, the rubric distinguishes between AI used in internal processes (e.g., logistics, marketing) and in external products or services (e.g., smart devices). A binary label is assigned to each company based on the presence of at least one positive classification. Additionally, a weighted intensity index (AIint) is constructed to capture the breadth and nature of AI integration across business functions. It combines: (i) AI use in internal processes (15%), (ii) the proportion of Oslo Manual-defined process areas with AI (35%), (iii) AI use in client-facing products (25%), and (iv) whether AI use is radical (i.e., disruptive rather than incremental; 25%).

Figure 1 summarises the sample construction process. We begin with the full population of firms listed in SABI (n = 1,956,748). A large share is removed during data cleaning because the firms are inactive (n = 1,072,276) or lack essential information, most notably the absence of any website reference (626,806 firms). After applying these filters and retaining only observations with complete financial records and valid AI-related website data, the final analytical sample consists of 62,525 active Spanish firms. A detailed breakdown of these firms by economic sector and size category is provided in Appendix 7.1.

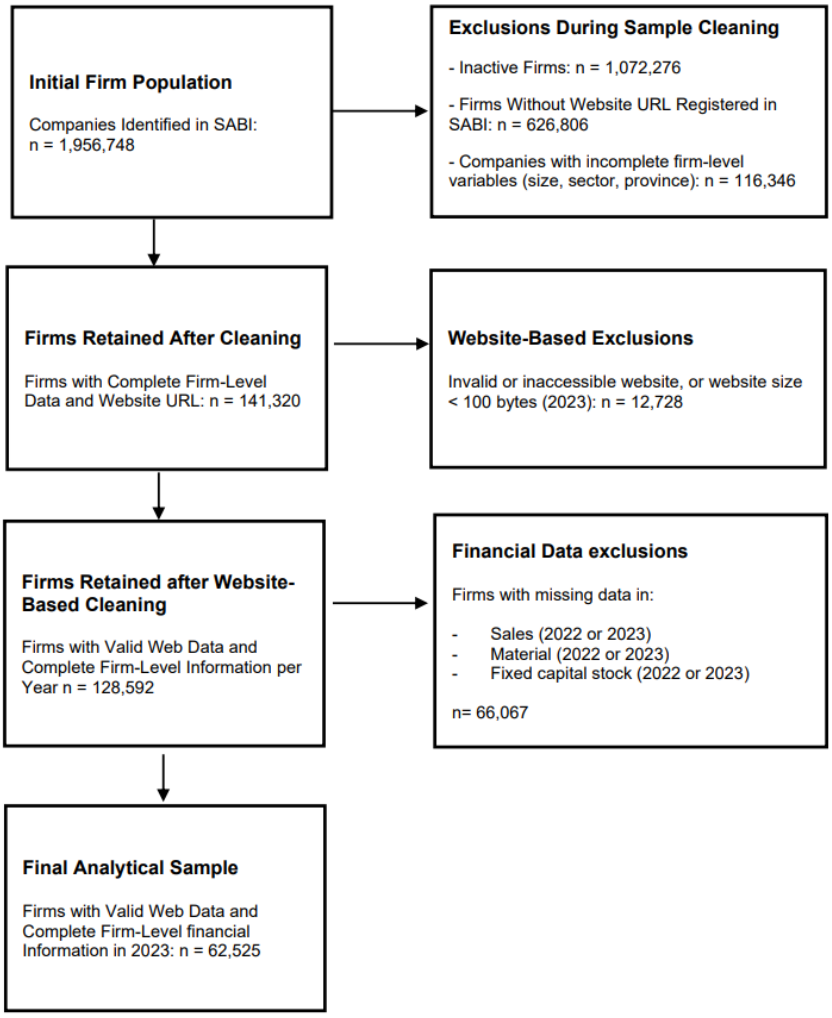


Figure 1: Flowchart of the Sample Creation Process. The diagram illustrates the steps taken to construct the final sample for the study.

Table 1 outlines the definitions and sources of all variables used in the analysis. Table 2 complements this by presenting comparative summary statistics by AI adoption status, highlighting key differences in firm characteristics across user groups.

Summary statistics reveal notable differences between AI adopters and non-adopters. Firms using AI are, on average, larger in terms of turnover, value added, and employment, and show stronger growth across these dimensions. They also exhibit broader AI integration, as reflected in a significantly higher intensity index, and are more likely to hold patents and report R&D expenditures. Additionally, AI users tend to be younger on average, suggesting a greater propensity for technological experimentation. These patterns point to clear structural differences between the two groups, underscoring the need to control for firm-level heterogeneity in the empirical analysis.

Table 1: Variable Definitions and Sources

Variable	Description	Source
AI	Equals 1 if the firm uses AI by 2023; 0 otherwise.	Web + LLM
AIint	Weighted index of AI use in processes and products, including whether product-related AI is radical or incremental.	Web + LLM
lnSALES	Logarithm of sales in 2023, in thousands of euros.	SABI (BvD)
lnVA	Logarithm of gross value added in 2023 (sales minus materials), in thousands of euros.	SABI (BvD)
lnEMP	Logarithm of the number of full-time employees in 2023.	SABI (BvD)
lnCAP	Logarithm of the fixed capital stock in 2023, in thousands of euros.	SABI (BvD)
lnMAT	Logarithm of material input costs in 2023, in thousands of euros.	SABI (BvD)
PATENT	Equals 1 if the firm held at least one patent in 2023; 0 otherwise.	SABI (BvD)
lnAGE	Logarithm of the number of years since the firm's founding.	SABI (BvD)
$\Delta \ln$(SALES)	First difference of the logarithm of sales between 2022 and 2023.	SABI (BvD)
$\Delta \ln$(EMP)	First difference of the logarithm of employment between 2022 and 2023.	SABI (BvD)
$\Delta \ln$(MAT)	First difference of the logarithm of material input costs between 2022 and 2023.	SABI (BvD)
$\Delta \ln$(CAP)	First difference of the logarithm of fixed capital between 2022 and 2023.	SABI (BvD)
lnDistance	Logarithm of the distance (km) between the firm and the nearest Digital Innovation Hub (DIH) of its Autonomous Community (NUTS 2 level), computed from firm and DIH coordinates.	European Comission
GoogleTrends	Normalized search intensity for the term "AI" by Autonomous Community (NUTS 2 level) in 2022.	Google Trends

