SPANISH FIRMS' USE OF ARTIFICIAL INTELLIGENCE: RECENT PROGRESS AND FACTORS LINKED TO ITS USE

2026

BANCO DE ESPAÑA
Eurosistema

Documentos Ocasionales
N.º 2624

Jacob Hess and Diana Posada Restrepo

SPANISH FIRMS' USE OF ARTIFICIAL INTELLIGENCE: RECENT PROGRESS AND FACTORS LINKED TO ITS USE

Jacob Hess

BANCO DE ESPAÑA

Diana Posada Restrepo

BANCO DE ESPAÑA

Documentos Ocasionales. N.º 2624

November 2026

https://doi.org/10.53479/44865

The Occasional Paper Series seeks to disseminate work conducted at the Banco de España, in the performance of its functions, that may be of general interest.

The opinions and analyses in the Occasional Paper Series are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España or the Eurosystem.

The Banco de España disseminates its main reports and most of its publications via the Internet on its website at: http://www.bde.es.

Reproduction for educational and non-commercial purposes is permitted provided that the source is acknowledged.

© BANCO DE ESPAÑA, Madrid, 2026

ISSN: 1696-2230 (online edition)

Abstract

The adoption of artificial intelligence (AI) among Spanish firms has increased significantly between 2024 and 2026, although with substantial heterogeneity. While small and medium-sized firms continue to use AI primarily on an experimental basis, large firms use it more intensively, with persistent differences across firm sizes and sectors. The impact on employment remains limited, although improvements in productivity and investment are already emerging. AI-adopting firms are characterised by higher productivity, higher wages, and a larger share of intangible assets, pointing to complementarities between AI adoption and skilled human capital. Barriers to adoption vary across firms: resource constraints and the perception of limited usefulness are predominant among non-adopters, while a smaller group of firms faces technical or regulatory barriers.

Keywords: artificial intelligence, AI, technology, firms, EBAE, Central Balance Sheet Data Office.

JEL classification: O33, L25, D22, J24.

Resumen

La adopción de la inteligencia artificial (IA) en las empresas españolas ha aumentado de forma significativa entre 2024 y 2026, aunque con gran heterogeneidad. Mientras las pequeñas y medianas empresas mantienen un uso mayoritariamente experimental, las grandes empresas muestran una utilización más intensiva, además de persistir en las diferencias por tamaño y sector. El impacto sobre el empleo es aún limitado, pero ya se observan mejoras en la productividad y la inversión. Las empresas adoptantes destacan por tener mayor productividad, salarios más altos y mayor peso de activos intangibles, lo que refleja la complementariedad con el capital humano cualificado. Los obstáculos a la adopción de la IA varían entre las empresas: entre las no adoptantes predominan las restricciones de recursos y la percepción de baja utilidad, mientras que un grupo más reducido enfrenta barreras técnicas o regulatorias.

Palabras clave: inteligencia artificial, IA, tecnología, empresas, EBAE, Central de Balances.

Códigos JEL: O33, L25, D22, J24.

Contents

1 Introduction 8

2 How firms use AI 9

2.1 Recent trends in AI adoption 9
2.2 Barriers to adopting AI 9
2.3 How AI is changing the way firms work 10

3 Firm characteristics and AI adoption: evidence from balance sheet data 14

3.1 Characteristics of firms adopting AI 14
3.2 Barriers to adoption and firm characteristics 17

4 Conclusions 19

References 20

1 Introduction

In recent years, artificial intelligence (AI) has become a prominent topic in economic and business discussions. The rapid development of new tools, particularly generative AI, has raised expectations about its potential to transform production processes, reshape how firms organise their work and affect productivity and employment. Yet despite this growing interest, more empirical evidence is needed on how firms are putting these technologies to use, how much they use them, what barriers they face and what effects they report. Business surveys are particularly valuable here. They offer insight into the spread of AI from firms' own perspective and offer a useful addition to the overall body of available evidence.

This paper examines how Spanish firms use AI, drawing on the responses to a particular set of questions on the subject in the Banco de España Business Activity Survey (EBAE) for 2026 Q1.

These data, along with the fact that they can be compared against the 2024 findings (Fernández-Cerezo, Hidalgo e Izquierdo, 2025), make it possible to track recent developments in AI adoption and reveal the main patterns by firm size, sector and type of use.

The analysis of the survey is supplemented with data from the Banco de España's Integrated Central Balance Sheet Database (CBI). This allows for a more in-depth exploration of the differences between AI adopters and non-adopters and to examine more systematically the factors associated with the likelihood of adoption in relation to certain production, organisational and financial characteristics.

This joined-up approach sheds light on the factors shaping the spread of AI across Spanish firms and where gaps in uptake may emerge. It highlights the role of firms' capabilities in this process and offers insights that are useful for economic analysis and designing policies to help them adopt this technology.

2 How firms use AI

2.1 Recent trends in AI adoption

The EBAE findings show a substantial increase in the use of AI over the past two years. In 2026 Q1, between 30% and 35% of small and medium-sized enterprises (SMEs) reported using predictive or generative AI. This was roughly double the proportion in 2024 (an increase of 16 percentage points, pp) (Chart 1.a). Among large firms, the share using these technologies rose by nearly 17 pp to around 70% of those surveyed. Despite these leaps, a sizeable gap in AI use remains between SMEs and large firms, much as it did in 2024.

Adopting AI usually involves a learning curve. Firms tend to start by experimenting, before gradually integrating it fully into their production processes and using it more intensively. Among SMEs, the increase in generative AI use since 2024 has been split almost equally between occasional use (up 8.4 pp) and moderate or intensive use (up 8.5 pp) (Chart 1.b). Large firms are already further along this path. Their progress since 2024 has mainly been towards more intensive use, with the share reporting moderate or intensive use rising by 14 pp.

AI adoption has increased across sectors. However, the largest increases have been in those that were already using AI more intensively in 2024, thus widening the gap seen two years ago. Accordingly, information and communication continues to lead the way. In 2026, almost 60% of firms in this sector use predictive or generative AI, compared with around 40% two years earlier. Professional and scientific activities come next, with uptake of close to 50%. The sectors that lagged furthest behind in 2024 (agriculture and construction) have also stepped up their adoption of AI, particularly generative AI. Almost 30% of firms in these sectors now use it, nearly 20 pp more than two years ago.

2.2 Barriers to adopting AI

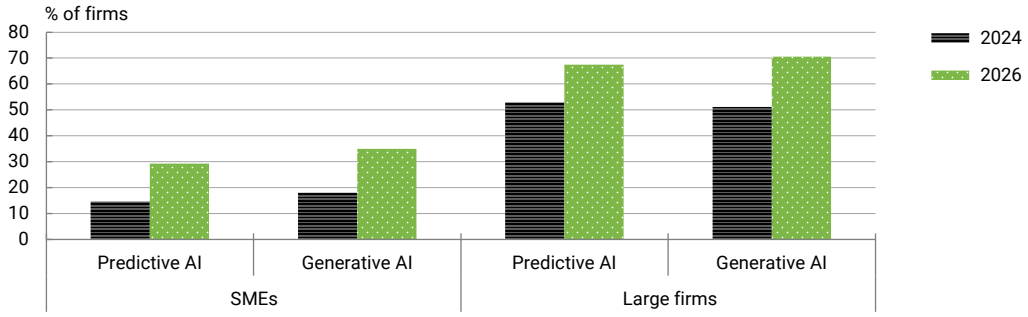
The increase in AI adoption is consistent with firms reporting fewer barriers than in 2024. Broadly speaking, fewer firms cite any of the obstacles covered by the survey, with the decline somewhat more pronounced among SMEs. The largest falls came in the shares of SMEs citing high costs (18 pp), a lack of skilled staff (16 pp) and uncertainty surrounding legal consequences (16 pp). For large firms, the biggest falls were in the shares citing uncertainty surrounding legal consequences (16 pp), ethical considerations (15 pp) and high costs (15 pp) (Chart 1.c).

