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THE ECONOMIC IMPACT OF ARTIFICIAL INTELLIGENCE: EVIDENCE FROM ITALIAN FIRMS

by Tiziano Ropele* and Alex Tagliabracci**

Abstract

We study the adoption of artificial intelligence (AI) technologies among Italian firms and their effects on firm–level outcomes, using newly collected survey data linked to administrative balance sheet and employer–employee records. We document that, as of 2024, AI adoption remains limited: about 10 per cent of firms report current use, while nearly 30 per cent plan to adopt AI within the next two years. Adoption is concentrated among larger and more knowledge-intensive firms, as well as among firms with higher labour costs, pointing to the importance of organizational capacity, technological complementarities and efficiency considerations. Using a difference-in-differences framework, we show that AI adoption increases labour productivity and profitability, and leads to a reallocation of employment toward higher-skilled occupations through a statistically significant expansion of white-collar employment and a contraction of blue-collar employment, with no detectable effects on overall employment. Finally, we examine firms' expectations and find that AI-adopting firms anticipate smaller increases in their own prices and lower medium- to long-term inflation than non-adopters. These patterns suggest that AI adoption is associated with expected efficiency gains that shape both firms' pricing behaviour and their macroeconomic expectations.

JEL Classification: E3, L2, O14, O33.

Keywords: artificial intelligence, firm performance, productivity, expectations.

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1 Introduction[1]

The diffusion of artificial intelligence (AI) is widely seen as one of the most consequential technological developments of recent decades, with the potential to reshape firms' organization, productivity, and labor demand. A rapidly growing literature shows that AI can reallocate tasks, transform production processes, and alter competitive dynamics across industries (e.g., Acemoglu and Restrepo, 2022; Acemoglu, 2024). While some studies emphasize substantial efficiency gains, innovation spillovers, and opportunities for upgrading (e.g., Czarnitzki et al., 2023), others point to the risks of task displacement, widening inequality, and rising productivity dispersion (e.g., Acemoglu and Restrepo, 2019; Acemoglu, 2021). Despite these important contributions, we still know little about how firms actually integrate AI into production and management processes, what determines adoption, and how the resulting changes in organization and workforce composition translate into firm performance and macroeconomic expectations.

Italy offers a particularly informative setting for examining these questions. The country has experienced persistently weak productivity growth since the early 2000s, alongside concerns about long-run competitiveness (e.g., Bugamelli et al., 2018). AI technologies – ranging from predictive and generative models to robotics and cloud-based tools – may help overcome these structural weaknesses. More broadly, Italy's economic structure, with a large share of small and medium-sized firms, substantial regional heterogeneity, and slow technology diffusion, mirrors challenges faced by many advanced economies. While the diffusion and main drivers of AI adoption among Italian firms have been documented in several studies, systematic evidence on its economic implications remains limited.

This paper addresses this gap by combining survey and administrative firm-level data from three sources: the Bank of Italy's *Survey on Inflation and Growth Expectations* (SIGE), the *Company Accounts Data System* (CADS), and administrative workforce records from the *Italian National Social Security Institute* (INPS). The SIGE survey conducted in the third quarter of 2024 among firms with at least 50 employees includes specific questions on firms' current AI adoption, their adoption plans, and intended uses. Merging these data with balance-sheet and employer-employee information enables us to (*i*) document the diffusion of AI across Italian firms, (*ii*) identify the main firm-level determinants of adoption, and (*iii*) estimate the effects of AI adoption on firm performance and labor composition, and document a novel channel through

[1]The views expressed in this article are those of the authors and do not necessarily represent the positions of the Bank of Italy or the Eurosystem. Without implications, we would like to thank Fabio Busetti, Luca Citino, Sara Formai, Alessandro Secchi, Giordano Zevi and Roberta Zizza for valuable inputs and comments at different stages of this work. All the remaining errors and omissions remain our own responsibility.

which technological innovation shapes expectations at both the micro level (e.g., firms' own selling prices) and the macro level (e.g., aggregate inflation).

Four main findings emerge. First, as of 2024, AI adoption remains limited among Italian firms with at least 50 employees operating in industry and non-financial private services. About 11% of firms report already using AI in their operations, while 28% plan to adopt it within two years. Roughly one-third consider AI irrelevant for their business, and 27% respond *"Don't know/Prefer not to answer"*, indicating substantial uncertainty or limited awareness regarding the applicability of these technologies.

Second, firm size is the strongest predictor of adoption, consistent with larger firms' financial, managerial, and organizational capacity to integrate advanced technologies. Adoption is also more prevalent in knowledge-intensive industries and among firms with higher labor costs, pointing to both technological complementarity and efficiency motives.

Third, using a difference-in-differences approach, we find that AI adoption improves firms' profitability and labor productivity. At the same time, adopters adjust their workforce composition: AI adoption is associated with a statistically significant increase in white-collar employment and a decline in blue-collar employment, leading to a shift in employment shares toward higher-skill occupations – a pattern consistent with task-based models in which AI substitutes for routine tasks while complementing high-skill labor.[2]

Fourth, AI adoption shapes firms' price-setting behavior and their macroeconomic expectations. Relative to non-adopters, AI-adopting firms report smaller expected increases in their own selling prices, consistent with anticipated efficiency gains translating into lower firm-level price pressures. At the macro level, while many firms anticipate a broadly positive impact of AI on the Italian economy, adopters expect noticeably lower medium- to long-term inflation. These patterns are consistent with AI-adopting firms associating AI diffusion with gradual efficiency gains and improved cost conditions relevant for their own pricing decisions.

Our contribution relates to three strands of research. A first body of research examines the adoption and diffusion of advanced technologies (e.g., Comin and Hobijn, 2010; Kalyani et al., 2025), with increasing attention to AI. Early firm-level evidence from the United States documents that adoption of automation and AI technologies

[2]The literature offers differing perspectives on which segments of the workforce are most exposed to AI. Some studies, particularly those analyzing generative AI, highlight displacement risks in routine white-collar roles such as administrative support, customer service, and data entry (e.g., Chelliah, 2017; Felten et al., 2023; Eloundou et al., 2023). By contrast, task-based models suggest that AI primarily substitutes routine tasks, regardless of occupational category, while complementing abstract, non-routine skills often concentrated in high-skill white-collar roles (e.g., Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2018). Our evidence is consistent with this latter view, supporting the notion of skill-biased technological change: AI substitutes routine work while complementing high-skill labor, reshaping firm-level workforce composition.

remained limited in the late 2010s and highlights barriers such as costs, organizational inertia, and skill shortages (Acemoglu et al., 2024). Subsequent contributions examine the diffusion of AI-related skills (Acemoglu et al., 2022), the clustering of AI adoption among large and high-performing firms (Acemoglu et al., 2023; Babina et al., 2024) and occupational exposure (see Dalla Zuanna et al. (2024) for the Italy and Pizzinelli et al. (2023) for a cross-country analysis), determinants of adoption (Bencivelli et al., 2025), and the labor productivity effect of robotics (Dottori, 2020; Cullen et al., 2025). We contribute to this literature by linking newly collected survey measures of AI adoption and expectations to detailed balance-sheet and employer-employee data.

A second strand studies the economic effects of AI adoption. A large theoretical and empirical literature, often grounded in task-based models (e.g., Acemoglu and Restrepo, 2018), analyzes how automation affects productivity, wages, and labor allocation. Empirical evidence shows that AI adoption can enhance productivity and financial performance (e.g., Czarnitzki et al., 2023), and that firms relying on AI-based pricing experience faster growth in sales, employment, and market value (Adams et al., 2026). At the same time, concerns persist regarding the uneven distribution of these gains and the potential for labor displacement (Acemoglu, 2021). Recent evidence for Europe is provided by Aldasoro et al. (2026), who, using data from the European Investment Bank Investment Survey, show that AI adoption increases labour productivity through capital deepening, rather than labour displacement, with gains unevenly distributed and concentrated among medium- and large-sized firms. We add to this literature by providing new micro-evidence on profitability and labor-composition adjustments and by showing that AI adoption affects firms' expected price-setting behavior, a channel that has received little empirical attention so far.

A third, rapidly expanding strand of literature investigates how firms form expectations about prices, labor demand, investment, and macroeconomic conditions. Prior work shows that firms' expectations respond systematically to shocks (e.g., Weber et al., 2022; Candia et al., 2023) and to uncertainty (e.g., Bachmann et al., 2013; Bloom, 2009; Bloom et al., 2018). A separate line of research documents how firms process information and update beliefs in noisy, inattentive, or state-dependent ways (e.g., Coibion and Gorodnichenko, 2015; Afrouzi, 2024; Weber et al., 2025). Yet, despite the growing evidence on expectation formation, much less is known about how technological innovation shapes firms' beliefs. Our data allow us to show that innovation – specifically, AI adoption – affects both micro expectations (such as firms' own selling prices) and macro expectations (such as medium- and long-run inflation). In doing so, we identify a novel channel through which technological change influences expectation formation and, ultimately, aggregate dynamics by shifting firms' perceptions of future economic conditions.

The remainder of the paper is organized as follows. Section 2 describes the survey and administrative data used to measure AI adoption and link it to firm-level outcomes. Section 3 provides preliminary evidence on AI adoption, including firms' perceived importance of AI, their engagement with AI-related survey questions, and self-reported effects of adoption. Section 4 outlines the econometric strategy. Section 5 presents the estimation results for firm behavior and forward-looking assessments, drawing on both observed outcomes and survey-based plans and assessments. Section 6 analyzes the aggregate implications of AI adoption, focusing on firms' reported macroeconomic effects and their inflation expectations. Section 7 concludes.

2 Data sources

The data used in this paper come from three main sources.

Bank of Italy's Survey on Inflation and Growth Expectations. The first source of data is the *Survey on Inflation and Growth Expectations* (SIGE), which is a quarterly business survey conducted by the Bank of Italy since December 1999. The reference universe consists of firms headquartered in Italy that operate in industry, non-financial private services and construction with at least 50 employees. The sample is stratified by three sectors of economic activity (industry, non-financial private services, and construction), four geographical areas (North-West, North-East, Centre, and South and Islands), and three size classes in terms of number of employees ($50-199$, $200-999$, and $1,000$ and over). In recent years before 2025, each wave saw the participation of about $1,500$ firms (650 in industry, 650 in non-financial private services, and 200 in construction). The list of firms used to extract the sample is drawn from the *Italian National Social Security Institute* (INPS) and *Italian Chambers of Commerce* (InfoCamere) databases. Sampling weights are provided to ensure that the distribution of firms in the sample represents the distribution of firms in the reference population. The survey is carried out by a specialist company that distributes the questionnaire to company managers who are best informed about the topics covered in the survey.[3]

The purpose of the survey is to elicit information on firms' expectations regarding inflation, the general economic situation, own-product prices and demand, investment, and employment. Most of the data, with the exception of own-product price changes (past and expected), aggregate inflation expectations, and current number of employees, are qualitative and relate to firms' assessments about their own business activity as well as about macroeconomic matters in the reference quarter and looking ahead. Most of the questions are repeated across waves. Occasionally, the survey includes questions on specific aspects of the economy that warrant further investigation. In the third quarter of 2024, the survey included a whole section of questions on the

[3] More information about the survey is provided in Grasso and Ropele (2018).

use of AI for all firms except those in construction sector. The full questionnaire is shown in the Appendix A1.

Cerved Group's Company Accounts Data Service. The second source of data that we match with SIGE is the *Company Accounts Data Service* (CADS). This proprietary database, owned by Cerved Group – a leading information provider in Italy and one of Europe's largest credit rating agencies – provides comprehensive balance sheet information on Italian limited liability companies. CADS contains detailed records of balance sheets and profit and loss accounts for almost all Italian limited liability companies since 1993. The information is drawn from official data filed with the *Italian Register of Companies* and financial statements filed with the *Italian Chambers of Commerce*, which companies are legally required to submit. Financial statements are updated annually for each firm. From this dataset, we extract yearly balance sheet information on key assets and liabilities (e.g., tangible and intangible fixed assets, total assets, financial debt, and net equity) and income statement data (e.g., sales, value added, EBITDA, EBIT).

Italian National Social Security Institute's Data Archives. The third data source comes from INPS, which compiles extensive archives on the national social security system. These archives are based on administrative records that employers in the private, non-agricultural sectors are required to submit when paying pension contributions for their employees. The information includes, among other details, each worker's gross take-home pay (i.e., the net wage grossed up by labor income taxes and employee pension contributions) and their occupational category (e.g., blue- or white-collar). From this rich administrative archive, INPS constructs several firm-level datasets in which each firm is uniquely identified by its fiscal code, allowing linkage with other data sources. In this study, we use annual firm-level information on employment, as well as annual averages of gross wages by occupational category and the composition of different types of workers.