Table 2: Summary Statistics by AI Adoption Group

Variable	Non-AI Users (n = 60,194)				AI Users (n = 2,331)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
AI	0	0	0	0	1	0	1	1
AIint	0	0.001	0	0.058	0.533	0.281	0	1
lnSALES	7.520	1.130	−2.160	14	7.710	1.250	0.042	12.500
lnVA	8.010	1.180	2.410	14.700	8.170	1.260	4.580	13.100
lnEMP	2.630	0.803	1.390	7.280	2.920	0.921	1.390	6.180
lnCAP	5.260	1.880	−11.500	13.400	4.720	2.080	−11.500	10
lnMAT	6.990	1.330	1.970	14	7.080	1.420	3.220	12.400
PATENT	0.023	0.149	0	1	0.046	0.209	0	1
lnAGE	3.040	0.587	0.693	4.810	2.860	0.617	0.693	4.740
$\Delta \ln$(SALES)	0.057	0.271	−9.820	7.050	0.100	0.327	−3.500	5.250
$\Delta \ln$(EMP)	0.047	0.241	−4.940	4.550	0.064	0.253	−4.450	2.640
$\Delta \ln$(MAT)	0.034	0.281	−4.110	7.590	0.080	0.323	−3	2
$\Delta \ln$(CAP)	0.047	0.550	−14.800	11.700	0.061	0.782	−6.170	12
lnDistance	4.090	0.095	3.490	4.300	4.100	0.092	3.490	4.290
GoogleTrends	75.600	17.100	45	100	78.500	16.600	45	100

4 Results

This section presents the main findings on the relationship between AI adoption and firm performance. The analysis examines three key dimensions of output: total sales, sales growth, and value added. For each outcome, results are reported using two complementary measures of AI use: a binary adoption indicator and a continuous intensity index that reflects the breadth of AI integration across business functions. The estimates are organised to facilitate direct comparison between 2SLS and GMM estimations. In addition, a series of robustness checks using IV–Translog production function models are provided in Appendix 7.2, confirming the stability of the main results.

4.1 Impact of AI on Sales Levels

Tables 3 and 4 report the Entropy Balanced IV estimates of the impact of AI adoption on firm sales. The use of entropy balancing ensures that AI and non-AI firms are comparable in observable characteristics before estimation, reducing selection bias and strengthening the credibility of the results.

Table 3 shows that the binary AI indicator (`AI`) exerts a positive and statistically significant effect on firm sales across all specifications. The IV–2SLS and IV–GMM estimates yield coefficients of 0.5511 and 0.5334, both significant at the 10% level. When standard errors are clustered at the NACE 2-digit level, the coefficient remains 0.5511 and retains statistical significance, confirming that the estimated effect is robust to within-industry correlation in the error structure.

The control variables behave consistently with expectations: labor (`lnEMP`) and materials (`lnMAT`) display large and highly significant positive associations with sales, while capital (`lnCAP`) remains small and statistically insignificant. Firm age (`lnAGE`) is positively associated with sales in the robust specifications, though its significance diminishes once clustered errors are applied. Patents (`PATENTS`) become marginally significant under clustered inference, suggesting a modest link between innovative activity and sales performance.

Table 4 replaces the binary adoption measure with AI intensity (`AIint`). The estimated coefficients range from 0.7386 to 0.7588 and remain statistically significant across estimation methods. These results indicate that firms using AI more intensively achieve substantially higher sales compared to those with minimal or no adoption. The coefficients for the control variables remain highly stable, and patents exhibit consistent marginal significance, suggesting complementarities between deeper AI use and innovation capabilities.

To evaluate robustness, the same Entropy Balanced IV–2SLS and IV–GMM estimations were replicated using broader NACE 1-digit industry classifications. These additional estimates, reported in Appendix 7.3, confirm that the positive relationship between AI and sales holds under alternative levels of industry aggregation.

Overall, the Entropy Balanced IV results demonstrate that firms adopting AI—and particularly those using it more intensively—achieve markedly higher sales, underscoring the economic relevance of more advanced or widespread AI use within firms.

Table 3: Impact of AI on lnSALES via Entropy Balanced IV 2SLS and GMM estimations

Dependent Variable: lnSALES	(1)	(2)	(3)
AI	0.5511*	0.5334*	0.5511*
	(0.2933)	(0.2893)	(0.3284)
lnEMP	0.3849***	0.3843***	0.3849***
	(0.0136)	(0.0135)	(0.0451)
lnCAP	-0.0108	-0.0105	-0.0108
	(0.0072)	(0.0071)	(0.0073)
lnMAT	0.6503***	0.6508***	0.6503***
	(0.0100)	(0.0100)	(0.0407)
lnAGE	0.0334**	0.0343**	0.0334
	(0.0143)	(0.0142)	(0.0219)
PATENTS	0.0418	0.0420	0.0418*
	(0.0275)	(0.0282)	(0.0242)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS
Standard errors	Robust	Robust	Clustered (NACE 2D)
Observations	62,525	62,525	62,525

Notes: NACE 2D level fixed effects included.