Across sectors, firms generally viewed the various barriers to AI adoption as less significant in 2026 than in 2024. Implementation costs and the lack of skilled staff saw the sharpest declines. In the accommodation and food service activities sector, the shares of firms citing these two barriers fell by around 29 pp and 28 pp respectively. In agriculture, the decline in the share citing high costs was particularly marked, at 26 pp. Concerns about regulation and the legal implications of these technologies also eased significantly. In non-market services, for example, the share of firms pointing to regulatory obstacles as a significant barrier fell by more than 30 pp, while the share citing uncertainty about the legal consequences dropped by around 28 pp. Taken together, these findings suggest that firms see AI adoption as less challenging than before. Nevertheless, the lack of skilled staff remains the main obstacle, cited by around half of firms. That share exceeds 55% in sectors such as industry and energy, transport and agriculture.

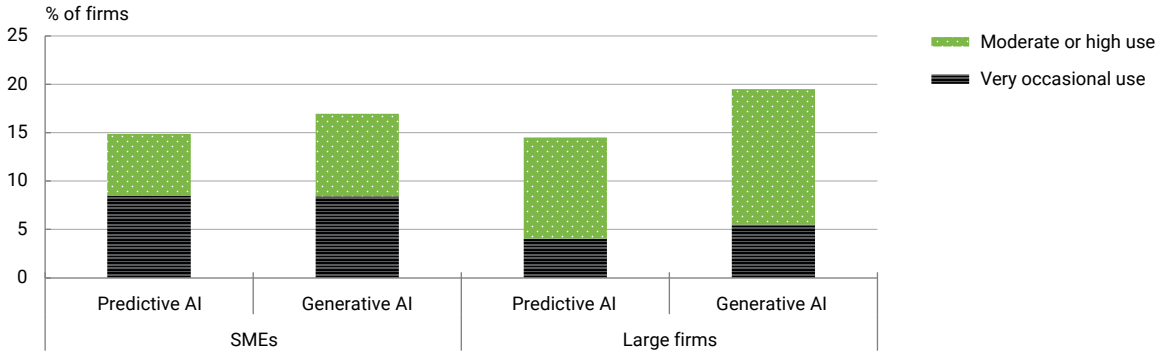
Chart 1

Firms' use of AI

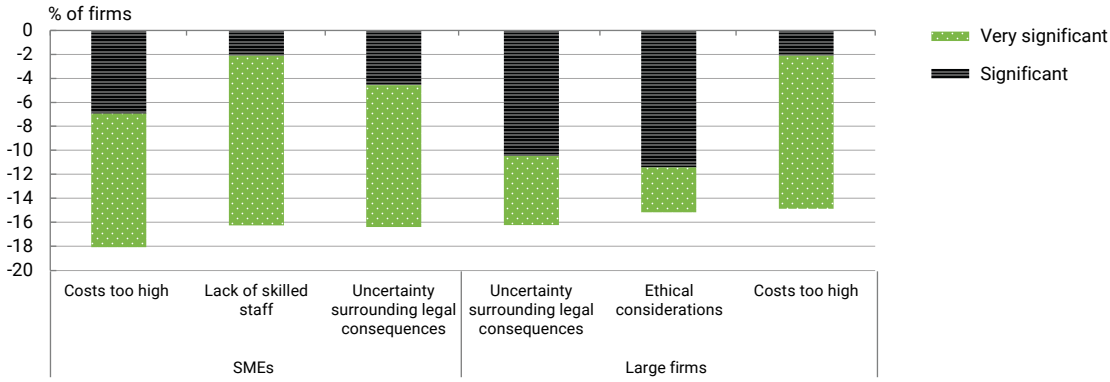
1.a Use of predictive and generative AI in 2026, by firm size



Change between 2024 and 2026 in the use of predictive and generative AI, by firm size



1.c Change between 2024 and 2026 in the barriers to AI use, by firm size



SOURCE: Banco de España Business Activity Survey.

2.3 How AI is changing the way firms work

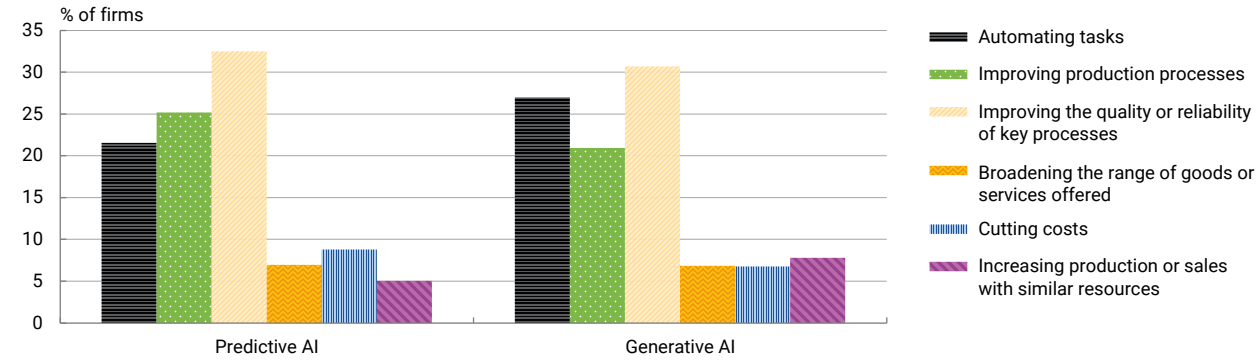
For the first time, the 2026 EBAE included questions on how adopting AI may be changing the internal workings of Spanish firms. Specifically, questions were included relating to four areas: i) the factors behind AI deployment in firms; ii) the observed effects so far on employment, investment and productivity; iii) firms' expectations for the future path of the aforementioned variables and the most affected job profiles; and iv) the organisational impacts associated with AI adoption.

First, the results shed light on what drives firms to incorporate AI into their production processes. Among firms already using AI, the main reasons for adoption relate to improving the quality or reliability of processes (32.5% for predictive AI and 30.7% for generative AI), automating tasks previously carried out by staff (21.5% and 27.0% respectively) and improving production processes that are already automated (25.2% and 20.9%). Fewer firms cite aims such as expanding their range of goods or services, cutting costs or increasing output or sales (Chart 2.a).