3 Survey-based descriptive evidence on AI adoption

This section documents descriptive evidence on how Italian firms perceive and engage with AI technologies. We begin by examining firms' self-assessed views of the importance of AI for their business activities. We then analyze the characteristics associated with AI adoption and provide a descriptive overview of how firms integrate these technologies into their production processes.[4]

[4]The evidence in this section reflects firms' responses at the time of the survey, which predates the rapid acceleration in AI diffusion observed over the past year. Recent external sources, including official ISTAT statistics for 2025, document a marked increase in AI adoption among Italian firms, particularly among large and knowledge-intensive enterprises. The results should therefore be interpreted as a

3.1 Importance of AI for business activity

The first question in the SIGE survey on the use of AI is formulated as follows:

> **Question G1:** "How important is the use of artificial intelligence (e.g., cloud computing, predictive and/or generative artificial intelligence, robotics) to your company's activities?"
> ☐ It is important and we are adopting it ☐ It is important and we intend to adopt it within the next 2 years ☐ It is not important for our business ☐ Don't know, don't want to answer

Figure 1 shows the frequency of responses to question G1, highlighting that the importance of AI varies considerably across firms. A minority of respondents (11.2%) reported that AI was important and was already being used in their activities. A larger proportion (28.4%) recognized the importance of AI and indicated an intention to adopt it within the next two years. Interestingly, the largest proportion (33.4%) indicated that AI was not important to their activities, pointing to that a significant share of firms did not at that time perceive AI as relevant to their business. Finally, a notable 26.9% of respondents were unsure and did not provide a definitive answer, possibly indicating a lack of awareness of the potential impact of AI or were simply reluctant to complete this part of the questionnaire.

This descriptive evidence suggests a mixed level of engagement with AI among Italian firms as of the third quarter of 2024.[5] On the one hand, a non-negligible share recognized AI's importance and intended to adopt it; on the other hand, a large fraction either dismissed its relevance or remained uncertain. This pattern is consistent with recent survey data from the 2024 Eurostat's "ICT usage in enterprises", according to which only 8.2% of Italian firms with at least ten employees reported using AI technologies, well below the EU average of 13.5%.[6]

3.2 Engagement with AI-related survey questions

Building on the descriptive evidence above, we next examine firms' engagement with AI-related survey questions. In particular, to better understand the observed variation

snapshot of firms' perceptions and adoption patterns at an early stage of diffusion. Moreover, the survey identifies whether AI is currently used or planned, but does not capture the intensity, scope, or investment size of adoption; heterogeneous forms of AI use are thus grouped together. The analysis should accordingly be read as reflecting firms' engagement with AI, rather than the depth of technological transformation.

[5] These patterns are consistent with the evidence in Bencivelli et al. (2025), who document – using the Bank of Italy's Survey of Industrial and Service Firms – a gradual but still limited diffusion of AI among Italian firms, with adoption rising from 4% in 2020 to 13% in 2024. Aldasoro et al. (2026) show that similarly low and uneven adoption rates characterize other European countries.

[6] For more recent evidence on the diffusion of AI technologies among Italian firms in 2025, see the official statistics reported in ISTAT (2025).

in responses, it is instructive to analyze which firm characteristics are associated with providing a definite response versus selecting "Don't know, don't want to answer," and which characteristics relate to positive versus negative attitudes toward AI. To address these questions, we adopt a two-step empirical strategy.

In the first step, we distinguish firms that select "*Don't know, don't want to answer*" – indicating uncertainty or unwillingness to take a stance – from those providing any substantive response. We estimate a logistic regression to assess which firm characteristics predict the likelihood of withholding a clear opinion. In the second step, we restrict the sample to firms that do express a view and compare those that consider AI unimportant with those that regard it as important, either through current use or planned adoption. Also this comparison is carried out via logistic regression. In both stages, we control for a comprehensive set of covariates: (*i*) firm-level characteristics, including sector (a dichotomous indicator distinguishing manufacturing from services), geographic location (a categorical variable identifying firms located in the North-West, North-East, Center, or South and Islands), firm size (measured by the logarithm of employment), export orientation (a categorical variable capturing the share of sales accounted for by exports: 0 percent, up to one third, between one third and two thirds, and more than two thirds), and firm age (measured as the number of years since establishment); (*ii*) survey participation, proxied by the firm's count of surveys completed in the previous year;[7] and (*iii*) balance-sheet and operational characteristics capturing multiple dimensions of firm heterogeneity, including business profitability (cash-flow-to-sales ratio), capital structure (ratios of tangible and intangible fixed net assets to total assets), knowledge intensity,[8] workforce composition (cost of labor per employee, share of blue-collar workers, and wage-adjusted blue-collar worker share), and overall productive efficiency, measured by total factor productivity.

First-step regression. Table 1 presents the results of the first-stage regression. Among the covariates, only the sector of activity shows a statistically significant association: service firms are more likely than manufacturing firms to state a definite opinion. This finding suggests that service-sector firms may be more attuned to developments in AI, possibly reflecting their greater exposure to digital and data-intensive technologies. No other explanatory variables significantly predict the likelihood of responding. Engagement with the AI question does not vary systematically with geography, size, export orientation, or age, casting doubt on the idea that younger or

[7]We control for survey participation to account for heterogeneity in firms' response behavior and engagement with the survey. Firms that participate more frequently may be less likely to withhold an opinion or select residual response categories, independently of their underlying views on AI, reflecting greater familiarity with the questionnaire or a higher propensity to exert effort when answering.

[8]For service sectors, knowledge intensity is defined according to Eurostat's KIS (Knowledge-Intensive Services) classification, which identifies activities with a high reliance on knowledge creation and specialised expertise (e.g., R&D, professional and technical services). For manufacturing, we rely on an OECD-based taxonomy grouping industries by R&D intensity and skill requirements.

larger firms are inherently more attentive to frontier technologies. Survey participation frequency is similarly uninformative.

The absence of significant coefficients for most firm characteristics highlights the heterogeneous nature of firms' engagement with AI. While sectoral differences matter, factors such as size, location, export orientation, and age do not systematically shape whether firms pay attention to AI, suggesting that the topic resonates broadly across diverse types of firms.

Second-step regression. We next examine the determinants of AI adoption, where "adoption" is broadly defined to include both current use and stated intention to adopt AI in the future. We estimate a logistic model in which the dependent variable equals 1 if a firm reports that AI is important to its activities and 0 if it considers AI unimportant.[9] To assess the firm-level drivers of AI adoption, we incorporate a comprehensive set of balance sheet indicators capturing key dimensions of firm heterogeneity (profitability, asset structure, knowledge intensity, workforce composition, and productivity). These variables are introduced sequentially – first one at a time and then jointly – and are measured as averages over the 2014-2016 period. The purpose of focusing on this time window is not to assert causal identification of determinants of AI adoption, but rather to mitigate concerns about simultaneity and reverse causality. By relying on firm characteristics measured before the launch of Italy's major digital-transformation incentive programs (*Impresa 4.0*, *Transizione 4.0* and *Transizione 5.0*), we obtain a clearer portrait of firms' underlying fundamentals prior to any diffusion of AI.[10]

Table 2 presents the estimation results. Firm size (log employment) consistently emerges as a statistically significant and positive determinant of AI adoption, supporting the view that larger firms possess the financial resources, organizational capacity, and managerial expertise needed to integrate advanced technologies.[11] Labor cost per employee and knowledge intensity also play important roles. Firms with higher la-

[9] In this step, we adopt a binary definition of AI adoption that groups together firms currently using AI and those planning to adopt it in the future. While a multinomial specification distinguishing between non-adopters, intended adopters, and current adopters could in principle be considered, we do not pursue this approach here. Our focus is on whether firms perceive AI as relevant for their activities, rather than on the timing of adoption. Moreover, responses on intended adoption may be subject to greater measurement uncertainty, as they refer to future plans rather than realized behavior. Pooling current and prospective adopters therefore provides a more parsimonious and robust characterization of firms' engagement with AI.

[10] Impresa 4.0 (2017–2019) incentivised firms to invest in digital technologies via super-amortisation and tax credits. Transizione 4.0, launched in 2020, replaced super-amortisation with investment tax credits. More recently, Transizione 5.0 – adopted in 2024 – expanded the incentive regime to cover both digital and energy-efficiency investments as part of Italy's PNRR. For an evaluation of the Transizione 4.0 program see the interim report produced by the institutional committee comprising the Ministry of Economy and Finance, the Ministry of Enterprises and Made in Italy, and the Bank of Italy (2024) available at the following link: `https://www.bancaditalia.it/pubblicazioni/altri-rapporti/2024-mef/Gli_incentivi_in_investimenti_4.0.pdf`.

[11] Related evidence for Italy is provided by Bencivelli et al. (2025), who show that AI adoption is strongly correlated with firm size, export activity, group affiliation, innovation capacity, managerial quality, and prior digital investments.

bor cost per employee are more likely to adopt AI, possibly viewing these advanced technologies as a way to enhance efficiency. Likewise, firms with a higher share of intangible assets or those operating in knowledge-intensive sectors – whether high-tech manufacturing or knowledge-intensive services – exhibit a significantly greater propensity to adopt AI. By contrast, several other variables do not show systematic associations with AI adoption or lose statistical significance once the complete set of controls is included. These include export intensity,[12] profitability, workforce composition, and total factor productivity.

3.3 Self-reported effects of AI adoption

Firms that, in Question G1, indicated that AI is important for their business (whether already in use or planned for adoption) were subsequently asked:

> **Question G2:** "What is or will be the main use of AI in your business?"
> ☐ Task automation ☐ Improving production and support methods and/or processes ☐ Improving the quality of goods and/or services produced ☐ Expanding the range of goods and/or services produced ☐ Other

Respondents were instructed to select a single option. Figure 2 reports the distribution of responses. The most frequently cited application, chosen by 54% of firms, was "*improving production and support methods and/or processes*", highlighting the central role of operational efficiency and process optimization in firms' motivations for adopting AI. The second most common response, selected by 24.8% of firms, was "*task automation*", in line with the broader narrative that firms increasingly deploy AI to reduce reliance on repetitive, labor-intensive tasks, freeing human capital for more complex or value-added activities. A smaller share of firms (13.9%) reported "*improving the quality of goods and/or services*" as their primary use of AI, indicating that quality enhancement, while relevant, is generally secondary to efficiency gains. Finally, only 3.6% of firms cited either "*expanding the range of goods and/or services*" or "*other*" uses, indicating that more transformative or experimental applications remain relatively uncommon. Overall, these results point to a pragmatic approach to AI adoption, with firms primarily focusing on applications that yield immediate and tangible benefits in terms of efficiency and cost reduction.

[12] International exposure yields a nuanced pattern. A limited export intensity is positively associated with adoption in some specifications, consistent with exporting firms operating in more competitive and innovation-driven environments. However, this effect becomes insignificant once additional firm-level controls are included.

4 Econometric strategy

In this section, we describe our empirical approach to estimating the effects of AI adoption on firm-level outcomes. We implement a difference-in-differences (DiD) framework that exploits variation across firms in their adoption of AI technologies and over time between pre-adoption and post-adoption periods. This setup allows us to identify the causal impact of AI adoption on business activity, investment, and other firm performance measures while controlling for firm-specific characteristics and aggregate time shocks.

We define treatment and control groups as follows. Firms are classified into the *treatment group* if, in question G1 of the survey, they report that AI has *already* been adopted within their organization. The *control group* consists of firms that report AI as "not important" for their business. This categorization ensures a clear conceptual distinction between firms that have integrated AI into their operations and those that remain largely unaffected by the technology. Firms that view AI as "important but not yet adopted" are excluded to avoid ambiguity about treatment timing and intensity.

Defining the pre- and post-adoption periods is more challenging, as the survey does not record the exact timing of adoption. To construct a credible identification strategy, we rely on external evidence on the diffusion of AI technologies in Italy. As discussed in detail in Appendix A3, national innovation surveys and sector-specific reports indicate that AI adoption began to gain measurable traction in the early 2020s, with an especially pronounced acceleration around 2022–2023. Guided by this evidence, we define 2016–2022 as the pre-treatment window - a sufficiently long period to test for parallel trends - and 2023-2024 (unless otherwise specified) as the post-treatment period. For analyses using the quarterly survey data, and in particular for variables capturing firms' forward-looking assessments and expectations, we slightly advance the onset of the post-treatment period to mid-2022. This adjustment accounts for the fact that these indicators typically embed information on conditions expected over the subsequent 12 months or more, and thus may respond to emerging AI-related developments with some anticipation.

Our baseline specification follows an augmented two-way fixed effects (TWFE) model in which standard time fixed effects are replaced by a richer set of time-varying sector and area controls. Concretely, we estimate the following specification:

$$Y_{it} = \gamma_i + \lambda_{s(i),t} + \lambda_{a(i),t} + \beta\,(\text{Treated}_i \times \text{Post}_t) + \mathbf{X}'_{it}\delta + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the outcome of interest for firm i in period t, γ_i are firm fixed effects, $\lambda_{s(i),t}$ denote sector-by-time fixed effects and $\lambda_{a(i),t}$ denote area-by-time fixed effects.[13]

[13]To avoid overloading the model with fixed effects, we consider four categories for the sector of

These saturated time-varying fixed effects absorb all shocks common to firms operating in the same sector-period, thereby offering a more stringent control for differential trends that could otherwise confound the effect of AI adoption. The vector $\mathbf{X}_{it}$ includes a set of firm-level controls designed to capture observable heterogeneity that may correlate with both AI adoption and the outcomes of interest. Specifically, we control for firm size (the log of the number of employees)[14], overall scale (the log of total assets), business activity (the log of total sales), balance-sheet structure (the ratio of fixed to total assets), debt servicing ratio (the ratio of financial expenses to EBITDA), and short-term liquidity conditions (the current liquidity ratio).