*p<0.10; **p<0.05; ***p<0.01

Table 4: Impact of AIint on lnSALES via Entropy Balanced IV 2SLS and GMM estimations

Dependent Variable: lnSALES	(1)	(2)	(3)
AIint	0.7588*	0.7386*	0.7588**
	(0.4157)	(0.4134)	(0.3629)
lnEMP	0.3775***	0.3772***	0.3775***
	(0.0111)	(0.0112)	(0.0394)
lnCAP	-0.0064	-0.0063	-0.0064
	(0.0055)	(0.0054)	(0.0039)
lnMAT	0.6512***	0.6517***	0.6512***
	(0.0100)	(0.0101)	(0.0372)
lnAGE	0.0440***	0.0444***	0.0440*
	(0.0106)	(0.0106)	(0.0254)
PATENTS	0.0670*	0.0667*	0.0670*
	(0.0361)	(0.0363)	(0.0321)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS
Standard errors	Robust	Robust	Clustered (NACE 2D)
Observations	62,525	62,525	62,525

Notes: NACE 2D level fixed effects included.

*p<0.10; **p<0.05; ***p<0.01

Tables 5 and 6 report the first-stage regressions for both AI adoption (`AI`) and AI intensity (`AIint`). In all specifications, the two instruments—`lnDistance` and `GoogleTrends`—are strong and statistically significant.

For `AI`, `lnDistance` shows a coefficient of 0.1160, significant at the 5% level (and at 10% with clustered standard errors). For `AIint`, the effect is slightly smaller—0.0820—but becomes even more significant under clustering (1% level). In both cases, firms located closer to a DIH are more likely to adopt AI and to integrate it more deeply.

The regional information indicator `GoogleTrends` is consistently strong across all models, with positive and statistically significant at the 1% level coefficients. This confirms that firms in regions with higher AI-related search activity display higher adoption and greater intensity of use.

Overall, the instruments are clearly relevant for both measures of AI, providing a strong first stage for the IV estimations.

Table 5: First-Stage Regression for `AI` Using `lnDistance` and `GoogleTrends`

	(1)	(2)	(3)
`lnDistance`	0.1160**	0.1160**	0.1160*
	(0.0544)	(0.0545)	(0.0648)
`GoogleTrends`	0.0008***	0.0008***	0.0008***
	(0.0003)	(0.0003)	(0.0003)
`lnEMP`	-0.0370***	-0.0370***	-0.0370**
	(0.0068)	(0.0069)	(0.0151)
`lnCAP`	0.0216***	0.0216***	0.0216***
	(0.0028)	(0.0028)	(0.0022)
`lnMAT`	0.0279***	0.0279***	0.0279**
	(0.0052)	(0.0052)	(0.0122)
`lnAGE`	0.0337***	0.0337***	0.0337**
	(0.0078)	(0.0078)	(0.0137)
`PATENTS`	-0.0399	-0.0399	-0.0399
	(0.0260)	(0.0258)	(0.0244)
Estimation method	IV-2SLS	IV-GMM	IV-2SLS
Standard errors	Robust	Robust	Clustered (NACE 2D)
Observations	62,525	62,525	62,525

Notes: NACE 2D level fixed effects included.

All models are estimated using entropy-balancing weights.

*p<0.10; **p<0.05; ***p<0.01

Table 6: First-Stage Regression for `AIint` Using `lnDistance` and `GoogleTrends`

	(1)	(2)	(3)
`lnDistance`	0.0820**	0.0820**	0.0820***
	(0.0412)	(0.0412)	(0.0303)
`GoogleTrends`	0.0006***	0.0006***	0.0006***
	(0.0002)	(0.00023)	(0.0002)
`lnEMP`	-0.0171***	-0.0171***	-0.0171
	(0.0054)	(0.00542)	(0.0118)
`lnCAP`	0.0099***	0.0099***	0.0099***
	(0.0020)	(0.00201)	(0.0019)
`lnMAT`	0.0190***	0.0190***	0.0190***
	(0.0041)	(0.00408)	(0.0071)
`lnAGE`	0.0105*	0.0105*	0.0105
	(0.0060)	(0.005997)	(0.0110)
`PATENTS`	-0.0623***	-0.0623***	-0.0623**
	(0.0185)	(0.01845)	(0.0257)
Estimation method	IV – 2SLS	IV – GMM	IV – 2SLS
Standard errors	Robust	Robust	Clustered (NACE 2D)
Observations	62,525	62,525	62,525

Notes: NACE 2D level fixed effects included.
All models are estimated using entropy-balancing weights.

*p<0.10; **p<0.05; ***p<0.01

4.2 Impact of AI on Sales Growth

Table 7 reports the impact of AI adoption and AI intensity on firms' sales growth, measured as the annual change in log sales between 2022 and 2023.

Across all models, both AI and AI intensity display positive and statistically significant effects on sales growth. In Columns (1)–(2), the estimated coefficients for `AI` are 0.0890 and 0.0895, both significant at the 10% level, indicating that AI adoption is associated with roughly 9% higher annual sales growth. In Columns (3)–(4), the coefficients for `AIint` are slightly larger—0.1318 in both the 2SLS and GMM models—also significant at the 10% level, suggesting that firms with more intensive AI use experience about 13% higher sales growth.

Control variables behave as expected. Growth in materials ($\Delta \ln$(MAT)) and employment ($\Delta \ln$(EMP)) are strong predictors of sales expansion, with coefficients around 0.60 and 0.15, respectively, while capital growth ($\Delta \ln$(CAP)) contributes modestly but significantly (around 0.011).