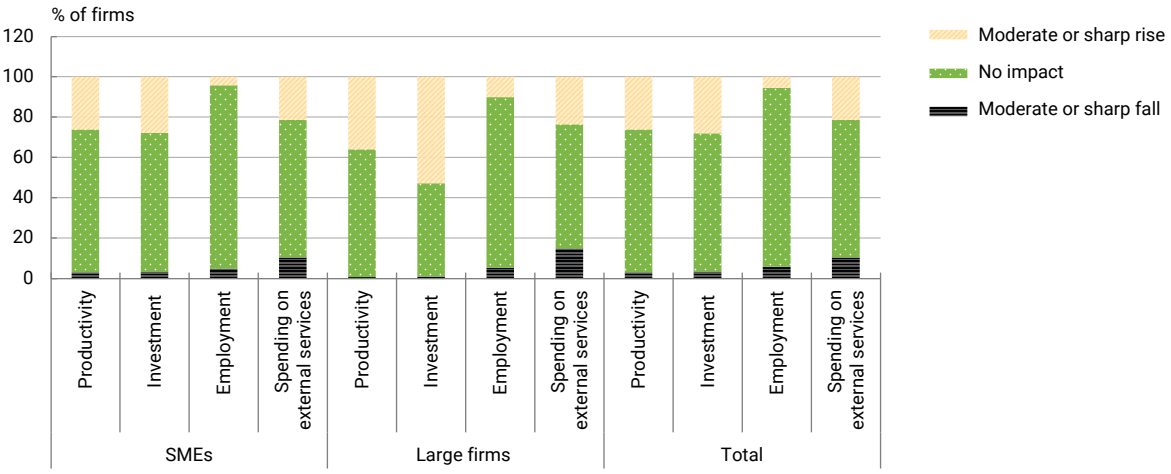
Chart 2

Effects of AI use on employment and productivity

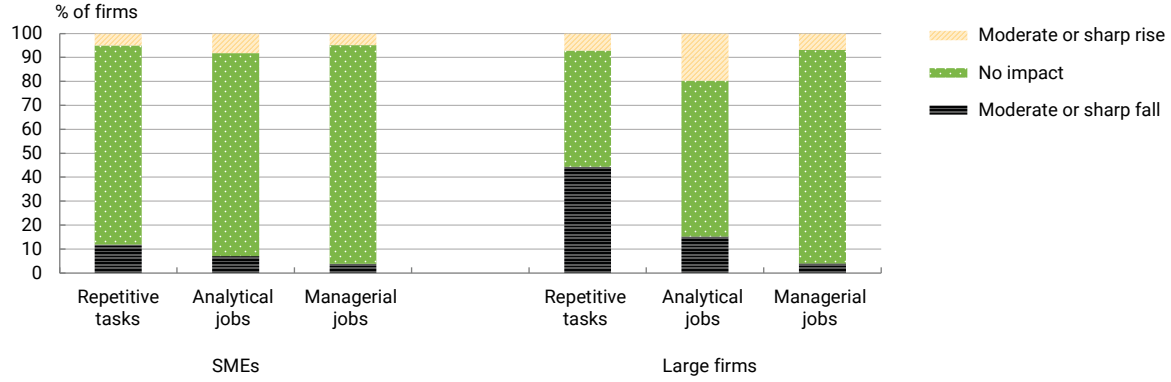
2.a Reasons for using predictive and generative AI



2.b Impact of AI in the last three years, by firm size



2.c Perception of the change in the number of employees in different groups



SOURCE: Banco de España Business Activity Survey.

Second, incorporating AI into production processes can affect variables such as staffing levels, productivity, costs and investment. Most of the firms surveyed report that the introduction of AI has had no significant effects in the last three years (close to 89%), while the percentage of firms that reduced or increased headcount was close to 6% in both cases (Chart 2.b). The effects are somewhat more pronounced among firms that make greater use of AI. Among intensive users of generative AI, around 13% report having increased their workforce, while close to 10% report having reduced it. Among moderate users, around 8.5% report an increase in staff numbers and 7.0% a reduction.

For productivity and investment, a sizeable share of firms (more than 25%) report increases over this same period. The impact is positive for both SMEs and large firms, but somewhat smaller for SMEs. This difference could be related to smaller firms being at an earlier phase in the use of these technologies. Consistent with this, the effects on productivity and investment are greater the more intensively firms use AI. For example, more than 60% of firms using generative AI report productivity gains over the past three years, as well as increases in investment. This share falls to around 40% among firms that use these tools moderately. The share is lower still among firms that use generative AI only occasionally, with around 14% reporting productivity gains and close to 18% reporting higher investment. Only a small share of firms report declines in productivity or investment, regardless of how intensively they use AI.

Lastly, the impact in terms of spending on external services such as marketing agencies, translation services and legal advice is somewhat more uneven. Close to 21% of firms increased their spending and around 11% saw it decrease. Here too, the share reporting higher spending rises with the intensity of AI use. Among intensive users of generative AI, around 39% report having increased spending on these services, while 13% report having reduced it.

Looking ahead to the next three years, large firms expect AI to have a greater positive impact on productivity and investment than SMEs do. Specifically, 61% of large firms expect productivity gains as opposed to 27% of SMEs. The gap is slightly wider for investment: 69% of large firms expect it to rise, compared with 30% of SMEs. Expectations of a positive impact are highest in sectors that rely most heavily on knowledge and technology. Around 45% of firms engaged in information and communication and in professional, scientific and technical activities expect productivity gains. These sectors also have the highest shares of firms expecting investment to rise. Expectations are more modest in sectors such as accommodation and food services, construction and agriculture, where around 25% of firms anticipate productivity gains.

The types of jobs that firms expect AI adoption to affect most also vary considerably with firm size. Most SMEs (83%) expect no change in jobs involving repetitive or routine tasks, while a relatively sizeable share of large firms (44%) expect the number of these jobs to fall. By contrast, jobs with a higher analytical content could benefit, especially in large firms, where employment in this type of occupation is expected to increase by around 20%. Managerial posts are overall set to be the least affected by AI adoption (Chart 2.c).

Lastly, incorporating these technologies poses important organisational challenges, particularly in terms of training, internal reorganisation and task reallocation. Over the next three years, the majority of large firms (79%) plan to step up training and hire more specialised staff (62%), compared with only 35% and 17% of SMEs, respectively. Both groups also recognise the need to reallocate tasks internally, albeit to varying extents (57% and 21%, respectively). Training needs and the associated organisational changes appear to be greater among firms anticipating larger AI-related productivity gains and higher investment.

Overall, the use of AI technologies has risen markedly between 2024 and 2026 across both SMEs and large firms. This increase appears to have been underpinned by a broad-based decline in the barriers to AI adoption perceived by firms. Nevertheless, adoption remains uneven across firm sizes and sectors: the gap between SMEs and large firms persists, while sectoral disparities have widened.

At present, firms are adopting AI primarily to improve the quality and reliability of processes and to further automate tasks, rather than to increase output or cut costs. As for the effects observed so far, firms' responses point to a limited impact on employment in the last three years, with a sizeable share of firms, especially larger firms, reporting growth in productivity and investment. Looking ahead, firms expect these effects to intensify, accompanied by organisational changes and greater training needs, albeit to markedly different degrees depending on firm size.

These descriptive findings reveal broad patterns in AI adoption, both in the intensity of use and in heterogeneity across firm sizes and sectors. These differences may partly reflect variation in firms' capabilities and resources, which are correlated with firm size and sector as well as with the likelihood of adoption.

To explore these mechanisms in greater depth, the next section builds on the survey evidence by linking firms' EBAE responses to their balance sheet data drawn from the CBI. By comparing firms within the same sector and controlling for size, this approach helps determine to what extent the observed heterogeneity in AI adoption patterns is associated with firm characteristics such as productivity, average remuneration, intangible asset intensity and financial position.