The coefficient of interest (β) captures the average effect on the "treated" firms, that is the change in the dependent variable (for instance, a measure of business profitability) for AI adopters relative to non-adopters after 2022, net of firm-specific characteristics and aggregate time shocks. Specifically, under the standard parallel trends assumption, β can be interpreted as the *causal* effect of AI adoption on firm outcomes.

All regressions are estimated by ordinary least squares (OLS), with standard errors computed using the Driscoll–Kraay estimator to account for potential heteroskedasticity, serial correlation, and cross-sectional dependence across firms. All quantitative variables are winsorized at the 1% tails to mitigate the influence of outliers. Tables A1, A2, A3 and A4 in Appendix A2 report summary statistics for the full set of continuous outcome variables, separately by firms' choices among the response options to Question G1.

5 Firm Behavior and Forward-Looking Assessments

This section reports the main empirical effects of AI adoption on firm behavior. We begin with results based on observed firm data and then turn to survey-based measures of firms' pricing plans, investment intentions, and expectations.

activity (i.e. "manufacturing", "other industrial sectors", "retail trade services" and "other services") and two categories for the area (i.e. "North" and "Centre and South and Islands").

[14]We measure employment using administrative records from the INPS archives, which are available through 2023. For 2024, as administrative data are not yet available, we complement the dataset using employment information from the SIGE survey. Specifically, we compute the annual average of the quarterly employment figures reported by firms in 2024.

[14]We test the parallel trends assumption by estimating, in the pre-treatment period, a specification interacting the treatment indicator with a linear time trend. The interaction coefficient captures differential pre-treatment trends between treated and control firms. For ordered categorical outcomes, separate binary indicators are constructed for each category and the same pre-treatment trend test is applied. The corresponding p-values are reported in the estimation tables.

5.1 Evidence from Observed Firm Data

Performance and profitability. We begin by assessing the impact of AI adoption on firm performance using a broad set of operating and profitability indicators, as reported in Table 3. Across multiple dimensions - return on assets (ROA), cash flow relative to assets, and EBITDA scaled by either assets or sales - we find consistently positive and statistically significant effects of AI adoption. In quantitative terms, AI adopters experience an increase in ROA of approximately 0.5 percentage points, a 0.6 p.p. rise in cash flow over assets, a 0.7 p.p. increase in EBITDA over assets, and a 2.0 p.p. improvement in EBITDA over sales. These results across distinct performance metrics suggests that AI strengthens operational efficiency and profitability, underscoring its multifaceted contribution to firm performance. Two outcome variables, namely return on sales (ROS) and the cash flow to sales ratio, also display positive point estimates, though they are not statistically significant, indicating weaker effects along these specific dimensions.

Labor productivity and labor costs. Table 4 reports the estimated effects of AI adoption on labor productivity and labor cost indicators. Across all productivity-related outcomes, we find positive and statistically significant effects of AI adoption. In particular, AI adoption is associated with an increase of about 5.2 percent in value added per employee and 11.9 percent in EBITDA per employee, indicating sizable gains in the amount of value and operating surplus generated per worker. These results are consistent with AI technologies enhancing production efficiency, improving output quality, and accelerating task completion.

Importantly, these productivity gains are not accompanied by a significant increase in labor cost per employee, suggesting that the effects of AI adoption are not driven solely by higher average labor compensation. Consistent with this interpretation, column (4) shows no statistically significant effect of AI adoption on unit labor costs, measured as the ratio of labor costs to value added. Taken together, these findings imply that AI adoption raises labor productivity without increasing labor costs per unit of output, pointing to genuine efficiency gains rather than cost-shifting mechanisms.

Such efficiency improvements can arise even in the absence of higher labor costs or employment growth through changes in task allocation and the organization of production within firms.[15] Next, we investigate this potential channel.

[15] A simple task-based framework, in the spirit of Acemoglu and Restrepo (2019), helps illustrate this mechanism. Let output be given by $Y = \int_0^1 y(j)\,dj$, where tasks $j \in [0,1]$ can be performed either by labor or by AI. Prior to AI adoption, all tasks are performed by labor, $y(j) = a_L(j)L(j)$. After AI adoption, a subset of relatively routine tasks $j \in \mathcal{J}_{AI}$ – typically associated with manual or routine occupations – is performed by AI with higher efficiency, $y(j) = a_{AI}(j)AI(j)$, where $a_{AI}(j) > a_L(j)$ for $j \in \mathcal{J}_{AI}$. Workers previously assigned to these tasks are reallocated toward the remaining tasks $j \notin \mathcal{J}_{AI}$, which are more intensive in cognitive, supervisory, or coordination activities. This reallocation increases average output per worker, Y/L, even if total employment L and average labor costs remain unchanged.

Employment dynamics and workforce composition. Table 5 examines how AI adoption affects employment levels and workforce composition at the firm–level. The table reports estimates for the logarithm of total employment and the logarithm of employment by occupational category (managers, white-collar workers, blue-collar workers, and apprentices), and complements these results with estimates for the corresponding employment shares. Employment data are drawn from the administrative archives of INPS and are available through 2023, which defines the post-treatment window for the annual employment outcomes.

Consistent with the productivity results discussed above, column (1) shows no statistically significant effect of AI adoption on total employment. This finding suggests that, at least in the short run, AI adoption neither leads to workforce expansion nor to contraction among adopting firms. Importantly, however, columns (2)–(5) reveal substantial heterogeneity across worker categories. While employment for managers is statistically indistinguishable from zero, AI adoption is associated with a statistically significant increase in white-collar employment and a decline in blue-collar employment. The estimates also point to a weakly positive effect on apprentices; however, this result should be interpreted with caution, as the parallel-trends assumption is not satisfied for this outcome. Taken together, these heterogeneous employment responses suggest that AI adoption is likely to induce meaningful changes in workforce composition, which we examine next.[16]

Columns (6)–(9) show that AI adoption induces a marked reallocation of labor within firms. In particular, the share of white-collar workers increases by approximately 0.7 percentage points, while the share of blue-collar workers declines by about 1.1 percentage points.[17] Changes in the shares of managers and apprentices are positive but modest in magnitude and not statistically significant.

Overall, the employment level and share results point to a clear skill-biased transformation of the workforce associated with AI adoption. Rather than reducing overall employment, AI appears to reshape labor demand within firms by increasing the relative importance of higher-skilled, non-routine cognitive occupations. This pattern is consistent with AI technologies complementing analytical, coordination, and decision-making tasks while reducing the relative demand for more routine or manual activities.

These firm-level findings are consistent with expectations reported in the 2024Q3 SIGE survey, which asked firms directly about the anticipated labor implications of

[16]Further evidence for Italy is provided by Dalla Zuanna et al. (2024), who use a task-based approach to measure occupational exposure to AI and distinguish between complementary and substitutable activities. They document substantial heterogeneity across occupations and show that, among highly exposed workers, most are employed in occupations where AI is more likely to complement existing tasks, especially in services and among skilled workers.

[17]The estimated effect on the share of blue-collar workers should be interpreted with caution, as the pre-treatment parallel trends assumption is not satisfied for this outcome.

AI adoption. As shown in Figure 3, approximately 70% of respondents expect no direct impact on employment, while around 17% anticipate a reduction, reinforcing the interpretation that AI primarily affects the composition rather than the size of the workforce.

5.2 Evidence from Survey-based Firm Plans and Sentiment

The quarterly SIGE survey collects detailed information on firms' current conditions as well as their forward-looking assessments and expectations. In this section, we analyze a subset of survey questions that provide insights into both realized and anticipated pricing behavior, as well as the drivers underlying firms' price-setting plans.[18]

Selling pricing decisions. We begin by examining the effects of AI adoption on firms' pricing strategies. The survey asks firms to report the realized percentage change in their selling prices over the past 12 months as well as the expected percentage change over the next 12 months. Responses to these questions are quantitative, measured with one decimal point of precision. For expected price changes, firms are additionally asked to assess the role of various factors in driving their anticipated price adjustments, including: total demand, raw material prices, intermediate input costs, labor costs, competitors' prices, inflation expectations, and financial conditions. For each factor, firms provide qualitative judgments indicating both the direction (positive, neutral, negative) and the intensity (low, average, high) of its expected effect on prices. For ease of analysis, we re-code this categorical scale into three numerical values, i.e. -1 for negative, 0 for neutral, $+1$ for positive, capturing the overall directional contribution of each factor.

Table 6 reports the estimated relationship between AI adoption and firms' realized and expected price changes, as well as the drivers underlying expected adjustments. We find that the estimated effect of AI adoption for realized price changes is statistically insignificant, pointing that, over the 2023–2024 post-treatment period, AI adoption has not materially affected firms' actual prices. By contrast, the coefficient for expected price changes is negative and statistically significant (-0.4), indicating that AI-adopting firms anticipate more moderate price increases. This finding is consistent with the hypothesis that AI adoption generates productivity gains (as previously documented in Table 4), enabling firms to moderate future price adjustments without compromising profitability.

Examining the drivers of firms' price expectations, we find that the cost of inter-

[18] The SIGE survey data are available at a quarterly frequency. Accordingly, in the DiD specification we include year-quarter fixed effects. For balance-sheet controls, which are available only at an annual frequency, we assign the same annual value to each corresponding quarter within that year. Quarterly information on the number of employees is taken directly from the SIGE survey. Furthermore, in this case the sample size goes from the first quarter of 2016 to the fourth quarter of 2024.

mediate inputs, the labor cost, and inflation expectations all exert significant negative effects on anticipated price changes. Other factors – including demand, competitors' prices, and financial conditions – do not appear statistically significant. These findings suggest that, in the context of AI adoption, firms' forward-looking pricing strategies are primarily shaped by labor, input, and macroeconomic pressures, highlighting how AI-related efficiency gains may interact with cost structures to influence firms' pricing behavior.

Investment plans, sentiment, and subjective uncertainty. The SIGE survey also includes a set of forward-looking questions that capture firms' medium- and longer-term assessments regarding investment activity and business conditions. Two questions focus on investment plans, asking firms to evaluate whether their investment spending will be *much lower, somewhat lower, about the same, somewhat higher*, or *much higher* either over the next six months (relative to the previous six months) or over the next calendar year. Consistent with our previous approach, we re-code these qualitative responses into a three-point numerical scale: -1 for lower investment, 0 for no change, and $+1$ for higher investment.

The survey further asks firms to evaluate their broader business prospects. First, firms report how they expect overall conditions in their own business to evolve over the next three years, choosing among *much worse, worse, the same, better*, and *much better*. Second, firms assign subjective probabilities to the three possible outcomes – worse (p_w), the same (p_s), or better (p_b) – over the same horizon. Following Bachmann et al. (2013), we use these probabilities to construct an index of subjective uncertainty: $U^{3y} = \sqrt{p_b + p_w - (p_b - p_w)^2}$. This index ranges from 0, indicating complete certainty about future conditions, to 1, indicating maximal uncertainty.

Table 7 reports the estimated results. Across all outcomes, the interaction coefficients are statistically indistinguishable from zero, suggesting that AI adoption does not materially affect firms' investment plans, their medium-term assessment of future business conditions, or the uncertainty surrounding those expectations.[19]

The absence of detectable effects on broad investment indicators does not imply that AI adoption is irrelevant for investment dynamics. Contemporary AI deployment increasingly relies on inputs—such as cloud-based computing services, subscription software, externally provided AI tools, and organizational investments in training, data preparation, and process redesign—that are typically expensed rather than capitalized on firm balance sheets. As a result, AI-related adjustments may not be fully captured by conventional measures of capital accumulation, especially at this early

[19]For the three-year business-conditions indicator, the parallel-trends assumption is not fully satisfied; this result should therefore be interpreted with caution. We also examined a range of shorter-horizon survey responses and found no statistically significant effects. This pattern is consistent with the possibility that AI adoption unfolds gradually and that short-term expectations may be difficult for firms to assess reliably.

stage of diffusion.[20]

6 Survey-Based Expectations About Aggregate Economic Effects

In this section we examine firms' perceptions of the macroeconomic implications of AI adoption. We begin by analyzing their self-reported assessments of the effects that a *widespread* adoption of AI technologies could have on the Italian economy as a whole. We then turn to firms' inflation expectations, which the SIGE survey collects at multiple forecast horizons.

6.1 Self-reported macroeconomic effects of AI adoption

The ad-hoc part of the SIGE survey on AI concludes with a question designed to capture firms' views on the broader economic consequences of AI diffusion. The wording is as follows:

> **Question G4:** "In your opinion, what effects could the widespread use of AI technologies in firms' production processes have on the Italian economy over the next two years?"
>
> ☐ very negative ☐ moderately negative ☐ neither positive nor negative
> ☐ moderately positive ☐ very positive ☐ don't know

Figure A3, panel (a), shows the distribution of responses to Question G4 pooling all firms in the survey. The modal response (47.3%) is "moderately positive," indicating a broadly optimistic assessment of the economy-wide effects of AI adoption. An additional 7.5% of firms expect the impact to be "very positive." Taken together, a clear majority of respondents anticipates beneficial macroeconomic effects from the widespread use of AI technologies. At the same time, a sizeable share of firms (25.2%) select "don't know," revealing substantial uncertainty regarding the aggregate implications of AI. This uncertainty likely reflects the early stage of diffusion, the limited availability of empirical evidence, and the coexistence of potentially offsetting channels, ranging from productivity gains to adjustment costs and labor market frictions. Only a small minority of firms expects negative effects (6.2% moderately negative and 2.0% very negative), while 11.9% foresee no net effect, suggesting that some firms view the overall macroeconomic impact of AI as modest or largely neutral.