To assess robustness, the same IV specifications were re-estimated using broader NACE 1-digit industry classifications. As shown in Appendix 7.4, the positive effects of both AI adoption and AI intensity persist under this alternative aggregation.

Overall, the results indicate that AI enables firms to grow faster, and that more intensive AI integration is associated with even stronger short-term performance improvements.

Table 7: Impact of `AI` and `AIint` on Sales Growth ($\Delta \ln$(`SALES`)) via Entropy Balanced IV 2SLS and GMM estimations

Dependent Variable: `lnVA`	`AI`		`AIint`	
	(1)	(2)	(3)	(4)
`AI / AIint`	0.0890*	0.0895*	0.1318*	0.1318*
	(0.0564)	(0.0469)	(0.0559)	(0.0689)
$\Delta \ln$(`EMP`)	0.1465***	0.1465***	0.1473***	0.1473s***
	(0.0000)	(0.0036)	(0.0000)	(0.0037)
$\Delta \ln$(`CAP`)	0.0111***	0.0111***	0.0114***	0.0114***
	(0.0000)	(0.0013)	(0.0000)	(0.0013)
$\Delta \ln$(`MAT`)	0.6077***	0.6077***	0.6047***	0.6047***
	(0.0000)	(0.0030)	(0.0000)	(0.0031)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS	IV - GMM
Observations	62,525	62,525	62,525	62,525

Notes: NACE 2D level fixed effects included.

*p<0.10; **p<0.05; ***p<0.01

4.3 Impact of AI on Value Added

Table 8 presents the results for the effect of AI adoption and AI intensity on firms' value added, using Entropy Balanced IV–2SLS and IV–GMM estimations with NACE 2-digit fixed effects.

Across all specifications, both AI adoption and AI intensity display positive and statistically significant relationships with value added. In Columns (1)–(2), the estimated coefficients for `AI` are 0.4886 and 0.4833, both significant at the 1% level, implying that AI adoption is associated with substantially higher value added. In Columns (3)–(4), the effects strengthen further: the coefficients for `AIint` are 0.6724 and 0.6645, again significant at the 1% level, indicating that firms integrating AI more intensively achieve even larger productivity gains.

Control variables behave as expected. Material inputs and employment exhibit the strongest positive associations with value added, while capital has a small but negative effect. Older firms generate slightly more value added, and patents show positive and statistically significant coefficients, suggesting complementarities between innovation activity and AI use.

To assess robustness, the same Entropy Balanced IV–2SLS and IV–GMM estimations were repeated using broader NACE 1-digit industry classifications. As shown in Appendix 7.5, the positive effect of both AI adoption and AI intensity on value added remains stable under this alternative aggregation.

Overall, the results indicate that AI adoption—and especially higher AI intensity—is strongly linked to improved value added, supporting the view that integrating AI into firm processes enhances productivity beyond what can be explained by traditional inputs alone.

Table 8: Impact of `AI` and `AIint` on Value Added via Entropy Balanced IV 2SLS and GMM estimations (NACE 2D level)

Dependent Variable: `lnVA`	`AI`		`AIint`	
	(1)	(2)	(3)	(4)
`AI / AIint`	0.4886**	0.4833**	0.6724**	0.6645**
	(0.2138)	(0.2134)	(0.3058)	(0.3066)
`lnEMP`	0.2813***	0.2812***	0.2747***	0.2748***
	(0.0105)	(0.0105)	(0.0088)	(0.0088)
`lnCAP`	-0.0130**	-0.0130**	-0.0091**	-0.0090**
	(0.0055)	(0.0055)	(0.0043)	(0.0043)
`lnMAT`	0.7517***	0.7518***	0.7525***	0.7525***
	(0.0076)	(0.0077)	(0.0077)	(0.0078)
`lnAGE`	0.0156	0.0158*	0.0250***	0.0251***
	(0.0096)	(0.0096)	(0.0072)	(0.0072)
`PATENTS`	0.0359*	0.0363*	0.0583**	0.0574**
	(0.0203)	(0.0205)	(0.0269)	(0.0271)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS	IV - GMM
Observations	62,525	62,525	62,525	62,525

Notes: NACE 2D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001

5 Discussion

The implications of AI adoption for firm performance have garnered increasing attention across academic, policy, and business domains. This section reflects on the relationship between AI and productivity, exploring how our results align or diverge from prior empirical studies, what they reveal about the Spanish context within the broader European digital landscape. We highlight both converging insights and outstanding debates in the literature, analyze sectoral and regional adoption patterns within Spain and Europe.

5.1 Alignment and Contrasts with Previous Studies

Our results indicate that AI adoption is strongly and positively associated with firm-level productivity across sales, sales growth, and value added, with the largest gains observed when AI is integrated more broadly within the firm. This pattern is consistent with Czarnitzki et al. (2023), who also document significant productivity improvements using IV estimation on survey-based data from German firms. Despite differences in data sources and measurement—our approach relies on web-scraped information and LLM-based detection—both studies converge on the conclusion that AI adoption, especially when coupled with organizational readiness, can meaningfully enhance firm performance.

Importantly, our results also reveal that large firms capture the greatest productivity benefits from AI, consistent with the presence of economies of scale. This aligns with Nakatani (2023), who shows that economies of scale amplify the productivity effects of intangible assets—such as AI—within infrastructure and network industries in the digital era. These findings suggest that the productivity advantages of AI adoption are not evenly distributed, but rather accrue disproportionately to firms with the scale and resources necessary to exploit complementary digital and organizational assets.