3 Firm characteristics and AI adoption: evidence from balance sheet data

This section examines whether AI adoption patterns reflect differences in firm characteristics such as productivity, workforce composition, intangible asset intensity and financial position. To this end, individual EBAE responses are linked to firm-level data from the Banco de España's CBI for the 2023 financial year,[1] the latest information available, although this introduces a time lag relative to the 2026 EBAE responses. The findings in this section should therefore be interpreted as associations between firms' prior characteristics and subsequent AI adoption, rather than as contemporaneous or necessarily causal relationships.

3.1 Characteristics of firms adopting AI

Using CBI data, a comparison can be drawn between the balance sheet profiles of firms that have adopted AI and those that have not within the same sector. Four variables are considered: (i) total factor productivity (TFP), as a measure of the firm's overall efficiency; (ii) average wage per employee, as an indicator of the skills composition of the workforce; (iii) the share of intangible assets in total productive capital; and (iv) the debt ratio.[2] The four variables are normalised at the two-digit sector level of the Spanish National Classification of Economic Activities (CNAE), so that a value of zero represents the typical firm in each sector.[3]

The most pronounced difference between AI adopters and non-adopters can be observed in the stock of intangible assets. Firms using AI have an appreciably higher share of intangible assets than their peers in the same sector (Chart 3.d), supporting the view that AI builds on firms' existing stock of intangible capital. Firms that have already invested in software, databases or proprietary algorithms can deploy AI tools at a lower marginal cost. The TFP distribution also shifts to the right among adopters (Chart 3.a), whose mean is around 4 log points above the sectoral average, compared with a slightly negative mean for non-adopters. Although the distributions overlap substantially and many non-adopters are more productive than the median adopter, the gap is visible both in the group means and in the top tail of the distribution.

Adopters also pay higher wages (Chart 3.b), approximately 4 log points above the sectoral mean, consistent with a more skilled workforce that is better placed to integrate AI tools into day-to-day tasks. By contrast, debt ratios are broadly similar across the two groups (Chart 3.c): both distributions are centred around the sectoral mean, suggesting that, within sectors, adopters cannot be distinguished from non-adopters on the basis of their financial position.

1 The CBI contains information on the financial statements of more than 800,000 Spanish non-financial corporations for each financial year. This analysis uses CBI data for 2023, the latest financial year for which balance sheet data are available. Since the EBAE survey round used here was conducted in February 2026, the financial data predate the survey responses by approximately two years. The balance sheet variables should therefore be interpreted as indicators of firms' structural characteristics around the time they were making their AI adoption decisions, rather than as contemporaneous measures. EBAE responses are matched to CBI data at firm level using the tax identification number.

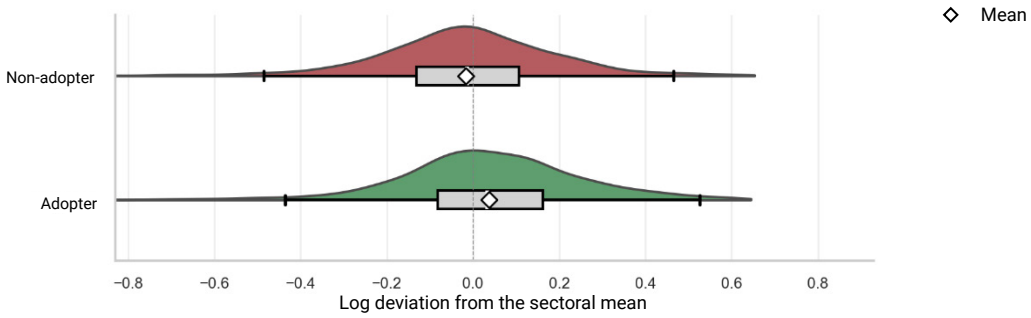
2 According to the Spanish General Chart of Accounts, intangible assets include capitalised software, development expenses, acquired intangible assets such as patents, trademarks, goodwill and administrative concessions. Accordingly, the share of intangible assets (defined as intangible assets relative to total productive fixed assets) is an imperfect indicator of a firm's stock of digital and technological capital, for two reasons: first, because some components (notably goodwill and concessions) are not directly related to digital capacity and, second, because it excludes internally developed intangible assets that have been recognised as expenses rather than capitalised. The debt ratio is defined as interest-bearing debt relative to total assets.

3 TFP is estimated at the two-digit CNAE sector level, following the methodology of Wooldridge (2009). For TFP and the average wage, normalisation consists of subtracting the sectoral mean of the log-transformed variable, so that the values are expressed in log-point deviations (approximately percentage points). For the debt ratio and the share of intangible assets, normalisation consists of subtracting the sectoral mean and dividing by the sectoral standard deviation.

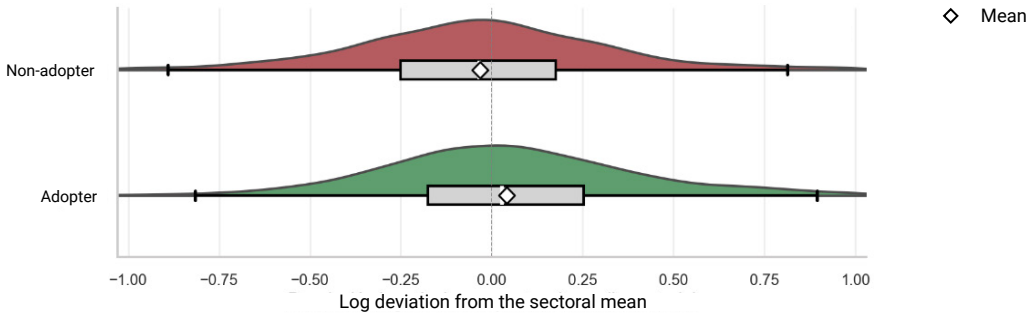
Chart 3

Distribution of the CBI variables normalised across sectors, according to the degree of AI adoption