[20] Complementary evidence from the Bank of Italy's INVIND survey (see Appendix A4) supports this interpretation. During the sample period, AI use among Italian firms remains largely limited or experimental, with many firms reporting zero investment in advanced technologies and, among adopters, relatively small and highly skewed expenditure shares.

Panel (b) of Figure A3 disaggregates responses by AI adoption status, distinguishing between AI non-adopters, current adopters, and firms planning to adopt AI in the future. Clear differences emerge across groups. Current and prospective adopters are substantially more likely than non-adopters to report positive assessments of the macroeconomic effects of AI. In particular, firms planning to adopt AI display the most optimistic views, with nearly two-thirds anticipating a moderately positive effect. By contrast, non-adopters are more likely to express neutral views or uncertainty, as reflected in higher shares selecting "neither positive nor negative" or "don't know."

Overall, these patterns suggest that direct exposure to AI technologies, or concrete plans to adopt them, are associated with more optimistic perceptions of their economy-wide implications. At the same time, uncertainty remains sizeable across all groups, underscoring that firms' assessments of the aggregate effects of AI are still tentative and heterogeneous. Importantly, these responses capture broad subjective views on macroeconomic outcomes and should therefore be interpreted as descriptive evidence, complementing the analysis of firms' inflation expectations presented in the following section.

6.2 On firms' inflation expectations

Question G4 is inherently broad, asking firms only to assess the overall macroeconomic effects of a widespread use of AI on the Italian economy. It does not inquire about the specific mechanisms through which such effects might materialize, nor does it differentiate across the short-, medium-, or long-run horizons. One important exception in the SIGE survey, however, is firms' inflation expectations, which are elicited at several time horizons ranging from a few months to multiple years ahead.[21] These expectations offer a valuable lens through which to examine whether AI adoption shapes firms' views about future inflationary pressures, thereby providing one of the few forward-looking macro indicators available in the dataset.

Table 8 reports the estimated relationship between AI adoption and inflation expectations at horizons of 6, 12, 24, and 48 months ahead. Consistent with a limited near-term role for AI-related cost adjustments, the results show no statistically significant effect on short-term expectations (6 months ahead). At the 12-month horizon, the estimated coefficient remains small but still not statistically significant. By contrast, the interaction terms for the 24- and 48-month horizons are negative and statistically significant at the 5% level. Their magnitudes - roughly one-quarter and one-third of a percentage point, respectively - indicate that AI-adopting firms foresee noticeably

[21] These questions differ slightly in wording because of the information treatments embedded in the survey design (see, e.g., Coibion et al., 2020; Bottone et al., 2022). Firms are randomly assigned to treatment groups and receive distinct formulations. To account for this, all regressions include fixed effects for the information treatment.

lower inflationary pressures in the medium and long run relative to non-adopters.

Importantly, this pattern should be interpreted as reflecting the expectations of AI-adopting firms regarding the medium- to long-term evolution of costs and prices relevant to their own production and pricing decisions, rather than as a direct statement about aggregate inflation dynamics.[22] The gradual emergence of these effects is consistent with the notion that the economic consequences of AI adoption unfold over time, as productivity gains, process improvements, and cost-saving innovations require time to materialize.

While these findings are suggestive of potential disinflationary forces associated with AI, they do not rely on assumptions about the extent or speed of AI diffusion across the broader economy. Instead, they highlight how firms that have already adopted AI revise their longer-term price expectations as the anticipated benefits of adoption are progressively incorporated into their outlook.

Productivity enhancements, process improvements, and cost-saving innovations associated with AI adoption typically take time to materialize. As a result, their effects on firms' cost structures and pricing decisions are more likely to be reflected in medium- to long-term expectations rather than at short horizons. In this sense, the findings are consistent with a gradual incorporation of anticipated efficiency gains by AI-adopting firms into their longer-term inflation outlook.

7 Conclusions

This paper investigates the adoption of AI technologies among Italian firms, combining newly collected survey data with detailed balance-sheet and employer-employee records. Using firm-level responses, we assess the perceived importance of AI, the determinants of adoption, and its broader economic implications at both micro and macro levels. Our analysis shows that, as of 2024, AI adoption among Italian firms with at least 50 employees remains limited: only a small share of firms report having already integrated AI into their operations, while nearly 30% recognize AI's increasing relevance and plan to adopt these technologies within the next two years.

We identify firm size, operation in knowledge-intensive sectors, and higher labor costs as the strongest predictors of adoption, highlighting that AI integration depends not only on financial, organizational, and managerial capacity but also reflects efficiency considerations and strategic positioning in competitive markets. These patterns

[22]Recent experimental evidence suggests that firms' beliefs about the diffusion of advanced technologies are imperfect and do not necessarily reflect expectations of widespread adoption. For instance, Cullen et al. (2025) show that firms often underestimate competitors' adoption of AI and robotics and update their beliefs when provided with information. This supports an interpretation of our results as reflecting firms' own anticipated cost and pricing dynamics rather than assumptions about economy-wide AI diffusion.

are consistent with selection effects documented in the literature, whereby AI adoption is concentrated among larger, high-performing firms capable of leveraging advanced technologies effectively.

Regarding economic outcomes, we find that AI adoption is associated with improvements in firm-level profitability and labor productivity. Adopting firms adjust workforce composition, with employment shifting toward skilled and white-collar occupations and away from more routine tasks, consistent with task-based models of automation. Beyond micro-economic effects, AI adoption also shapes firms' expectations. Adopting firms anticipate smaller increases in their own selling prices and lower medium- to long-term inflation relative to non-adopters, consistent with a gradual incorporation of expected efficiency gains into their pricing outlook. While these results primarily reflect firm-level expectations, they are suggestive of mechanisms through which the diffusion of AI could, over time, exert disinflationary pressures at the macroeconomic level.

While this study provides a first comprehensive assessment of AI adoption in Italian firms, several important avenues remain to be explored. First, as AI technologies diffuse more broadly, it will be critical to examine their long-term effects on labor markets, including task reallocation, wage dynamics, and the emergence of new skill requirements. Second, investigating sector-specific adoption pathways and the role of complementary organizational investments could shed light on heterogeneous productivity gains and the mechanisms through which AI reshapes firm performance. Third, understanding the macroeconomic implications of AI – particularly its impact on inflation dynamics, sectoral competitiveness, and aggregate productivity growth – will require integrating firm-level evidence with broader structural and macroeconomic models. Such analyses could provide valuable insights for monetary policy, as widespread AI adoption may influence future inflationary pressures, the output gap, the natural rate of interest and the transmission of policy interventions. Finally, evaluating the effectiveness of policy measures, such as digitalization incentives or skill-development programs, in facilitating AI adoption could inform strategies to accelerate technological modernization and reduce structural barriers.

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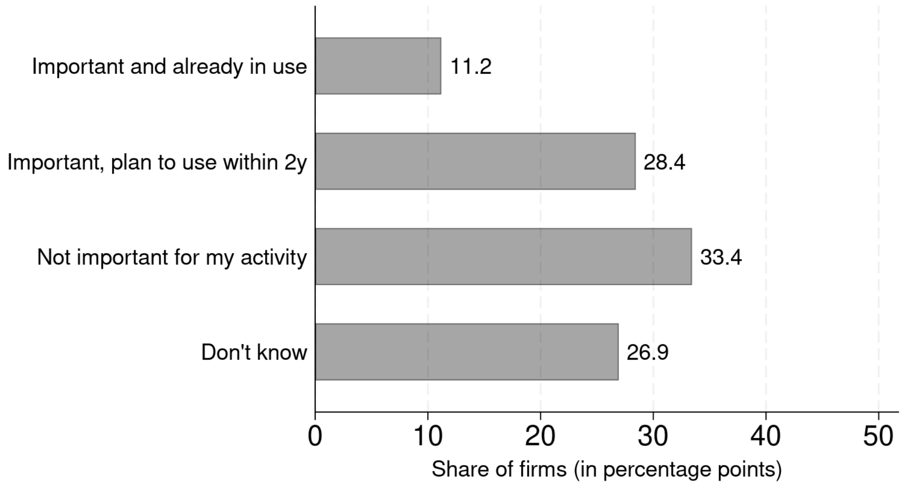
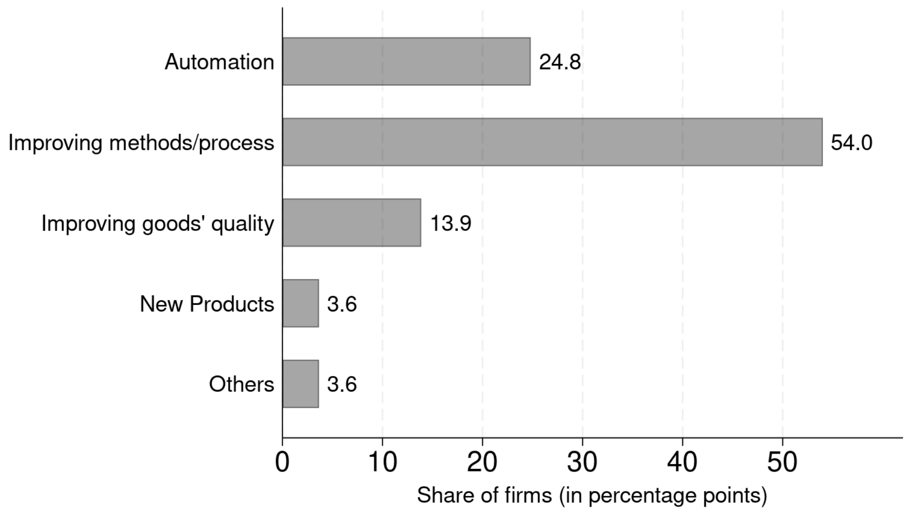
Figures and Tables

Figure 1: Importance of AI for business activity



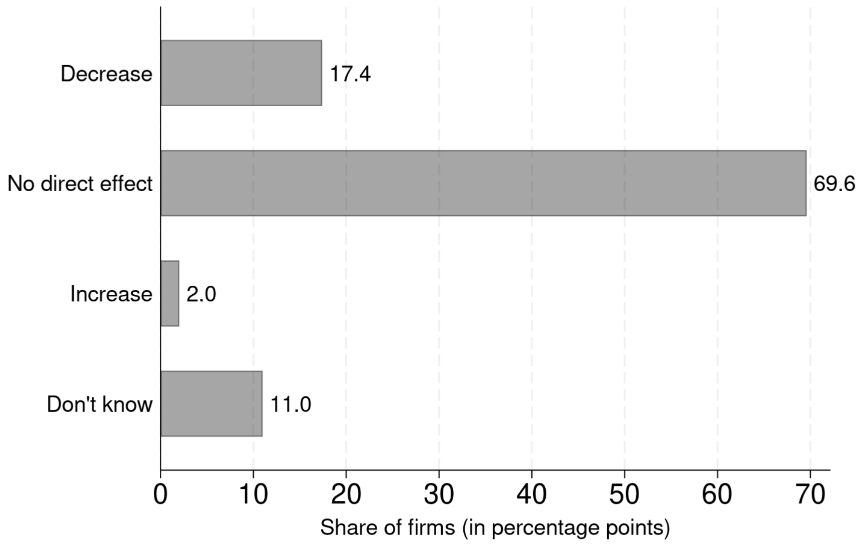
Notes: This figure shows the frequency of responses to question G1 that reads as: *"How important is the use of artificial intelligence (e.g., cloud computing, predictive and/or generative artificial intelligence, robotics) to your company's activities?"*. Frequencies are computed using sampling weights.

Figure 2: Specific use of AI technologies



Notes: This figure shows the frequency of responses to question G2 that reads as: *"What is or will be the main use of AI in your business?"*. Frequencies are computed using sampling weights.