Our findings also resonate with cross-country evidence. Marioni et al. (2024) report that AI-adopting firms across 15 European countries enjoy substantial productivity premiums, particularly among those starting further from the productivity frontier. This is consistent with our IV results, where firms with broader AI integration and innovation-related capabilities experience the largest productivity gains, suggesting that AI can act as a catch-up technology for lagging firms under the right conditions.

At the same time, our results contrast with studies documenting limited or null short-term effects. For instance, Vu et al. (2024) find no immediate productivity gains from AI adoption in Canadian firms during 2020–2021, which likely reflects early-stage implementation lags and the absence of complementary investments. In line with the "productivity paradox" literature, our evidence suggests that measurable returns emerge once firms accumulate experience and deploy AI across multiple functions, capturing a more mature phase of diffusion in 2023—particularly with the spread of machine learning and generative AI applications.

Overall, our study complements existing research by providing large-scale, timely evidence from Spanish firms using a novel, web-based detection method. The results reinforce the broader conclusion that AI adoption can generate substantial productivity improvements, but only when supported by complementary resources and effective integration within the firm.

5.2 Spanish Context and the European Perspective

Our findings should be interpreted within the context of Spain's evolving digital landscape. Despite notable recent progress, AI adoption remains modest and uneven. By 2024, only 11% of Spanish firms with 10+ employees had adopted AI, compared to 13.5% in the EU (Fernández Cerezo et al., 2025). Among large firms, uptake reached 31%, placing Spain above Italy but still well below Germany's 46%. This situates Spain in an intermediate position within Europe's digital transition, where current productivity effects appear to be concentrated among frontier firms, while broader improvements will likely depend on wider diffusion over time.

Adoption patterns are also highly heterogeneous across sectors. Knowledge-intensive industries such as information and communications technologies (ICT) and professional services report AI usage rates above 30%, particularly in generative and predictive applications (Fernández Cerezo et al., 2025). In contrast, traditional sectors like agriculture and hospitality remain below 15%. Larger, digitally mature, and innovation-oriented firms are leading adoption, while many smaller or less-resourced firms continue to face structural barriers, including limited digital skills and resource constraints. This digital divide helps to explain our results: current productivity gains are primarily realized by firms already positioned to integrate AI effectively.

These disparities mirror broader European patterns. Northern and Western countries generally display higher levels of AI readiness, whereas Southern and Eastern regions—including Spain—face constraints in infrastructure, digital skills, and innovation ecosystems (Bergeaud et al., 2025). Spain's performance on EU digital indices reflects this dual profile: strengths in broadband access and emerging tech hubs coexist with persistent gaps in ICT capabilities and innovation diffusion. From a European perspective, our results can therefore be interpreted as reflecting an early stage of AI-driven productivity gains, which are likely to broaden only as adoption becomes more widespread and complementary capabilities diffuse across sectors and regions.

5.3 Limitations

Several limitations of this study should be acknowledged. First, our sampling framework is based on the SABI database, which does not cover all active Spanish firms, and many entries correspond to inactive or incomplete records. This issue extends to the broader ORBIS database from which SABI is derived. Although research on their representativeness is limited, Bajgar et al. (2020) and Kalemlİ-Özcan et al. (2024) show that ORBIS disproportionately covers large, well-established, and productive firms. Consequently, our estimates may be slightly overstated, reflecting a bias toward firms that are larger, more productive, and digitally mature.

Second, the correspondence between firms and websites is imperfect. Some firms share a single URL (e.g., franchises), while others operate multiple domains. Focusing on firms with a functional website introduces selection bias, since companies without an online presence are excluded. However, maintaining a website generally implies a minimum level of digital infrastructure, which is a reasonable prerequisite for observing AI-related activities.

Third, merging structured (SABI) and unstructured (web) data inevitably entailed attrition. As shown in Figure 1, over one million firms were excluded due to inactivity, missing URLs, or incomplete financial data, resulting in a final sample of 62,525 firms. Since the total number of web-matching attempts is unknown, the attrition rate cannot

be fully assessed, implying that firms with stronger digital footprints—typically larger, more innovative, more consolidated, and therefore also older—are more likely to appear in the dataset. This pattern is reflected in the age distribution: while Nakatani (2024), also using SABI, reports an average firm age of about 11 years, the mean age in our merged sample is above 20 years. This substantial difference highlights the presence of selection effects towards more mature and digitally visible firms.

Fourth, our AI detection method relies on publicly available website content, which may underrepresent firms with limited online communication or internally oriented AI applications. The binary and intensity indicators used also simplify a complex phenomenon, as "artificial intelligence" encompasses multiple technologies and degrees of implementation not fully captured here.

Finally, the analysis is cross-sectional, complemented by a simple difference specification for 2022–2023. While this provides short-term insights, it does not capture unobserved firm heterogeneity or long-term effects. Future research should build longitudinal panels to trace AI adoption dynamics over time. Broader limitations of web-based data—such as heterogeneous site quality, marketing bias, multilingual inconsistencies, and asynchronous updates—must also be noted (Gök et al., 2015; Bottai et al., 2024). Despite these constraints, the combined use of web scraping and large language models offers a scalable and replicable foundation for future research on AI and firm performance.

6 Conclusion

This study offers robust empirical evidence that artificial intelligence adoption substantially enhances firm-level productivity in Spain. By introducing a novel methodology that combines web scraping and large language models to detect AI use from corporate websites, we provide a scalable and timely alternative to traditional survey-based approaches. Our econometric analysis, based on a large and diverse sample of Spanish firms, demonstrates that AI adopters experience significant productivity gains—especially when AI is integrated across multiple business functions. These findings are obtained from instrumental variable estimations, which consistently show sizeable effects.