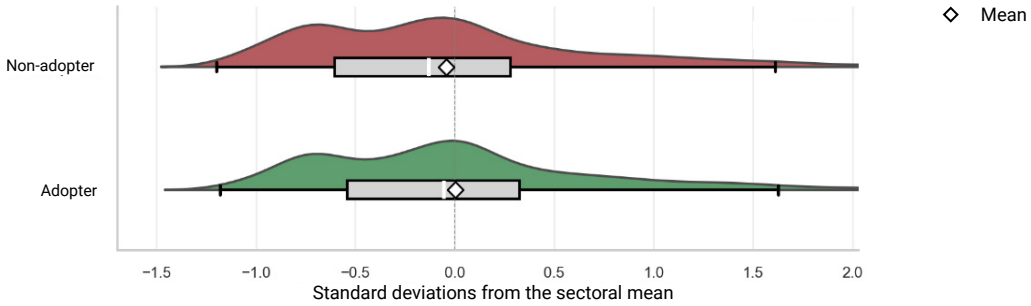
3.a TFP



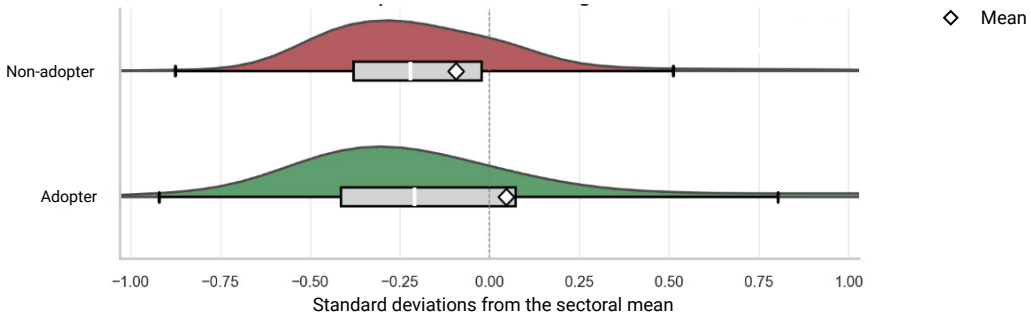
3.b Average wage



3.c Leverage ratio



3.d Percentage of intangible assets

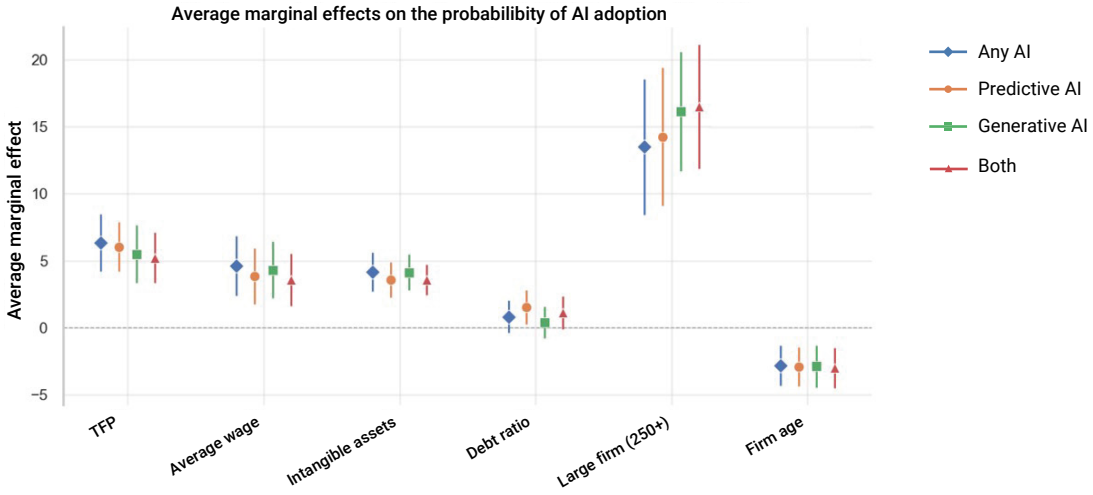


SOURCES: Banco de España Business Activity Survey and Banco de España Integrated Central Balance Sheet Database.

a Each panel shows the density of the distribution, the interquartile range, the group median and mean, according to the degree of adoption. TFP and average wage per employee are expressed as log deviations relative to the sectoral mean at the two-digit CNAE sector level. The debt ratio and share of intangible assets are standardised within each sector.

Chart 4

Average marginal effects of the logistic regression of AI adoption (a)



SOURCES: Banco de España Business Activity Survey and Banco de España Integrated Central Balance Sheet Database.

a Average marginal effects of the logit estimation. The continuous variables are standardised (average 0, SD 1); each coefficient represents the effect of an increase of a standard deviation on the probability of adoption. All the specifications include sector fixed effects at the two-digit CNAE sector level.

To quantify these associations while simultaneously controlling for the four variables, as well as firm size and age, Chart 4 presents the average marginal effects estimated from logistic regressions of AI adoption.[4] The continuous balance sheet variables are standardised (mean 0, standard deviation 1), making the coefficients directly comparable: each represents the change in the probability of adoption, in percentage points, associated with a one-standard-deviation increase in the variable. The baseline specification defines adoption broadly: a firm is classified as an AI adopter if it reports any use, whether experimental, moderate or intensive, of predictive or generative AI. The adopter category therefore encompasses very different degrees of technological integration. TFP emerges as the strongest predictor among the continuous variables: a one-standard-deviation increase is associated with a 6.3 pp higher probability of adoption. Average wage has the second-largest effect (4.6 pp per standard deviation), consistent with the role played by workforce skills in the adoption of these technologies. The share of intangible assets follows closely (4.1 pp), reinforcing the complementarity between AI and existing digital capital. The effect of the debt ratio is economically and statistically insignificant (0.8 pp).

These associations should be interpreted with caution. As noted above, the analysis does not establish the direction of the relationships. For instance, the link between productivity and adoption may operate in both directions: more productive firms may find it easier to adopt AI, but early adoption may also have contributed to

4 The dependent variable takes the value of 1 if the firm reports any use of AI (experimental, moderate or intensive) and 0 otherwise. Four specifications use different definitions of adoption: any AI, i.e. the use of predictive or generative AI; predictive AI only; generative AI only; and both types simultaneously. All continuous balance sheet variables (log TFP, log average wage, debt ratio, share of intangible assets and firm age expressed in logarithms) are standardised to have a mean of 0 and a standard deviation of 1 before estimation, so that the average marginal effects are expressed in common units and can be compared across variables. The large firm indicator is included as a binary variable. All regressions include sector fixed effects at the two-digit CNAE level. Standard errors are clustered at the sector level.

productivity gains (Brynjolfsson, Rock and Syverson, 2021). Similar considerations apply to the share of intangible assets and workforce composition.

3.2 Barriers to adoption and firm characteristics

As documented in the preceding sections, approximately 70% of firms report that they have not yet adopted AI tools. The EBAE asked these non-adopters to identify their main barrier to adoption. Chart 5.a groups their responses into four categories: resource constraints (high implementation costs or a lack of skilled staff); technical readiness (incompatibility with existing systems or insufficient data availability); regulatory and ethical concerns, and perceived lack of relevance (the firm sees no useful application or is unfamiliar with AI systems). Resource constraints are the predominant barrier, reported by 61% of non-adopters, followed by perceived lack of relevance (18%), technical readiness (11%) and regulatory or ethical concerns (8%).

The perceived barriers correspond to the observable differences in firm characteristics. Chart 5.b shows the mean of each normalised variable within each sector for adopters (black diamonds) and for each group of non-adopters, with the dashed line at zero representing the sectoral mean. Groups further below this line display larger negative deviations from the sectoral mean. TFP and average wage are expressed as log deviations (percentage points), while the debt ratio and the share of intangible assets are expressed as standard deviations within each sector. Two broad patterns emerge.

Firms reporting resource constraints or perceived lack of relevance display the largest gaps relative to adopters. Both groups pay wages well below their sectoral mean (by 6 and 7 log points, respectively), whereas adopters pay 4 log points above it, resulting in an overall wage gap of approximately 10 log points. Their holdings of intangible assets follow a similar pattern: both groups are below the sectoral mean, while adopters are above it, with overall gaps of around 0.17 standard deviations. Despite reporting very different barriers (one group states that it cannot afford AI, while the other sees no useful application), their balance sheets are remarkably similar. Both appear to lack the workforce skills and complementary digital assets that facilitate AI adoption.

By contrast, firms citing technical readiness or regulatory barriers resemble adopters more closely in terms of human capital. Firms in the technical readiness group have the smallest wage gap relative to adopters among all non-adopter groups (around 5 log points), while firms with regulatory concerns pay wages close to the sectoral mean (Chart 5.b). These firms appear to have the workforce capabilities needed to adopt AI, but face specific obstacles such as shortcomings in data infrastructure or regulatory uncertainty.