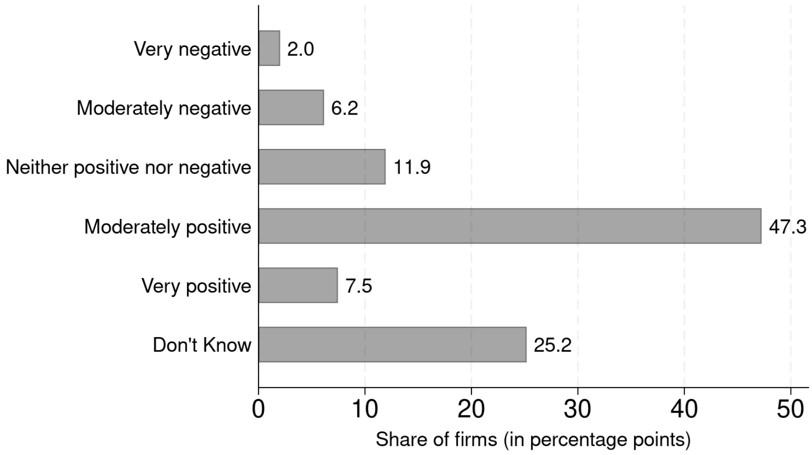
Figure 3: Effects of AI on firms' labor force



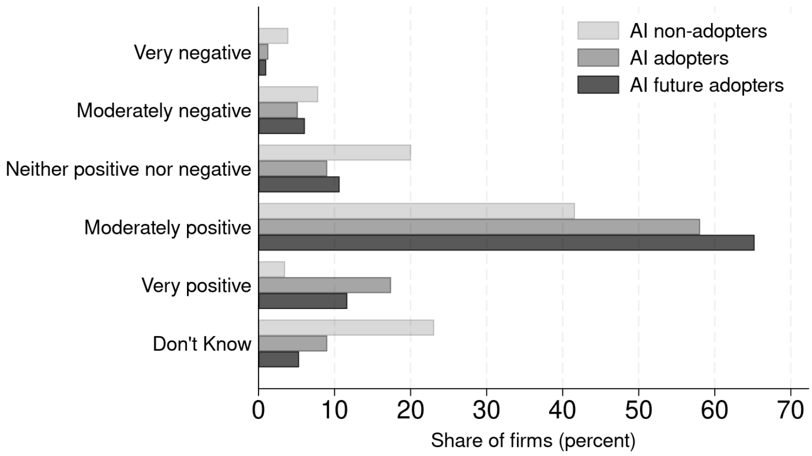
Notes: This figure shows the frequency of responses to question G3 that reads as: *"In your opinion, what has been (will be) the impact of AI on the number of employees in your firm?"*. Frequencies are computed using sampling weights.

Figure 4: Economic effects of AI on the aggregate economy

(a) All firms



(b) AI adopters vs future adopters vs non-adopters



Notes: Panel (a) shows the distribution of responses to Question G4, which asks: *"In your opinion, what effects could the widespread use of AI technologies in firms' production processes have on the Italian economy over the next two years?"*. Panel (b) reports the same distribution separately for AI non-adopters, AI adopters, and firms planning to adopt AI in the future. Within each group, percentages sum to 100. Frequencies are computed using sampling weights.

Table 1: Engagement with AI-related survey questions

	(1)	(2)	(3)
Sector (*base category*: Manufacturing)			
Services	0.089***	0.091***	0.091***
	(0.032)	(0.032)	(0.032)
Location (base category: North-West)			
North-East	0.020	0.022	0.024
	(0.034)	(0.035)	(0.035)
Centre	0.003	0.015	0.022
	(0.039)	(0.039)	(0.039)
South & Islands	0.022	0.019	0.024
	(0.038)	(0.040)	(0.040)
Number of employees (in logarithm)	0.000	0.000	0.000
	(0.012)	(0.013)	(0.013)
Share of revenues from exports (base category: zero)			
between 1% & 33%	-0.010	-0.011	-0.010
	(0.035)	(0.036)	(0.036)
between 34% & 66%	-0.013	-0.012	-0.014
	(0.041)	(0.042)	(0.042)
between 67% & 100%	-0.061	-0.058	-0.060
	(0.049)	(0.050)	(0.051)
Age		-0.000	-0.000
		(0.001)	(0.001)
Past participation in previous four waves (base category: zero)			
Once			-0.061
			(0.058)
Twice			-0.093*
			(0.056)
Three times			-0.092*
			(0.049)
Four times			-0.064
			(0.043)
Observations	1,374	1,331	1,331
Pseudo R^2	0.01	0.01	0.02

Notes: This table reports marginal effects from logit models estimating the probability that a firm provides a substantive response to Question G1, rather than selecting the option *"Don't know, don't want to answer"*. The dependent variable equals 1 for substantive responses and 0 otherwise. As controls, we include sector, geographic macro-area, log employment, export intensity (four bins), firm age, and survey participation frequency (number of participations in the previous four waves). Standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Determinants of adoption or intention to adopt AI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sector (*base category*: Manufacturing)							
Services	0.077*	0.087**	0.085**	0.105**	0.051	0.092**	0.085
	(0.042)	(0.042)	(0.042)	(0.046)	(0.049)	(0.043)	(0.053)
Location (*base category*: North-West)							
North-East	0.076*	0.075	0.074	0.063	0.083*	0.078*	0.055
	(0.046)	(0.047)	(0.047)	(0.048)	(0.046)	(0.047)	(0.047)
Centre	-0.029	-0.022	-0.025	-0.036	0.007	-0.023	-0.005
	(0.051)	(0.051)	(0.051)	(0.052)	(0.052)	(0.052)	(0.053)
South & Islands	0.026	0.037	0.037	0.039	0.094*	0.033	0.078
	(0.052)	(0.053)	(0.053)	(0.055)	(0.055)	(0.054)	(0.058)
Number of employees (in logarithm)	0.119***	0.115***	0.117***	0.107***	0.114***	0.113***	0.109***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
Share of revenues from exports (*base category*: zero)							
between 1% & 33%	0.100**	0.111**	0.113**	0.103**	0.075	0.103**	0.082
	(0.047)	(0.047)	(0.047)	(0.050)	(0.048)	(0.048)	(0.050)
between 34% & 66%	0.011	0.017	0.018	-0.002	-0.036	0.001	-0.026
	(0.058)	(0.059)	(0.058)	(0.061)	(0.059)	(0.059)	(0.062)
between 67% & 100%	0.095	0.101	0.101	0.089	0.045	0.089	0.050
	(0.064)	(0.064)	(0.065)	(0.068)	(0.065)	(0.065)	(0.068)
Age	0.000	0.000	0.000	0.000	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cash flow to sales ratio		0.004*					0.002
		(0.002)					(0.003)
Tangible fixed assets to total assets ratio			0.003				0.001
			(0.002)				(0.003)

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	Dependent variable						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intangible fixed assets to total assets ratio			0.001				0.002*
			(0.001)				(0.001)
Knowledge-intensive (*base category*: no)							
yes				0.111**			0.077*
				(0.043)			(0.045)
Cost of labor per employee					0.006**		0.005**
					(0.002)		(0.003)
Blue-collar worker share					0.001		0.002
					(0.003)		(0.003)
Wage-adjusted blue-collar worker share					-0.002		-0.002
					(0.002)		(0.002)
Total factor productivity						0.005	-0.001
						(0.005)	(0.005)
Observations	970	939	939	883	926	924	875
Pseudo R^2	0.04	0.04	0.04	0.05	0.06	0.04	0.07

Notes: This table reports average marginal effects from logistic regressions estimating the probability that a firm either adopts or plans to adopt AI (dependent variable = 1), relative to firms that consider AI unimportant. Columns progressively include controls for firm characteristics, financial indicators, labor composition, and productivity. Standard errors, clustered at the firm level, are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effects of AI adoption on firm performance and profitability

	ROS (1)	ROA (2)	$\frac{\text{Cash flow}}{\text{Asset}}$ (3)	$\frac{\text{Cash flow}}{\text{Sales}}$ (4)	$\frac{\text{EBITDA}}{\text{Asset}}$ (5)	$\frac{\text{EBITDA}}{\text{Sales}}$ (6)
Treatment × Post	0.658 (0.442)					
Time × Sector FE						
Firm FE						
Firm-level time-varying controls						
Observations	3,741					
Adjusted R-squared	0.120					
Parallel trends (p-value)						

Notes: This table reports difference-in-differences (DiD) estimates of the impact of AI adoption on firm-level outcomes. The treatment group comprises firms reporting AI adoption, while the control group includes firms indicating that AI is not relevant to their business. The pre-treatment period covers 2016–2022, and the treatment period spans 2023–2024. Outcome variables include various measures of business performance and profitability. The coefficient on the interaction term ("Treatment × Post") captures the causal effect of AI adoption, controlling for the fixed effects indicated in each specification and a set of firm-level covariates: firm size (log number of employees), overall scale (log total assets), business activity (log total sales), balance-sheet composition (ratio of fixed to total assets), financial leverage (ratio of gross financial charges to EBITDA), and short-term liquidity (current liquidity ratio). For each specification, the p-value from a formal test of the parallel trends assumption is reported, where the null hypothesis is that treated and control firms followed similar pre-treatment trajectories. Standard errors, computed using the Driscoll–Kraay estimator, are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Effects of AI adoption on productivity and labor efficiency indicators

	$\log \frac{\text{Value added}}{\text{Employees}}$ (1)	$\log \frac{\text{EBITDA}}{\text{Employees}}$ (2)	$\log \frac{\text{Labor cost}}{\text{Employees}}$ (3)	$\log \frac{\text{Labor cost}}{\text{Value added}}$ (4)
Treatment $\times$ Post	0.043**	0.084*	-0.013	-0.036
	(0.015)	(0.044)	(0.009)	(0.023)
Time $\times$ Sector FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm-level time-varying controls	Yes	Yes	Yes	Yes
Observations	3,741	3,358	3,741	3,741
Adjusted R-squared	0.372	0.403	0.526	0.043
Parallel trends (p-value)	0.257	0.095	0.937	0.129

Notes: This table reports difference-in-differences (DiD) estimates of the impact of AI adoption on firm-level outcomes. The treatment group comprises firms reporting AI adoption, while the control group includes firms indicating that AI is not relevant to their business. The pre-treatment period covers 2016–2022, and the treatment period spans 2023–2024. Outcome variables include various measures of labor productivity and labor efficiency indicators. The coefficient on the interaction term ("Treatment $\times$ Post") captures the causal effect of AI adoption, controlling for the fixed effects indicated in each specification and a set of firm-level covariates: firm size (log number of employees), overall scale (log total assets), business activity (log total sales), balance-sheet composition (ratio of fixed to total assets), financial leverage (ratio of gross financial charges to EBITDA), and short-term liquidity (current liquidity ratio). For each specification, the p-value from a formal test of the parallel trends assumption is reported, where the null hypothesis is that treated and control firms followed similar pre-treatment trajectories. Standard errors, computed using the Driscoll–Kraay estimator, are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effects of AI adoption on labor force growth and composition

	$\log(L_t^{tot})$	$\log(L_t^{m})$	$\log(L_t^{w})$	$\log(L_t^{b})$	$\log(L_t^{a})$	L_t^{m}/L_t^{tot}	L_t^{w}/L_t^{tot}	L_t^{b}/L_t^{tot}	L_t^{a}/L_t^{tot}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment × Post	0.004	0.001	0.023**	-0.077***	0.206*	0.021	0.739***	-1.142***	0.239
	(0.007)	(0.025)	(0.007)	(0.014)	(0.106)	(0.014)	(0.082)	(0.302)	(0.196)
Time × Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,327	1,811	3,307	2,910	1,573	3,327	3,271	3,315	3,327
Adjusted R-squared	0.434	0.064	0.266	0.340	0.073	0.050	0.116	0.207	0.022
Parallel trends (p-value)	0.868	0.142	0.265	0.082	0.003	0.160	0.217	0.000	0.002

Notes: This table reports difference-in-differences (DiD) estimates of the impact of AI adoption on firm-level employment levels and workforce composition. The treatment group consists of firms reporting AI adoption in 2023, while the control group includes firms indicating that AI is not relevant to their business. The pre-treatment period covers 2016–2022, while the post-treatment period consists of the year 2023. Columns (1)–(5) report estimates for the logarithm of total employment and the logarithm of employment by occupational category (managers, white-collar workers, blue-collar workers, and apprentices). Columns (6)–(9) report estimates for employment shares, defined as the ratio of employment in each category to total employment. The coefficient on the interaction term Treatment × Post captures the average effect of AI adoption on the respective outcomes. All specifications include firm fixed effects, time-by-sector fixed effects, and a set of firm-level time-varying controls, including firm size (log number of employees), scale (log total assets), business activity (log total sales), balance-sheet composition (ratio of fixed to total assets), financial leverage (ratio of gross financial charges to EBITDA), and short-term liquidity (current ratio). Standard errors are computed using the Driscoll–Kraay estimator and are reported in parentheses. The table also reports p-values from tests of the parallel-trends assumption for each specification, where the null hypothesis is that treated and control firms followed similar pre-treatment trends. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Effects of AI adoption on pricing decisions and expectations

	DPRE (1)	DPREZ (2)	DPR (3)	MPPR (4)	IICT (5)	CLPR (6)	PRPR (7)	AINF (8)	CFIN (9)
Treatment × Post	0.232	-0.390*	-0.018	-0.032	-0.049**	-0.051*	0.037	-0.053*	-0.008
	(0.193)	(0.219)	(0.028)	(0.026)	(0.020)	(0.026)	(0.030)	(0.026)	(0.021)
Time × Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time × Area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,015	9,015	8,884	8,881	8,805	8,889	8,865	7,484	7,463
Adjusted R-squared	0.195	0.140	0.052	0.087	0.082	0.036	0.056	0.102	0.025
Parallel trends (p-value) (-1)			0.850	0.339	0.861	0.050	0.000	0.155	0.008
Parallel trends (p-value) (0)			0.028	0.412	0.288	0.001	0.000	0.345	0.089
Parallel trends (p-value) (+1)			0.121	0.111	0.188	0.291	0.414	0.510	0.403
Parallel trends (p-value)	0.960	0.292							