The findings position AI as an emerging productivity-enhancing technology, in line with recent evidence from other European economies. Yet, the benefits are uneven: firms with higher AI intensity capture larger gains, while others experience more moderate short-term effects. In Spain's context—characterized by moderate adoption levels and uneven sectoral diffusion—our results suggest that productivity gains are currently concentrated among firms with broader AI integration, with wider economic benefits likely to materialize through gradual diffusion and the development of complementary capabilities.

From a broader perspective, these findings provide useful input for ongoing policy discussions rather than prescriptive recommendations. The observed heterogeneity aligns with the idea that reducing adoption frictions and supporting capability-building—such as improving data practices, technical skills, and organizational processes—may help firms translate AI into measurable performance improvements. Broader gains will likely emerge as adoption extends to a larger set of firms and sectors, accompanied by the gradual accumulation of human, organizational, and technological assets.

Future research could strengthen these findings by constructing panel datasets to track AI adoption over time, exploring sector-specific channels, and extending the LLM-based detection approach to other countries for cross-national comparisons. Additionally, examining how AI interacts with complementary digital technologies such as cloud computing,

IoT, and advanced analytics would provide deeper insights into the conditions under which adoption translates into sustained productivity growth.

In conclusion, this study shows that AI can be a powerful driver of firm-level productivity, though its benefits are neither automatic nor evenly distributed. Our web-based detection approach offers timely evidence that current gains are realized mainly by firms with higher AI intensity and broader integration. Achieving wider economic effects will depend on continued diffusion and the progressive accumulation of complementary capacities, enabling AI to evolve from a frontier technology into a widely shared engine of productivity.

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Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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7 Appendix

7.1 Appendix 1: Sample composition by economic sector and firm size.

Table 9: Sample composition by economic sector and firm size.

	Large	Medium	Small	Micro	Total
Agriculture, forestry, and fishing	4	92	401	211	**708**
Extractive industries	0	7	129	55	**191**
Manufacturing industry	22	1202	8624	4738	**14586**
Electricity, gas, steam, and air conditioning supply	0	4	63	34	**101**
Water supply, sanitation, waste management, and decontamination	1	32	206	92	**331**
Construction	7	488	4733	3065	**8293**
Wholesale and retail trade; vehicle repair	17	832	8955	7802	**17606**
Transportation and storage	5	261	1738	735	**2739**
Hospitality	11	353	2470	1074	**3908**
Information and communications	5	200	1101	844	**2150**
Financial and insurance activities	1	6	91	104	**202**
Real estate activities	0	10	194	316	**520**
Professional, scientific, and technical activities	8	220	2088	2117	**4433**
Administrative and support services	34	376	1321	829	**2560**
Education	2	131	544	386	**1063**
Healthcare and social services	10	163	907	755	**1835**
Artistic, recreational, and entertainment activities	5	87	333	255	**680**
Other services	1	37	307	274	**619**
Total	**133**	**4501**	**34205**	**23686**	**62525**

7.2 Appendix 2: Robustness Checks Based on IV–Translog Specifications

Table 10: Impact of AI and AIint on SALES via IV–Translog estimations (NACE_2D level)

	(1) IV–Translog (AI)	(2) IV–Translog (AIint)
AI / AIint	0.6343**	0.9299**
	(0.2802)	(0.4237)
lnEMP	0.9264***	0.9246***
	(0.0666)	(0.0687)
lnCAP	0.0439*	0.0337
	(0.0263)	(0.0277)
lnMAT	0.1348***	0.1671***
	(0.0375)	(0.0422)
lnAGE	0.2481***	0.3236***
	(0.0683)	(0.0863)
PATENTS	0.0039	-0.1032
	(0.3773)	(0.4559)
$[\text{lnEMP}]^2$	0.1060***	0.0952***
	(0.0214)	(0.0195)
$[\text{lnCAP}]^2$	0.0031**	0.0035***
	(0.0013)	(0.0012)
$[\text{lnMAT}]^2$	0.1433***	0.1399***
	(0.0072)	(0.0066)
$[\text{lnAGE}]^2$	-0.0164	-0.0477**
	(0.0227)	(0.0207)
[lnEMP] · [lnCAP]	0.0033	0.0051
	(0.0046)	(0.0051)
[lnEMP] · [lnMAT]	-0.1413***	-0.1404***
	(0.0106)	(0.0106)
[lnEMP] · [lnAGE]	0.0370**	0.0426***
	(0.0135)	(0.0136)
[lnEMP] · [PATENTS]	0.0370	0.0456
	(0.0391)	(0.0405)
[lnCAP] · [lnMAT]	-0.0015	-0.0025
	(0.0030)	(0.0029)
[lnCAP] · [lnAGE]	-0.0179***	-0.0127**
	(0.0056)	(0.0054)
[lnCAP] · [PATENTS]	-0.0055	-0.0140
	(0.0171)	(0.0171)
[lnMAT] · [lnAGE]	-0.0293***	-0.0323***
	(0.0095)	(0.0108)
[lnMAT] · [PATENTS]	-0.0277	-0.0090
	(0.0289)	(0.0360)
[lnAGE] · [PATENTS]	0.0560	0.0544
	(0.0506)	(0.0500)
Estimation method	IV–Translog (2SLS)	IV–Translog (2SLS)
Standard errors	Robust	Robust
Observations	62,525	62,525

Notes: NACE 2D level fixed effects included.