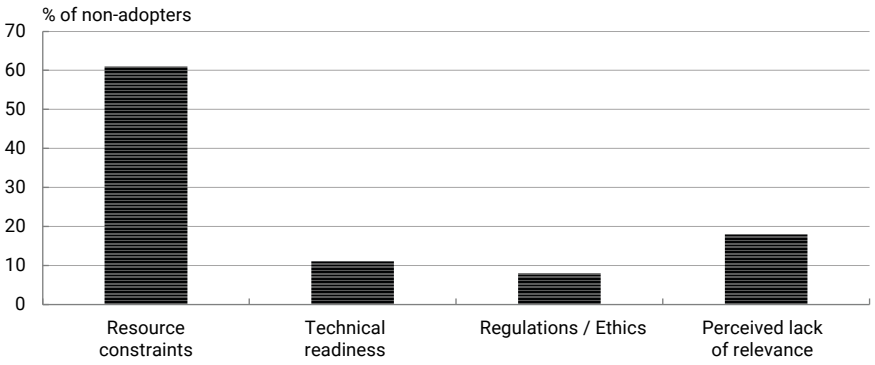
The share of intangible assets presents a somewhat different picture. All non-adopter groups hold fewer intangible assets than adopters, but the gap is largest for firms citing regulatory or ethical concerns (approximately 0.19 standard deviations below adopters). Debt ratios vary across groups, but the differences are generally imprecisely estimated, with wide confidence intervals that make it difficult to draw firm conclusions.

These patterns suggest that barriers to AI adoption are not uniform across the distribution of firms. For most non-adopters – those citing resource constraints or perceived lack of relevance (which together account for almost 80%) – the gap relative to adopters extends well beyond financing to encompass productivity, workforce skills and digital capital. For the smaller group held back by technical or regulatory barriers, the characteristics examined are closer to those of adopters.

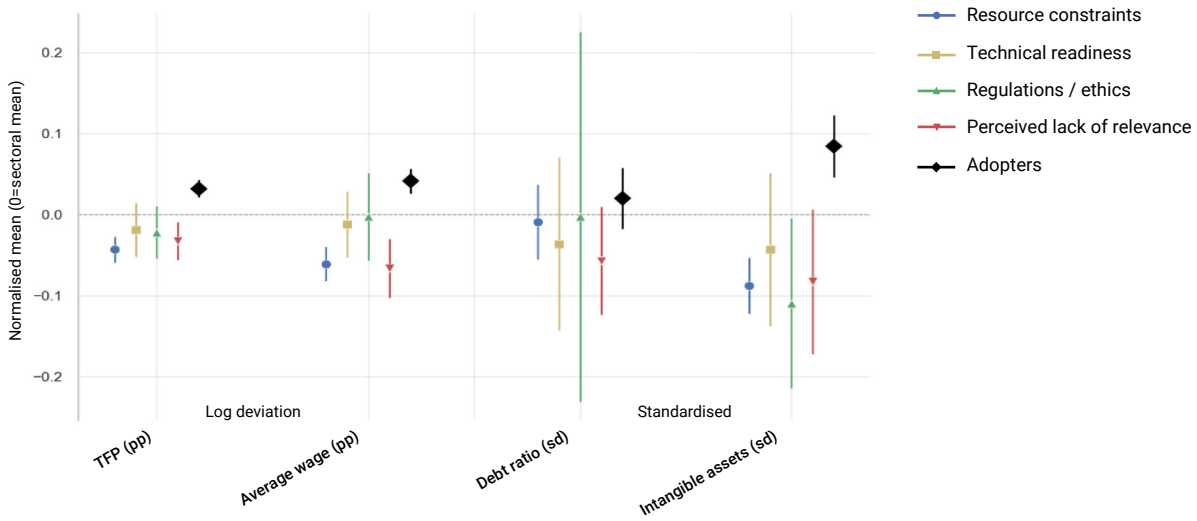
Chart 5

Barriers to adoption and firm characteristics

5.a Main barrier to AI adoption among non-adopters (a)



5.b Firm characteristics, by type of barrier and degree of adoption (b)



SOURCES: Banco de España Business Activity Survey and Banco de España Integrated Central Balance Sheet Database.

a Firms are classified according to their main reported barrier to AI adoption. N = 2,684 non-adopters.
b The markers indicate the group mean; the horizontal bars show 95% confidence levels. TFP and average wage per employee are expressed in log deviations relative to the two-digit CNAE sector-level mean. The debt ratio and the share of intangible assets are expressed as standard deviations across sectors. The dashed line at zero represents the sectoral mean.

4 Conclusions

Analysis of EBAE data highlights several features of recent AI adoption among Spanish firms. First, the use of these technologies has grown significantly between 2024 and 2026, among both SMEs and large firms, although it remains highly heterogeneous. While AI use is still predominantly experimental among SMEs, more intensive use is observed among large firms.

From this descriptive perspective, significant differences persist across firm sizes and sectors of activity. The gap between SMEs and large firms has not narrowed appreciably, while sectoral differences have widened, with AI use increasingly concentrated in more knowledge-intensive sectors. As regards the effects observed to date, the impact on employment appears limited, while a sizeable share of firms report increases in productivity and investment.

Second, combining EBAE data with balance sheet information allows the relationship between AI adoption and firm characteristics to be examined. On average, adopters have higher productivity, pay higher wages and have greater intangible asset intensity, but no significant differences are observed in their relative financial position. These associations should be interpreted with caution, as the analysis does not establish causal relationships.

The analysis of barriers to adoption supports this interpretation. For most non-adopters, the main obstacles relate to resource constraints and the perception of limited usefulness, alongside gaps in productivity, workforce skills and digital capital. Conversely, a smaller group of firms face technical or regulatory barriers despite being closer to adopters in terms of the characteristics examined.

Third, these findings have implications for the design of economic policies aimed at fostering the diffusion of AI in the business sector. The aggregate impact of these technologies will depend not only on the breadth of adoption, but also on the intensity of use and firms' ability to develop complementary assets, such as skilled human capital, organisational capabilities and digital assets.

From this standpoint, training policies, support for the digitalisation of internal processes and the reduction of technical or regulatory barriers can all play an important role in broadening the pool of firms able to integrate AI effectively. Without progress in these areas, there is a risk that the diffusion of these technologies will widen existing gaps between firms rather than foster convergence in productivity.