Notes: This table reports difference-in-differences (DiD) estimates of the impact of AI adoption on firm-level outcomes. The treatment group comprises firms reporting AI adoption, while the control group includes firms indicating that AI is not relevant to their business. The pre-treatment period covers 2016Q1–2022Q2, and the treatment period spans 2022Q3–2024Q4. Outcome variables include the the past change in selling prices (DPRE), the expected change in selling prices (DPREZ) and several determinants of expected change in selling prices: total demand (DPR), prices of raw materials (MPPR), cost of intermediate inputs (IICT), cost of labor (CLPR), pricing policies of firm's main competitors (PRPR), development in inflation expectations (AINF), changes in financial conditions (CFIN). The coefficient on the interaction term ("Treatment × Post") captures the causal effect of AI adoption, controlling for the fixed effects indicated in each specification and a set of firm-level covariates: firm size (log number of employees), overall scale (log total assets), business activity (log total sales), balance-sheet composition (ratio of fixed to total assets), financial leverage (ratio of gross financial charges to EBITDA), and short-term liquidity (current liquidity ratio). For each specification, the *p*-value from a formal test of the parallel trends assumption is reported, where the null hypothesis is that treated and control firms followed similar pre-treatment trajectories. Standard errors, computed using the Driscoll–Kraay estimator, are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Effects of AI adoption on other business expectations and assessments

	Investment plans in next 6 months (1)	Investment plans in next 12 months (2)	Business conditions in next 3 years (3)	Uncertainty about business conditions in next 3 years (4)
Treatment × Post	0.055	-0.004	0.005	0.002
	(0.042)	(0.046)	(0.029)	(0.008)
Time × Sector FE	Yes	Yes	Yes	Yes
Time × Area FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm-level time-varying controls	Yes	Yes	Yes	Yes
Observations	8,927	8,961	8,895	8,835
Adjusted R-squared	0.056	0.077	0.060	0.026
Parallel trends (p-value) (-1)	0.550	0.330	0.918	
Parallel trends (p-value) (0)	0.808	0.051	0.002	
Parallel trends (p-value) (+1)	0.798	0.773	0.000	
Parallel trends (p-value)				0.002

Notes: This table reports difference-in-differences (DiD) estimates of the impact of AI adoption on firm-level outcomes. The treatment group comprises firms reporting AI adoption in 2023, while the control group includes firms indicating that AI is not relevant to their business. The pre-treatment period covers 2016Q1–2022Q2, and the treatment period spans 2022Q3–2024Q4. The outcome variables encompass firms' investment plans, evaluations of expected future business conditions, and the uncertainty associated with the latter.The coefficient on the interaction term ("Treatment × Post") captures the causal effect of AI adoption, controlling for the fixed effects indicated in each specification and a set of firm-level covariates: firm size (log number of employees), overall scale (log total assets), business activity (log total sales), balance-sheet composition (ratio of fixed to total assets), financial leverage (ratio of gross financial charges to EBITDA), and short-term liquidity (current liquidity ratio). For each specification, the p-value from a formal test of the parallel trends assumption is reported, where the null hypothesis is that treated and control firms followed similar pre-treatment trajectories. Standard errors, computed using the Driscoll–Kraay estimator, are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Effects of AI adoption on inflation expectations

	Expected inflation 6-month ahead (1)	Expected inflation 1-year ahead (2)	Expected inflation 2-year ahead (3)	Expected inflation 4-year ahead (4)
Treatment × Post	0.084	-0.050	-0.232**	-0.310**
	(0.119)	(0.056)	(0.112)	(0.125)
Time × Sector FE	Yes	Yes	Yes	Yes
Time × Area FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm-level time-varying controls	Yes	Yes	Yes	Yes
Observations	9,015	9,015	9,015	9,015
Adjusted R-squared	0.700	0.615	0.492	0.383
Parallel trends (p-value) (-1)				
Parallel trends (p-value) (0)				
Parallel trends (p-value) (+1)				
Parallel trends (p-value)	0.988	0.437	0.058	0.155

Notes: This table reports difference-in-differences (DiD) estimates of the impact of AI adoption on firm-level outcomes. The treatment group comprises firms reporting AI adoption, while the control group includes firms indicating that AI is not relevant to their business. The pre-treatment period covers 2016Q1–2022Q2, and the treatment period spans 2022Q3–2024Q4. The outcome variables include firms' inflation expectations at different horizons.The coefficient on the interaction term ("Treatment × Post") captures the causal effect of AI adoption, controlling for the fixed effects indicated in each specification and a set of firm-level covariates: firm size (log number of employees), overall scale (log total assets), business activity (log total sales), balance-sheet composition (ratio of fixed to total assets), financial leverage (ratio of gross financial charges to EBITDA), and short-term liquidity (current liquidity ratio). For each specification, the p-value from a formal test of the parallel trends assumption is reported, where the null hypothesis is that treated and control firms followed similar pre-treatment trajectories. Standard errors, computed using the Driscoll–Kraay estimator, are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix - Supplementary Material:

"THE ECONOMIC IMPACT OF ARTIFICIAL INTELLIGENCE: EVIDENCE FROM ITALIAN FIRMS"

Tiziano Ropele   Alex Tagliabracci

Bank of Italy

A1 SIGE survey questionnaire

SURVEY ON INFLATION AND GROWTH EXPECTATIONS
BANCA D'ITALIA

September 2024

Company Name ____

A0. Which is your firm's main sector? |__| SETTON5

(1) Manufacturing

(2) Other Industry
- Mineral extraction from mines
- Elettrical. gas. vapour. air conditioning supply
- Water supply
- Sewerage, waste management, and redevelopment

(3) Trading

(4) Other Servicies

Fill in GREEN questionnaire

(5) Construction
- Buildings
- Engineering
- Special construction works
(demolition and preparation of building sites,
plant installation, completion and finishing. etc.)

Fill in LIGHT BLUE questionnaire

INDUSTRY EXCLUDING CONSTRUCTION AND SERVICES

Firm
Instructions: For percentage changes, indicate the sign in the first box on the left (+ :for increases; —: for decreases).

SECTION A – General Information

A1. Number of employees : |__|__|__|__|__| **ADD**

A2. Share of sales revenues coming from exports: |__|
(1= more than 2/3; 2= Between 1/3 and 2/3; 3= Up to 1/3 and more than zero; 4=Zero) **EXPORT4**

A3. Branch of activity Istat - Ateco2007: (first 5 digits) |__|__|__|__|__| **ATECO**

SECTION B – General economic situation of the country

	…in March 2025? **IT6**	…in September 2025? **IT12**	…in September 2026? **IT24**	… on average between September 2027 and September 2029? **IT48**
B1a. (about 3/5 of the sample) In July consumer price inflation, measured by the 12-month change in the harmonized index of consumer prices, was 1.6 per cent in Italy and 2.6 per cent in the euro area. What do you think it will be in Italy...	|__| |__|__|,|__|%	|__| |__|__|,|__|%	|__| |__|__|,|__|%	|__| |__|__|,|__|%
B1b. (about 1/5 of the sample) What do you think consumer price inflation in Italy, measured by the 12-month change in the harmonized index of consumer prices, will be…	|__| |__|__|,|__|%	|__| |__|__|,|__|%	|__| |__|__|,|__|%	|__| |__|__|,|__|%
B1c. (about 1/5 of the sample) Based on the most recent forecasts by leading private economic analysts, the consumer price inflation rate in Italy will be 1.5 per cent over the next 12 months. What do you think the consumer price inflation rate in Italy will be…	|__| |__|__|,|__|%	|__| |__|__|,|__|%	|__| |__|__|,|__|%	|__| |__|__|,|__|%

B3. Compared with 3 months ago, do you consider Italy's general economic situation is…? **SITGEN** ☐ Better ☐ The same ☐ Worse

B4. What do you think is the probability of an improvement in Italy's general economic situation **in the next 3 months**? **PROMIG**
☐ Zero ☐ 1-25 per cent ☐ 26-50 per cent ☐ 51-75 per cent ☐ 76-99 per cent ☐ 100 per cent

SECTION C – Your firm's business conditions

How do you think business conditions for your company will be:
C1. in the **next 3 months**? ☐ Much better ☐ Better ☐ The same ☐ Worse ☐ Much worse **SITIMP5**
C2. in the **next 3 years**? ☐ Much better ☐ Better ☐ The same ☐ Worse ☐ Much worse **SIMP36C5**

For each of the above forecasts imagine there are 100 points available; distribute them among the possible forecasts according to the probability assigned to each one. How do you think business conditions for your company will be:

	Better **SITM3M SITM3A**			The same **SITU3M SITU3A**			Worse **SITP3M SITP3A**			Total		
C3. In the next **3 months**										**1**	**0**	**0**
C4. In the next **3 years**										**1**	**0**	**0**

Please indicate whether and with what intensity the following FACTORS will affect your firm's business **in the next 3 months**.

Factors affecting your firm's business In the **next 3 months**	***Effect on business***			***Intensity*** *(if not nil)*		
	Negative	*Nil*	*Positive*	*Low*	*Average*	*High*
C5.1 Changes in demand **DISIT**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
C5.2 Changes in your prices **PRSIT**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
C5.3 Availability and the cost of credit **CRSIT**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
C5.4 Uncertainty due to econ. and political factors **POLIT**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
C5.5 Exchange rate dynamics **TACAM**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
C5.6 Oil price dynamics **PRPET**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
C5.7 International trade and investment policies **POSCA**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|

(*For firms in services*)
C6a. Net of seasonal factors, what is the change in your firm's turnover that you expect in the first quarter 2024 compared with the fourth quarter 2024? ☐ Below - 15% ☐ Between -15% and -10% ☐ Between -10% and -5% ☐ Between -5% and -2% ☐ Between -2% and +2% ☐ Between +2% and +5% ☐ Between +5% and +10% ☐ Between +10% and +15% ☐ Above +15% **CORVARS2**

(For firms in industry excluding construction)

C6b. Net of seasonal factors, what is the change in your firm's production that you expect in the first quarter 2023 compared with the fourth quarter 2024? ☐ Below - 15% ☐ Between -15% and -10% ☐ Between -10% and -5% ☐ Between -5% and -2% ☐ Between -2% and +2% ☐ Between +2% and +5% ☐ Between +5% and +10% ☐ Between +10% and +15% ☐ Above +15% **CORVARI2**

C7. Compared with 3 month ago, do you think conditions for investment are ... ? **SITINV** ☐ Better ☐ The same ☐ Worse

C8. What do you think your liquidity situation will be in the next 3 months. given the expected change in the conditions of access to credit?
☐ Insufficient ☐ Sufficient ☐ More than sufficient **LIQUID**

C9. Compared with three months ago, is the total demand for your products ... ? **DOMTOT**
☐ Much higher ☐ A little higher ☐ About the same ☐ A little lower ☐ Much lower

C10. How will the total demand for your products vary in the next 3 months? **PRETOT**
☐ Much higher ☐ A little higher ☐ About the same ☐ A little lower ☐ Much lower

(Answer to questions C11-C12 only if the share of sales revenues coming from exports is positive. otherwise go to C13)

C11. Compared with three months ago, is the foreign demand for your products…? **DOMEST**
☐ Much higher ☐ A little higher ☐ About the same ☐ A little lower ☐ Much lower

C12. How will the foreign demand for your products vary in the next 3 months? **PREEST**
☐ Much higher ☐ A little higher ☐ About the same ☐ A little lower ☐ Much lower

C13. Compared with three months ago, are credit conditions for your company ...? **SITCRE** ☐ Better☐ Unchanged ☐ Worse

C14. What do you expect credit access conditions for your firm to be in the next 3 months compared with the present? ☐ Better ☐ The same ☐ Worse **ASPCRE**

SECTION D – Changes in your firm's selling prices

D1. In the last 12 months, what has been the average change in your firm's prices? **DPRE** |__| |__|__|.|__|%

D2. For the next 12 months, what do you expect will be the average change in your firm's prices? **DPREZ** |__| |__|__|.|__|%

Please indicate direction and intensity of the following factors as they will affect your firm's selling prices **in the next 12 months**:

Factors affecting your firm's prices in the next 12 months	***Effect on firm's selling prices***			***Intensity*** *(if not nil)*		
	Downward	*Neutral*	*Upward*	*Low*	*Average*	*High*
D3.1. Total demand **DPR**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
D3.2. Raw materials prices **MPPR**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
D3.3. Intermediate Input **IICT**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
D3.4. Labour costs **CLPR**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
D3.5. Pricing policies of your firm's main competitors **PRPR**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
D3.6 Inflation expectations dynamics **AINF**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|
D3.7 Financial conditions **CFIN**	1|__|	2|__|	3|__|	1|__|	2|__|	3|__|

D4. In the last 12 months, what has been the average change in your firm's prices of goods and services bought in Italy and abroad?
__| |__|__|.|__|% **DPRE_INT**

D5. In the next 12 months, what do you expect will be the average change in your firm's prices of goods and services bought in Italy and abroad?
|__| |__|__|.|__|% **DPREZ_INT**

D6. Over the next 12 months, what do you expect will be the average change in the hourly compensation of employees at the same pay grade? **DRATT**
☐ They will fall ☐ No change ☐ Between 0% and +2% ☐ Between +2% and +4% ☐ Between +4% and +6% ☐ Above +6%

D7. Over the next 12 months, do you intend to change the mark-up, i.e. the difference between selling prices and production costs? **DMU**
☐ Yes, markedly downwards ☐ Yes, moderately downwards ☐ No ☐ Yes, moderately upwards ☐ Yes, markedly upwards

SECTION E – Investments

E1. What do you expect will be the nominal expenditure on (tangible and intangible) fixed investment in 2024 compared with that in 2023?
☐ Much higher ☐ A little higher ☐ About the same ☐ A little lower ☐ Much lower **INVPRE**

E2. And what do you expect will be the nominal expenditure in the first half of 2024 compared with that in the second half of 2023?
☐ Much higher ☐ A little higher ☐ About the same ☐ A little lower ☐ Much lower **INVSEM**

NOTE: The responses "much higher" and "much lower" also apply when, in the two periods compared, investments are zero.