*p<0.10; **p<0.05; ***p<0.01

Table 11: Impact of AI and AIint on Sales Growth ($\Delta \ln(\text{SALES})$) via IV–Translog estimations (NACE_2D level)

	(1) IV–Translog (AI)	(2) IV–Translog (AIint)
AI / AIint	0.2361**	0.2881**
	(0.0833)	(0.0993)
$\Delta \ln(\text{EMP})$	0.1141***	0.1131***
	(0.0045)	(0.0042)
$\Delta \ln(\text{CAP})$	0.0119***	0.0112***
	(0.0023)	(0.0021)
$\Delta \ln(\text{MAT})$	0.6233***	0.6185***
	(0.0044)	(0.0055)
$[\Delta \ln(\text{EMP})]^2$	0.0128**	0.0129**
	(0.0042)	(0.0041)
$\Delta \ln(\text{CAP})]^2$	-0.00005	-0.00020
	(0.00045)	(0.00045)
$\Delta \ln(\text{MAT})]^2$	-0.1298***	-0.1199***
	(0.0089)	(0.0066)
$[\Delta \ln(\text{EMP})] \cdot [\Delta \ln(\text{CAP})]$	-0.0033	-0.0057
	(0.0037)	(0.0040)
$[\Delta \ln(\text{EMP})] \cdot [\Delta \ln(\text{MAT})]$	0.1891***	0.1782***
	(0.0128)	(0.0098)
$[\Delta \ln(\text{CAP})] \cdot [\Delta \ln(\text{MAT})]$	0.0252***	0.0305***
	(0.0034)	(0.0043)
Estimation method	IV–Translog (2SLS)	IV–Translog (2SLS)
Standard errors	Robust	Robust
Observations	62,525	62,525

Notes: NACE 2D level fixed effects included.

*p<0.10; **p<0.05; ***p<0.01

Table 12: Impact of `AI` and `AIint` on Value Added via IV–Translog estimations (NACE_2D level)

	(1) IV–Translog (`AI`)	(2) IV–Translog (`AIint`)
`AI / AIint`	0.5508**	0.8074**
	(0.2022)	(0.3122)
`lnEMP`	0.7570***	0.7554***
	(0.0492)	(0.0513)
`lnCAP`	0.0148	0.0060
	(0.0195)	(0.0207)
`lnMAT`	0.3255***	0.3536***
	(0.0291)	(0.0326)
`lnAGE`	0.1660***	0.2315***
	(0.0500)	(0.0651)
`PATENTS`	-0.0351	-0.1281
	(0.2378)	(0.2998)
$[\texttt{lnEMP}]^2$	0.1011***	0.0917***
	(0.0169)	(0.0156)
$[\texttt{lnCAP}]^2$	0.0021*	0.0024**
	(0.0011)	(0.0010)
$[\texttt{lnMAT}]^2$	0.1204***	0.1174***
	(0.0058)	(0.0054)
$[\texttt{lnAGE}]^2$	-0.0020	-0.0290*
	(0.0163)	(0.0154)
`[lnEMP]` · `[lnCAP]`	0.0018	0.0033
	(0.0037)	(0.0041)
`[lnEMP]` · `[lnMAT]`	-0.1242***	-0.1234***
	(0.0080)	(0.0081)
`[lnEMP]` · `[lnAGE]`	0.0248**	0.0296**
	(0.0104)	(0.0105)
`[lnEMP]` · `[PATENTS]`	0.0348	0.0423
	(0.0288)	(0.0290)
`[lnCAP]` · `[lnMAT]`	0.0007	-0.0002
	(0.0024)	(0.0024)
`[lnCAP]` · `[lnAGE]`	-0.0118**	-0.0072*
	(0.0039)	(0.0039)
`[lnCAP]` · `[PATENTS]`	-0.0089	-0.0163
	(0.0125)	(0.0123)
`[lnMAT]` · `[lnAGE]`	-0.0242**	-0.0268***
	(0.0075)	(0.0084)
`[lnMAT]` · `[PATENTS]`	-0.0142	0.0020
	(0.0205)	(0.0259)
`[lnAGE]` · `[PATENTS]`	0.0379	0.0365
	(0.0353)	(0.0335)
Estimation method	IV–Translog (2SLS)	IV–Translog (2SLS)
Standard errors	Robust	Robust
Observations	62,525	62,525

Notes: NACE 2D level fixed effects included.*p<0.10; **p<0.05; ***p<0.01.

7.3 Appendix 3: Impact of AI on Sales (NACE 1D Level)

Table 13: Impact of `AI` on `lnSALES` via Entropy Balanced IV 2SLS and GMM estimations (NACE 1D level)

Dependent Variable: `lnSALES`	(1)	(2)	(3)
`AI`	0.4359**	0.4156*	0.4359*
	(0.2178)	(0.2153)	(0.2509)
`lnEMP`	0.3919***	0.3908***	0.3919***
	(0.0118)	(0.0118)	(0.0405)
`lnCAP`	-0.0099*	-0.0096*	-0.0099*
	(0.0055)	(0.0055)	(0.0058)
`lnMAT`	0.6481***	0.6488***	0.6481***
	(0.0088)	(0.0088)	(0.0380)
`lnAGE`	0.0433***	0.0441***	0.0433*
	(0.0114)	(0.0113)	(0.0222)
`PATENTS`	0.0295	0.0302*	0.0295
	(0.0253)	(0.0261)	(0.0244)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS
Standard errors	Robust	Robust	Clustered (NACE 1D)
Observations	62,525	62,525	62,525

Notes: NACE 1D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001

Table 14: Impact of `AIint` on `lnSALES` via Entropy Balanced IV 2SLS and GMM estimations (NACE 1D level)