References

Fernández Cerezo, Alejandro, Ignacio Hidalgo and Mario Izquierdo. (2025). "Adoption of artificial intelligence in Spanish firms: an initial analysis based on the Banco de España Business Activity Survey." *Economic Bulletin - Banco de España,* Article 06, 2025/Q2. https://repositorio.bde.es/handle/123456789/39725

Bonney, Kathryn, Cory Breaux, Catherine Buffington, Emin Dinlersoz, Lucia S. Foster, Nathan Goldschlag, John C. Haltiwanger, Zachary Kroff and Keith Savage. (2024). "Tracking Firm Use of AI in Real Time: A Snapshot from the Business Trends and Outlook Survey". NBER Working Paper Series, 32319, National Bureau of Economic Research. https://doi.org/10.3386/w32319

Brynjolfsson, Erik, Daniel Rock and Chad Syverson. (2021). "The Productivity J-Curve: How Intangibles Complement General Purpose Technologies". *American Economic Journal: Macroeconomics,* 13(1), pp. 333-372. https://doi.org/10.1257/mac.20180386

Calvino, Flavio, and Luca Fontanelli. (2023). "A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity". OECD Science, Technology and Industry Working Papers, 2023/02, Organisation for Economic Co-operation and Development Publishing. https://doi.org/10.1787/0fb79bb9-en

McElheran, Kristina, J. Frank Li, Erik Brynjolfsson, Zachary Kroff, Emin Dinlersoz, Lucia Foster and Nikolas Zolas. (2024). "AI Adoption in America: Who, What, and Where". *Journal of Economics & Management Strategy,* 33(2), pp. 375-415. https://doi.org/10.1111/jems.12576

Milgrom, Paul, and John Roberts. (1990). "The Economics of Modern Manufacturing: Technology, Strategy, and Organization". *The American Economic Review,* 80(3), pp. 511–528. https://www.jstor.org/stable/2006681

Wooldridge, Jeffrey M. (2009). "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables". *Economics Letters,* 104(3), pp. 112-114. https://doi.org/10.1016/j.econlet.2009.04.026

BANCO DE ESPAÑA PUBLICATIONS

OCCASIONAL PAPERS

2430 JOSE GONZÁLEZ MÍNGUEZ: The Letta report: a set of proposals for revitalising the European economy. (There is a Spanish version of this edition with the same number).
2431 MARIYA MELNYCHUK and JAVIER MENCÍA: A taxonomy of macro-financial risks and policies to address them.
2432 DMITRY KHAMETSHIN, DAVID LÓPEZ RODRÍGUEZ and LUIS PÉREZ GARCÍA: El mercado del alquiler de vivienda residencial en España: evolución reciente, determinantes e indicadores de esfuerzo.
2433 ANDRÉS LAJER BARON, DAVID LÓPEZ RODRÍGUEZ and LUCIO SAN JUAN: El mercado de la vivienda residencial en España: evolución reciente y comparación internacional.
2434 CARLOS GONZÁLEZ PEDRAZ, ADRIAN VAN RIXTEL and ROBERTO PASCUAL GONZÁLEZ: Navigating the boom and bust of global SPACs.
2435 PATROCINIO TELLO-CASAS: El papel de China como acreedor financiero internacional.
2436 JOSÉ RAMÓN MARTÍNEZ RESANO: CBDCs, banknotes and bank deposits: the financial stability nexus.
2501 PEDRO DEL RÍO, PAULA SÁNCHEZ, MARÍA MÉNDEZ, ANTONIO MILLARUELO, SUSANA MORENO, MANUEL ROJO, JACOPO TIMINI and FRANCESCA VIANI: La ampliación de la Unión Europea hacia el este: situación e implicaciones para la economía española y la Unión Europea.
2502 BANCO DE ESPAÑA: In-person access to banking services in Spain. 2024 monitoring report. (There is a Spanish version of this edition with the same number).
2503 ANDRÁS BORSOS, ADRIAN CARRO, ALDO GLIELMO, MARC HINTERSCHWEIGER, JAGODA KASZOWSKA-MOJSA and ARZU ULUC: Agent-based modeling at central banks: recent developments and new challenges.
2504 ANDRES ALONSO-ROBISCO, ANDRES AZQUETA-GAVALDON, JOSE MANUEL CARBO, JOSE LUIS GONZALEZ, ANA ISABEL HERNAEZ, JOSE LUIS HERRERA, JORGE QUINTANA and JAVIER TARANCON: Empowering financial supervision: a SupTech experiment using machine learning in an early warning system.
2505 JÉSSICA GUEDES, DIEGO TORRES, PAULINO SÁNCHEZ-ESCRIBANO and JOSÉ BOYANO: Incertidumbre en el mercado de bonos: una propuesta para identificar sus narrativas con GDELT.
2506 LAURA JIMENA GONZÁLEZ GÓMEZ, FERNANDO LEÓN, JAIME GUIXERES PROVINCIALE, JOSÉ M. SÁNCHEZ and MARIANO ALCAÑIZ: Evolución de la investigación neurocientífica del efectivo: revisión y perspectivas actuales.
2507 LUIS FERNÁNDEZ LAFUERZA, IRENE ROIBÁS and RAQUEL VEGAS SÁNCHEZ: Indicadores de desequilibrios de precios del mercado inmobiliario comercial.
2508 PANA ALVES and OLIVIER HUBERT: ¿Influye la eficiencia energética en el precio de la vivienda en España?.
2509 ALEJANDRO FERRER and ANA MOLINA: The interaction of liquidity risk and bank solvency via asset monetisation mechanisms. (There is a Spanish version of this edition with the same number).
2510 ISABEL ALCALDE and PATRICIA STUPARIU: Financial education at an early age. (There is a Spanish version of this edition with the same number).
2511 ALEJANDRO GONZÁLEZ FRAGA, AITOR LACUESTA GABARAIN, JOSÉ MARÍA LABEAGA AZCONA, MARÍA DE LOS LLANOS MATEA ROSA, SOLEDAD ROBLES ROMERO, MARÍA VALKOV LORENZO and SERGIO VELA ORTIZ: Estructura del mercado de electrolineras.
2512 FERNANDO ARRANZ GOZALO, CLARA I. GONZÁLEZ MARTÍNEZ and MERCEDES DE LUIS LÓPEZ: Sovereign assets and sustainable and responsible investment: the importance of climate metrics. (There is a Spanish version of this edition with the same number).
2513 IRMA ALONSO-ÁLVAREZ and DANIEL SANTABÁRBARA: Decoding Structural Shocks in the Global Oil Market.
2514 JOSÉ MANUEL CARBÓ, CLAUDIA TOLEDO and ÁNGEL IVÁN MORENO: Hacia un diccionario panhispánico de sentimiento de la estabilidad financiera.
2515 IGNACIO FÉLEZ DE TORRES, CLARA I. GONZÁLEZ MARTÍNEZ and ELENA TRIEBSKORN: The puzzle of forward-looking climate transition risk metrics.
2516 MIGUEL GARCÍA-POSADA: Un análisis de los efectos de la introducción del procedimiento especial de insolvencias para microempresas sobre la propensión a concursar.
2517 ADRIAN VAN RIXTEL: Whatever it takes? Economic policymaking in China in the context of a possible deflationary spiral.
2518 PATRICIA STUPARIU and JUAN RAFAEL RUIZ: Adding up the benefits: education, numeracy and financial literacy. (There is a Spanish version of this edition with the same number).
2519 DAVID CUBERES, AITOR LACUESTA, MARÍA DE LOS LLANOS MATEA and DANIEL OTO-PERALÍAS: El efecto de la regulación sobre el tamaño de las plantas fotovoltaicas.
2520 MARINA GARCÍA GIL and DMITRY KHAMETSHIN: Ayudas directas de la línea COVID-19: los determinantes de la asignación y el efecto sobre el crédito bancario.
2521 LUCÍA CUADRO-SÁEZ, CORINNA GHIRELLI, MAXIMILIANO MORENO-LÓPEZ and JAVIER J. PÉREZ: Monitoring and forecasting food prices in the euro area.

2522 LAURA HOSPIDO, JÚLIA MARTÍ LLOBET and CARLOS SANZ: ¿Qué políticas son efectivas para reducir la exclusión social? Evaluación de cinco proyectos piloto de inclusión social a través de ensayos aleatorizados.