SECTION G – Artificial intelligence (AI)

G1. How important is the use of artificial intelligence (e.g. cloud computing, predictive and/or generative AI, robotics) for your company's activities?
☐ It is important and we are adopting it ☐ It is important and we intend to adopt it within the next 2 years ☐ It is not important for our business ☐ Don't know, don't wish to answer **AI1**

[If you answered question G1 with option 1 or 2, please answer questions G2 and G3]

G2 What is or will be the main use of AI in your business? (choose the main item)
☐ Task automation ☐ Improving production and support methods and/or processes ☐ Improving the quality of goods and/or services produced ☐ Expanding the range of goods and/or services produced ☐ Other **AI2**

G3. In your opinion, what has been (will be) the impact of AI on the number of employees in your firm?

☐ Decrease in the number of employees ☐ No direct impact ☐ Increase in the number of employees ☐ Don't know **AI3**

[G4 is for all firms]

G4. In your opinion, what effects could the widespread use of AI technologies in firms' production processes have on the Italian economy over the next two years?

☐ Very negative ☐ Quite negative ☐ Neither positive nor negative ☐ Quite positive ☐ Very positive ☐ Don't know **AI4**

SECTION H – Inflation in the euro area

	…in March 2025? **EU6**	…in September 2025? **EU12**	…in September 2026? **EU24**	…and on average between September 2027 and September 2029? **EU48**
H1aa. (1/3 of those who were asked question B1a, i.e. 1/5 of the sample) Last July, the 12-month consumer price inflation rate was 2.6 per cent in the euro area. What will the euro-area consumer price inflation rate be …	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%
H1ab. (1/3 of those who were asked question B1a, i.e. 1/5 of the sample) Last July, the 12-month consumer price inflation rate was 2.6 per cent in the euro area. According to the latest forecasts published by the European Central Bank (ECB), the euro-area consumer price inflation rate will be 2.2 per cent in 2025 overall and 1.9 per cent in 2026 overall. What will the euro-area consumer price inflation rate be …	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%
H1ac. (1/3 of those who were asked question B1a, i.e. 1/5 of the sample) Last July, the 12-month consumer price inflation rate was 2.6 per cent in the euro area. According to the latest forecasts published by the European Central Bank (ECB), the euro-area consumer price inflation rate will be 2.2 per cent in 2025 overall and 1.9 per cent in 2026 overall. According to the ECB, there are both upside and downside risks in relation to these forecasts. What will the euro-area consumer price inflation rate be …	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%
H1b. (for those who were asked question B1b) What will the euro-area consumer price inflation rate be …	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%
H1c. (for those who were asked question B1c) Based on the most recent forecasts by leading private economic analysts, the consumer price inflation rate in the euro area will be 2.0 per cent in 2025 overall. What do you think the euro-area consumer price inflation rate will be …	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%	|__| |__|__|.|__|%

H2.1 (1/2 of the sample) You have already provided a forecast for Inflation in Italy over the next 12 months. Compared with Italy, do you think the consumer price inflation rate in Germany over the same time horizon will be **. . .INFLGE**

☐ Lower ☐ About the same ☐ Higher ☐ Don't know

H2.2 (1/2 of the sample) You have already provided a forecast of inflation in Italy over the next 12 months. Compared with Italy, do you think the consumer price inflation rate in France over the same time horizon will be **. . .INFLGE**

☐ Lower ☐ About the same ☐ Higher ☐ Don't know

A2 Descriptive statistics of continuous outcome variables

This appendix provides a set of tables reporting summary statistics for all continuous outcome variables. The statistics are presented separately for firms choosing each of the available options to Question G1, allowing for a comparison of firm characteristics across response groups. All variables are winsorized at the 1st and 99th percentiles, and the statistics are computed using sampling weights over the 2016–2024 period.

Table A1: Descriptive statistics of continuous outcome variables for firms that are adopting AI

	Panel A. Annual outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Return on Sales (ROS)	874	4.35	8.29	-1.30	0.73	3.08	6.64	13.76
Return on Assets (ROA)	874	3.86	5.80	-1.33	0.69	3.34	6.60	10.55
Cash flow to assets ratio	874	7.76	6.09	1.22	3.92	7.10	10.96	15.53
Cash flow to sales ratio	874	9.36	10.16	0.83	3.58	6.76	12.46	22.33
EBITDA to assets ratio	874	8.37	8.51	-1.42	3.56	8.14	13.12	19.63
EBITDA to value added ratio	874	27.02	34.80	0.94	14.10	31.85	45.93	60.20
Value added to employees ratio (log)	874	4.28	0.66	3.62	4.05	4.31	4.64	5.04
EBITDA to employees ratio (log)	774	3.08	1.21	1.50	2.50	3.24	3.87	4.51
Labor cost to employees ratio (log)	874	3.97	0.34	3.59	3.81	3.97	4.17	4.34
Labor cost to value added ratio (log)	874	4.18	0.51	3.68	3.99	4.22	4.45	4.60
YoY growth of employees	772	0.04	0.13	-0.05	-0.01	0.02	0.06	0.16
Share of managers	874	2.49	4.33	0.00	0.00	1.31	2.97	7.11
Share of white collars	867	58.08	32.34	14.04	21.16	67.65	88.61	95.84
Share of blue collars	874	35.63	34.27	0.00	0.00	26.16	73.80	83.73
Sahre of apprentices	874	3.14	5.12	0.00	0.00	0.55	3.79	11.07
YoY growth of intangible assets	759	0.76	3.86	-0.48	-0.25	-0.05	0.21	1.18
YoY growth of tangible assets	772	0.16	0.61	-0.18	-0.07	0.00	0.16	0.54
	Panel B. Quarterly outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Own price change over past 12 months	2299	2.86	6.17	0.00	0.00	1.00	5.00	10.00
Own price change over next 12 months	2299	2.21	4.38	0.00	0.00	1.00	3.00	7.00
Subjective uncertainty over next 3 years	2263	0.52	0.26	0.00	0.40	0.60	0.70	0.79
Expected inflation over next 6 months	2299	2.91	2.94	0.10	0.80	1.60	5.00	8.00
Expected inflation over next 12 months	2299	2.67	2.58	0.20	1.00	1.80	4.00	6.70
Expected inflation over next 24 months	2299	2.38	2.15	0.40	1.00	1.80	3.00	5.30
Expected inflation over next 48 months	2299	2.26	1.91	0.50	1.00	2.00	3.00	5.00

Notes: The table presents summary statistics for the continuous outcome variables. All variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. The statistics are computed over the 2016–2024 period and are weighted using the survey sampling weights.

Table A2: Descriptive statistics of continuous outcome variables for firms that do not intend to adopt AI

	Panel A. Annual outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Return on Sales (ROS)	2869	3.12	6.33	-0.88	0.49	2.16	5.75	10.05
Return on Assets (ROA)	2869	3.61	5.82	-0.93	0.55	2.51	6.34	10.90
Cash flow to assets ratio	2869	7.98	6.45	1.65	3.86	6.95	11.28	16.65
Cash flow to sales ratio	2869	7.51	7.19	1.20	3.19	6.31	10.65	16.20
EBITDA to assets ratio	2869	8.90	8.85	0.27	4.11	8.20	13.28	19.96
EBITDA to value added ratio	2869	25.55	30.86	1.90	13.11	27.14	42.39	56.41
Value added to employees ratio (log)	2869	4.09	0.67	3.23	3.75	4.15	4.48	4.83
EBITDA to employees ratio (log)	2600	2.78	1.30	0.99	2.09	2.96	3.64	4.26
Labor cost to employees ratio (log)	2869	3.76	0.39	3.20	3.60	3.81	4.00	4.15
Labor cost to value added ratio (log)	2869	4.22	0.44	3.77	4.05	4.29	4.46	4.59
YoY growth of employees	2542	0.04	0.14	-0.07	-0.02	0.01	0.07	0.16
Share of managers	2869	1.17	2.03	0.00	0.00	0.00	1.65	3.72
Share of white collars	2812	37.47	27.97	6.88	17.37	29.76	50.96	90.58
Share of blue collars	2855	57.54	29.72	0.00	43.47	65.90	79.91	90.42
Sahre of apprentices	2869	2.20	5.32	0.00	0.00	0.00	1.74	7.35
YoY growth of intangible assets	2394	0.58	3.24	-0.50	-0.28	-0.09	0.18	1.08
YoY growth of tangible assets	2541	0.13	0.54	-0.19	-0.07	-0.01	0.12	0.46

	Panel B. Quarterly outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Own price change over past 12 months	6716	2.55	5.71	-0.30	0.00	1.00	5.00	10.00
Own price change over next 12 months	6716	2.18	4.20	0.00	0.00	1.00	4.00	6.00
Subjective uncertainty over next 3 years	6572	0.51	0.27	0.00	0.40	0.59	0.70	0.79
Expected inflation over next 6 months	6716	2.74	2.85	0.20	0.90	1.50	4.00	7.50
Expected inflation over next 12 months	6716	2.58	2.54	0.30	1.00	1.70	3.50	6.50
Expected inflation over next 24 months	6716	2.39	2.22	0.40	1.00	1.80	3.00	5.50
Expected inflation over next 48 months	6716	2.30	2.01	0.50	1.00	2.00	3.00	5.00

Notes: The table presents summary statistics for the continuous outcome variables. All variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. The statistics are computed over the 2016–2024 period and are weighted using the survey sampling weights.

Table A3: Descriptive statistics of continuous outcome variables for firms that intend to adopting AI

	Panel A. Annual outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Return on Sales (ROS)	2670	3.40	6.40	-0.42	0.61	2.23	5.35	10.22
Return on Assets (ROA)	2670	3.52	5.19	-0.41	0.70	2.69	5.71	9.62
Cash flow to assets ratio	2670	7.79	6.21	1.61	3.66	6.59	11.30	15.99
Cash flow to sales ratio	2670	8.06	8.51	1.38	2.98	6.10	10.59	17.11
EBITDA to assets ratio	2670	8.36	7.97	-0.06	3.57	7.55	12.89	18.51
EBITDA to value added ratio	2670	26.98	29.56	1.26	13.69	27.36	43.42	59.81
Value added to employees ratio (log)	2670	4.22	0.62	3.53	3.86	4.23	4.58	4.92
EBITDA to employees ratio (log)	2408	2.96	1.21	1.35	2.32	3.04	3.76	4.36
Labor cost to employees ratio (log)	2670	3.87	0.36	3.40	3.68	3.90	4.10	4.28
Labor cost to value added ratio (log)	2670	4.20	0.45	3.69	4.04	4.29	4.46	4.59
YoY growth of employees	2362	0.05	0.14	-0.06	-0.02	0.02	0.07	0.16
Share of managers	2670	1.92	2.78	0.00	0.00	0.97	2.94	5.18
Share of white collars	2647	46.95	29.04	11.78	22.51	42.73	71.66	90.70
Share of blue collars	2666	47.70	31.03	0.00	18.08	52.23	73.80	85.48
Sahre of apprentices	2670	2.77	5.90	0.00	0.00	0.00	2.61	9.16
YoY growth of intangible assets	2315	0.62	3.48	-0.44	-0.24	-0.07	0.17	1.05
YoY growth of tangible assets	2354	0.14	0.52	-0.14	-0.05	0.01	0.13	0.47
	Panel B. Quarterly outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Own price change over past 12 months	6111	2.71	5.56	-0.50	0.00	1.00	5.00	10.00
Own price change over next 12 months	6111	2.18	3.80	0.00	0.00	1.50	3.50	5.20
Subjective uncertainty over next 3 years	6031	0.56	0.25	0.00	0.46	0.64	0.75	0.80
Expected inflation over next 6 months	6111	2.73	2.75	0.30	1.00	1.50	4.00	7.00
Expected inflation over next 12 months	6111	2.54	2.36	0.40	1.00	1.80	3.50	6.00
Expected inflation over next 24 months	6111	2.33	2.01	0.50	1.00	2.00	3.00	5.00
Expected inflation over next 48 months	6111	2.25	1.82	0.50	1.10	2.00	2.50	4.50

Notes: The table presents summary statistics for the continuous outcome variables. All variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. The statistics are computed over the 2016–2024 period and are weighted using the survey sampling weights.