Dependent Variable: `lnSALES`	(1)	(2)	(3)
`AIint`	0.6528*	0.6186*	0.6528*
	(0.3568)	(0.3524)	(0.3373)
`lnEMP`	0.3845***	0.3843***	0.3845***
	(0.0099)	(0.0099)	(0.0362)
`lnCAP`	-0.0074	-0.0072	-0.0074
	(0.0049)	(0.0049)	(0.0041)
`lnMAT`	0.6497***	0.6503***	0.6497***
	(0.0088)	(0.0088)	(0.0353)
`lnAGE`	0.0518***	0.0527***	0.0518*
	(0.0095)	(0.0094)	(0.0254)
`PATENTS`	0.0528	0.0536	0.0528
	(0.0343)	(0.0344)	(0.0348)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS
Standard errors	Robust	Robust	Clustered (NACE 1D)
Observations	62,525	62,525	62,525

Notes: NACE 1D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001

Table 15: First-Stage Regression for `AI` Using `lnDistance` and `GoogleTrends`

	(1)	(2)	(3)
`lnDistance`	0.1526***	0.1526***	0.1526**
	(0.0572)	(0.0575)	(0.0651)
`GoogleTrends`	0.0011***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0004)
`lnEMP`	-0.0415***	-0.0415***	-0.0415***
	(0.0067)	(0.0068)	(0.0160)
`lnCAP`	0.0213***	0.0213***	0.0213***
	(0.0029)	(0.0029)	(0.0024)
`lnMAT`	0.0313***	0.0313***	0.0313**
	(0.0049)	(0.0049)	(0.0142)
`lnAGE`	0.0259***	0.0259***	0.0259*
	(0.0081)	(0.0081)	(0.0149)
`PATENTS`	-0.0452*	-0.0452*	-0.0452*
	(0.0268)	(0.0265)	(0.0263)
Estimation method	IV-2SLS	IV-GMM	IV-2SLS
Standard errors	Robust	Robust	Clustered (NACE 1D)
Observations	62,525	62,525	62,525

Notes: NACE 1D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001

Table 16: First-Stage Regression for `AIint` Using `lnDistance` and `GoogleTrends`

	(1)	(2)	(3)
`lnDistance`	0.1073**	0.1073**	0.1073***
	(0.0435)	(0.0437)	(0.0364)
`GoogleTrends`	0.00063***	0.00063***	0.00063***
	(0.00024)	(0.00024)	(0.00021)
`lnEMP`	-0.0166***	-0.0166***	-0.0166
	(0.00533)	(0.00537)	(0.01207)
`lnCAP`	0.01032***	0.01032***	0.01032***
	(0.00208)	(0.00208)	(0.00202)
`lnMAT`	0.01868***	0.01868***	0.01868**
	(0.00390)	(0.00394)	(0.00794)
`lnAGE`	0.00428	0.00428	0.00428
	(0.00626)	(0.00629)	(0.01198)
`PATENTS`	-0.0659***	-0.0659***	-0.0659**
	(0.01987)	(0.02000)	(0.02789)
Estimation method	IV-2SLS	IV-GMM	IV-2SLS
Standard errors	Robust	Robust	Clustered (NACE 1D)
Observations	62,525	62,525	62,525

Notes: NACE 1D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001

7.4 Appendix 4: Impact of AI on Sales Growth (NACE 1D Level)

Table 17: Impact of `AI` and `AIint` on Sales Growth ($\Delta \ln$(`SALES`)) via Entropy Balanced IV GMM estimations (NACE 1D level)

Dependent Variable: $\Delta \ln$(`SALES`)	(1) `AI`	(2) `AIint`
`AI / AIint`	0.0509*	0.0865*
	(0.0379)	(0.0622)
$\Delta \ln$(`EMP`)	0.1466***	0.1472***
	(0.0036)	(0.0036)
$\Delta \ln$(`CAP`)	0.0108***	0.0109***
	(0.0013)	(0.0013)
$\Delta \ln$(`MAT`)	0.6086***	0.6065***
	(0.0029)	(0.0032)
Estimation method	IV - GMM	IV - GMM
Standard errors	Robust	Robust
Observations	62,525	62,525

Notes: NACE 1D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001

7.5 Appendix 5: Impact of AI on Value Added (NACE 1D Level)

Table 18: Impact of AI and AIint on lnVA_2023 via Entropy Balanced IV 2SLS and GMM estimations (NACE 1D level)

Dependent Variable: lnVA_2023	AI		AIint	
	(1)	(2)	(3)	(4)
AI / AIint	0.3646**	0.3608**	0.5509**	0.5515**
	(0.1522)	(0.1525)	(0.2570)	(0.2595)
lnEMP	0.2867***	0.2869***	0.2806***	0.2809***
	(0.0088)	(0.0089)	(0.0077)	(0.0078)
lnCAP	-0.0115***	-0.0115***	-0.0095**	-0.0096**
	(0.0042)	(0.0042)	(0.0039)	(0.0039)
lnMAT	0.7506***	0.7506***	0.7518***	0.7517***
	(0.0064)	(0.0064)	(0.0066)	(0.0067)
lnAGE	0.0240***	0.0237***	0.0311***	0.0311***
	(0.0070)	(0.0071)	(0.0062)	(0.0062)
PATENTS	0.0281	0.0280	0.0480*	0.0485*
	(0.0180)	(0.0183)	(0.0250)	(0.0253)
Estimation method	IV - 2SLS	IV - GMM	IV - 2SLS	IV - GMM
Standard errors	Robust	Robust	Robust	Robust
Observations	62,525	62,525	62,525	62,525

Notes: NACE 1D level fixed effects included.

*p<0.05; **p<0.01; ***p<0.001