2523 MARIO ALLOZA, MARÍA ELENA CRISTÓBAL RODRÍGUEZ, JULIA GARCÍA-ROYO DÍAZ, BEATRIZ GONZÁLEZ, ALBERTO MARTÍN DEL CAMPO SOLA, ANE MARTÍN UGARTE, ENRIQUE MORAL-BENITO and IRENE PINILLA MELGAREJO: Diagnóstico y consecuencias económicas del grado de competencia en las licitaciones públicas.

2524 ADRIÁN CARRO, JORGE E. GALÁN, ENRIC MARTORELL and RAQUEL VEGAS: A literature review on ex-ante and ex-post analysis of the implications of borrower-based macroprudential measures.

2525 PAULA SEMPERE and RAQUEL PANTOJA: Efectivo y *neuromarketing:* Concepto, funciones y aplicación.

2601 RODOLFO G. CAMPOS, JACOPO TIMINI, FRANCESCA VIANI and ELENA VIDAL: The EU-Mercosur agreement: analysis of its characteristics from a sectoral perspective. (There is a Spanish version of this edition with the same number).

2602 PABLO AGUILAR, CORINNA GHIRELLI and SAMUEL HURTADO: MTBE v2025: new version of the Quarterly Model of the Banco de España.

2603 IRMA ALONSO-ALVAREZ, EKATERINA BUKINA, MARINA DIAKONOVA, NINO KHITARISHVILI, JAVIER J. PÉREZ and PEDRO PIQUERAS: Geopolitical risk: a database of general and bilateral indices.

2604 RUBÉN DOMÍNGUEZ-DÍAZ, MARTA GARCÍA-RODRÍGUEZ, JAVIER QUINTANA and RUBÉN VEIGA-DUARTE: Estimación del crecimiento potencial de la economía española: una revisión metodológica.

2605 CARLES MANERA, FERRAN NAVINÉS, JAVIER FRANCONETTI, MIQUEL QUETGLAS and JOSÉ A. PÉREZ-MONTIEL: Regional outlook on labor productivity in Spain, 2000–2022.

2606 RICARDO BARAHONA: Current trends in performance and flows in the Spanish pension funds industry.

2607 FRANCISCO GONZÁLEZ RODRÍGUEZ, ALBERTO ORTS TORRES, JOSÉ MARÍA SERENA GARRALDA and MIQUEL TARÍ SÁNCHEZ: Issuance yield of MREL-eligible bank debt: a benchmarking model.

2608 MÓNICA CORREA-LÓPEZ, MAR DELGADO-TÉLLEZ and MARTA SUÁREZ-VALERA: Europa en transición energética: respuestas y desafíos tras dos crisis consecutivas.

2609 AITOR LACUESTA, MARÍA VALKOV and MICOLE DE VERA: Un análisis de los mecanismos de protección de los operadores económicos establecidos por la Ley de garantía de la unidad de mercado.

2610 Encuesta Financiera de las Familias (EFF) 2024: métodos, resultados y cambios desde 2022.

2611 ALFONSO CAMBA, MATÍAS COVARRUBIAS, JOSÉ LUÍS RODRÍGUEZ and RAQUEL TÁRREGA: El coste en bienestar de los márgenes en mercados de productos en España: un análisis con empresas heterogéneas.

2612 MICAELA ARIAS, LUCÍA CRIADO, JAVIER GARCÍA-VERDUGO, EDUARDO GUTIÉRREZ, ALMUDENA KESSLER, JOSÉ MANUEL MONTERO, SARA PEREIRA and PAU ROLDÁN-BLANCO: Evolución de la estructura de mercado y de los indicadores de competencia en España en las dos últimas décadas.

2613 ANDRÉS ALONSO-ROBISCO, JOSÉ MANUEL CARBÓ, CARLOS JOSÉ GARCÍA, JORGE QUINTANA and JAVIER TARANCÓN: Retriever or reasoner? Decomposing retrieval-augmented generation performance in external audit supervision.

2614 RUBÉN VEIGA-DUARTE, EDUARDO GUTIÉRREZ, ALBERTO MARCOS-FERNÁNDEZ, ENRIQUE MORAL-BENITO and JAVIER QUINTANA: Las fuentes del crecimiento en España y las principales economías europeas: productividad total de los factores y heterogeneidad sectorial.

2615 MATEO CACHO UZAL, M. DANIELA FILIP and DIANA POSADA RESTREPO: Regional convergence dynamics in the main european economies. (There is a Spanish version of this edition with the same number).

2616 IRMA ALONSO-ALVAREZ, IVÁN KATARYNIUK, DAVID LÓPEZ-SALIDO and JAVIER J. PÉREZ: Geopolitical Oil-Supply Scenarios and Macroeconomic Risks: A Bayesian Toolkit for Policy Analysis.

2617 MIHAI-VASILE CÎRJĂ and JORDI ROMEU GRANADOS: Transparency and accountability as drivers of cultural change. A comparative analysis of central banks and national competent authorities.

2618 LUCÍA CANALEJO GUIJOSA, FERNANDO LEÓN MARTÍNEZ and JOSÉ MARÍA SÁNCHEZ ECHAVE: The voice as a neurophysiological marker: applications in implicit emotion perception for Neurocash® and cash design.

2619 DANIEL DEJUAN-BITRIA: El proceso de desapalancamiento de las sociedades no financieras españolas en el período 2007-2024.

2620 MIGUEL GARCÍA-POSADA GÓMEZ y MARÍA RODRÍGUEZ MORENO: Determinantes de la modalidad del tipo de interés de las hipotecas y evolución de sus márgenes durante el período de endurecimiento de la política monetaria 2022-2023.

2621 MARÍA ALEJANDRA AMADO GARFIAS, JOÃO AMADOR, SÓNIA FÉLIX, JOANA M. GARCIA, VANDA GERALDES DA CUNHA, CORINNA GHIRELLI, ÁNGEL LUIS GÓMEZ JIMÉNEZ, EDUARDO GUTIÉRREZ CHACÓN, CRISTINA MANTEU, LUIS MOLINA SÁNCHEZ, ENRIQUE MORAL-BENITO, SERGIO PUENTE DÍAZ, JAVIER QUINTANA GONZÁLEZ, MARTÍN SALDÍAS, SHARMIN SAZEDJ, SOFIA TERLICA and JACOPO TIMINI: Perspectives on Iberian Economic Integration.

2622 CLARA I. GONZÁLEZ, PEDRO LINARES, SOLEDAD NÚÑEZ, ÍÑIGO LOSADA, ANIL MARKANDYA, AVINASH PERSAUD, FRANK ELDERSON, KEVIN STIROH, ROB PATALANO, ENRIQUE SERRANO, CASPAR SIEGERT, JAMES TALBOT, JUAN AYUSO, ELENA TRIEBSKORN, LUIS ÁNGEL MAZA, AGNIESZKA TRZCINSKA, CARMEN NUZZO and YANN MARIN: Climate Risk and Sustainable Finance: Bridging Policy, Research and Practice.

2623 IRENE PABLOS:The AI investment boom: capital formation, financing structures, interconnections and vulnerabilities.

2624 JACOB HESS and DIANA POSADA RESTREPO: Spanish firms' use of artificial intelligence: recent progress and factors linked to its use.