Table A4: Descriptive statistics of continuous outcome variables for firms that choose "Don't know/Don't want to answer"

	Panel A. Annual outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Return on Sales (ROS)	2494	3.23	5.88	-0.19	0.65	2.46	5.67	9.50
Return on Assets (ROA)	2494	3.64	5.36	-0.21	0.72	2.82	5.92	10.28
Cash flow to assets ratio	2494	8.13	5.78	2.29	4.43	7.48	11.03	15.23
Cash flow to sales ratio	2494	8.03	7.05	1.60	3.78	6.86	10.85	15.69
EBITDA to assets ratio	2494	9.23	7.58	1.29	4.70	8.53	12.86	19.01
EBITDA to value added ratio	2494	28.75	24.81	3.34	14.82	28.72	45.09	57.48
Value added to employees ratio (log)	2494	4.21	0.60	3.50	3.89	4.23	4.56	4.91
EBITDA to employees ratio (log)	2317	2.89	1.28	1.23	2.27	3.06	3.75	4.32
Labor cost to employees ratio (log)	2494	3.82	0.38	3.39	3.64	3.84	4.04	4.24
Labor cost to value added ratio (log)	2494	4.20	0.37	3.75	4.01	4.27	4.44	4.57
YoY growth of employees	2207	0.04	0.12	-0.05	-0.01	0.02	0.07	0.14
Share of managers	2494	1.27	1.87	0.00	0.00	0.31	1.90	3.81
Share of white collars	2462	39.84	27.07	9.80	19.34	32.66	56.47	86.26
Share of blue collars	2488	54.67	28.96	1.17	36.45	61.60	77.67	87.59
Sahre of apprentices	2494	3.17	7.32	0.00	0.00	0.13	3.14	8.86
YoY growth of intangible assets	2064	0.87	4.06	-0.50	-0.25	-0.07	0.19	1.60
YoY growth of tangible assets	2195	0.12	0.49	-0.15	-0.06	0.01	0.13	0.42
	Panel B. Quarterly outcomes							
	count	mean	sd	p10	p25	p50	p75	p90
Own price change over past 12 months	5521	2.81	5.51	0.00	0.00	1.00	5.00	10.00
Own price change over next 12 months	5521	2.20	3.95	0.00	0.00	1.00	3.00	6.00
Subjective uncertainty over next 3 years	5427	0.53	0.27	0.00	0.44	0.63	0.73	0.80
Expected inflation over next 6 months	5521	2.75	2.85	0.20	0.90	1.50	4.00	7.00
Expected inflation over next 12 months	5521	2.55	2.51	0.30	1.00	1.70	3.50	6.00
Expected inflation over next 24 months	5521	2.33	2.19	0.40	1.00	1.80	3.00	5.00
Expected inflation over next 48 months	5521	2.24	2.00	0.40	1.00	2.00	2.50	5.00

Notes: The table presents summary statistics for the continuous outcome variables. All variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. The statistics are computed over the 2016–2024 period and are weighted using the survey sampling weights.

A3 Dating Firms' AI Adoption

As discussed in the main text, the SIGE survey does not contain information on the precise timing of AI adoption at the firm level.[23] To construct a pre- and post-adoption distinction for our difference-in-differences analysis, we draw on auxiliary information from two complementary data sources.

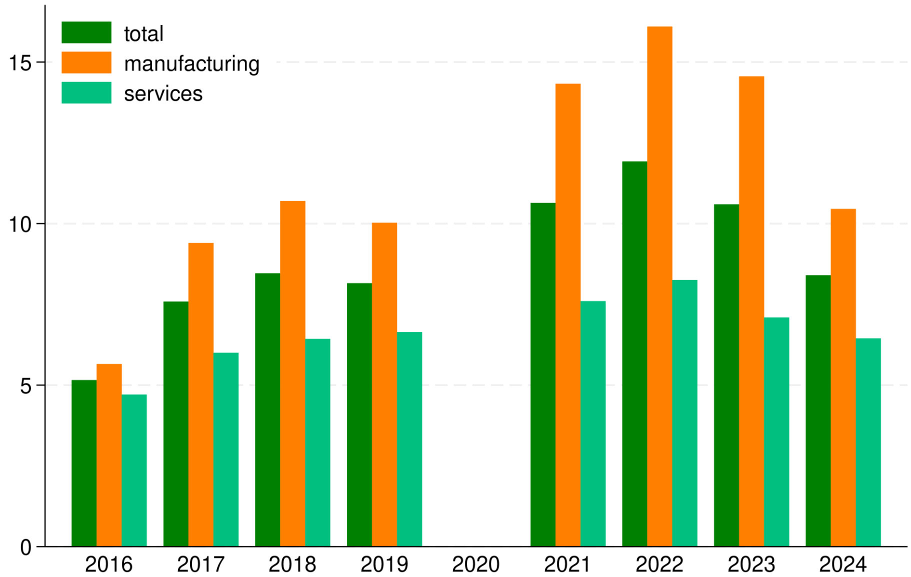
Bank of Italy's Survey of Industrial and Service Firms. The Survey of Industrial and Service Firms (INVIND, henceforth) is an annual survey conducted by the Bank of Italy. The questionnaire consists of (*i*) a fixed part - covering firm characteristics, organizational structure, investment activity, employment, turnover, operating results, capacity utilization, and financing - and (*ii*) *ad hoc* modules addressing topics of cyclical or structural interest. In the 2025 wave, firms were asked to qualify their use of advanced technologies by choosing among "extensive use", "limited use", "experimental use" and "currently not in use", separately for predictive AI, generative AI, and advanced robotics. With respect to AI, approximately 5% of firms reported extensive use, 12% limited use, and 14% experimental use. For advanced robotics, these shares were 15%, 20%, and 4%, respectively. These figures are broadly comparable to the SIGE evidence once one accounts for differences in survey design - most notably, the fact that the SIGE response option "Don't know/Prefer not to answer" likely absorbs the "experimental use" category present in INVIND. For the purpose of dating AI adoption, a more informative INVIND question has been collected since 2017 (with the exception of 2022), asking firms to report the share of their total investment devoted to advanced technologies.[24]

Figure A1 presents the evolution of these investment shares for firms with at least 50 employees, both in aggregate and separately for manufacturing and services. Investment in advanced technologies peaks in 2022. For manufacturing firms, the share reaches 16%, roughly double its average value over 2016–2019, while for services firms the corresponding share rises to about 8%, compared with a pre-2020 average of 5%. Investment shares decline somewhat in subsequent years but remain above pre-pandemic average levels. Available information does not allow us to attribute this gradual reversal to any specific type of technology.

[23] In future waves of the SIGE survey, we plan to ask firms an estimated date of their AI adoption. It must be acknowledged that this information is inherently difficult to collect, since firms may struggle to pinpoint a precise adoption date for technologies that diffuse incrementally and become integrated into multiple areas of the organization over time.

[24] The survey explicitly defines advanced technologies as including: mobile internet and cloud services, artificial intelligence and big data, internet of things applications, advanced robotics, 3D printing, and high-tech capital goods.

Figure A1: Investment in advanced technologies in Italy



Notes: This figure reports the share of investment devoted to advanced technologies among Italian firms with at least 50 employees surveyed in INVIND. Shares are computed using sampling weights. In 2021 (with reference year 2020) the question on investment in advanced technologies was not asked.

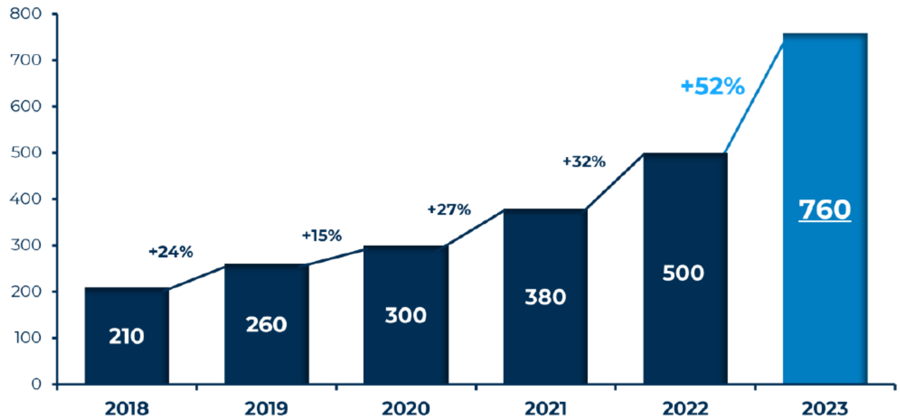
Osservatorio Artificial Intelligence of the Politecnico di Milano. The Osservatorio Artificial Intelligence of the Politecnico di Milano's School of Management is one of the main national institutions monitoring the development, adoption, and economic implications of AI technologies in Italy. The Osservatorio conducts annual surveys on large firms and SMEs, maps the diffusion of predictive, generative, and robotics-based AI solutions, and provides systematic measurements of the Italian AI market.

According to the 2024 edition, the Artificial Intelligence market in Italy reached a new record of 1.2 billion of euro, marking a 58% increase compared with 2023. Growth has been driven primarily by projects that incorporate Generative AI, which account for 43% of the market's value, while the remaining 57% is composed mainly of traditional Artificial Intelligence solutions. The Osservatorio attributes this surge primarily to large firms, which account for the bulk of investment and experimentation.

Additional evidence comes from the Osservatorio's contribution to the Italian Parliament's 2023–2024 "Indagine Conoscitiva" on the opportunities and risks of AI for the Italian productive sector. The report highlights a persistent structural divide between large firms and SMEs: while adoption among medium-large firms is rapidly accelerating, only a minority of smaller firms have yet implemented concrete AI projects. The document further stresses that many initiatives prior to 2023 were exploratory in nature, whereas the most recent period has seen a shift toward strategic and organization-wide deployment.

All in all, these patterns provide a picture suggesting that the early 2020s - particularly around 2022-23 - might represent a period of intensified adoption and scaling of advanced digital technologies, including AI.

Figure A2: Value of AI market in Italy



Notes: This figure, sourced from the Osservatorio Artificial Intelligence, shows the market value of AI in Italy, expressed as expenditure on AI projects. Values on the y-axis are in millions of euros.

A4 Intensity of AI Use and Investment: Evidence from INVIND

This appendix complements the survey-based evidence presented in the main text by documenting the intensity of use of artificial intelligence and the scale of related investment using data from the Bank of Italy's *Indagine sulle Imprese Industriali e dei Servizi* (INVIND). The evidence refers to the 2024 wave of the survey, conducted in spring 2025, which included a dedicated section on the adoption and use of advanced technologies. The survey relies on relatively broad definitions: artificial intelligence encompasses both predictive and generative applications, while robotics includes automatically controlled, reprogrammable, and multifunctional machines, as specified in the questionnaire. These definitions are broader than those adopted in the SIGE survey, which focuses on a narrower set of AI applications. Consequently, the evidence reported here should be interpreted as providing an upper bound on the intensity of AI-related use and investment relative to the SIGE-based measures. To ensure comparability with the SIGE sample used in the core analysis, the INVIND sample is restricted to firms with at least 50 employees in industry and services.

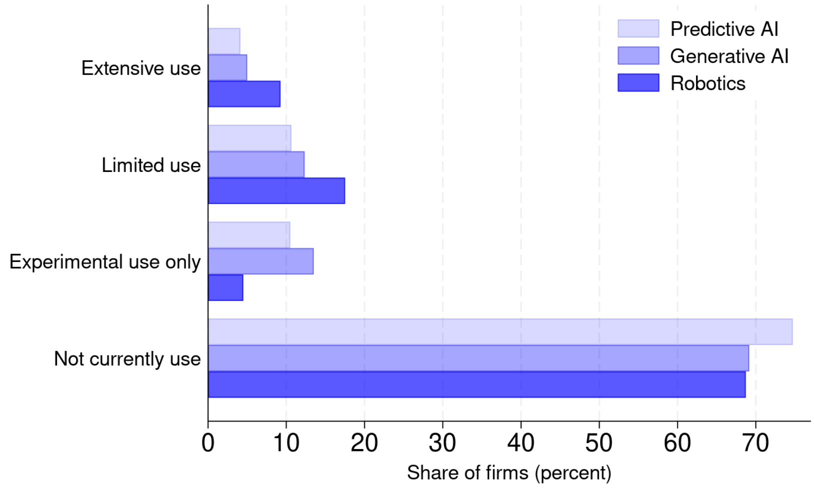
Panel (a) of Figure A4 reports the distribution of firms by intensity of use of advanced technologies, distinguishing between predictive AI, generative AI, and robotics. For all three technologies, the majority of firms report no current use, while adoption is concentrated in limited or experimental applications. Extensive use remains relatively uncommon, particularly for generative AI and robotics. This pattern suggests that, even among larger firms, AI technologies are typically deployed in a partial or exploratory manner rather than as part of a comprehensive reorganization of production processes.

Panel (b) of Figure A4 documents the share of total investment devoted to advanced technologies. Almost half of firms report zero investment in these technologies, and most positive responses fall below 10 percent of total investment. The vertical line marks the average investment share, which is modest in magnitude. Taken together, the evidence points to a distribution characterized by a large mass at zero and a thin right tail, indicating that only a small subset of firms allocates a substantial fraction of investment to advanced technologies.

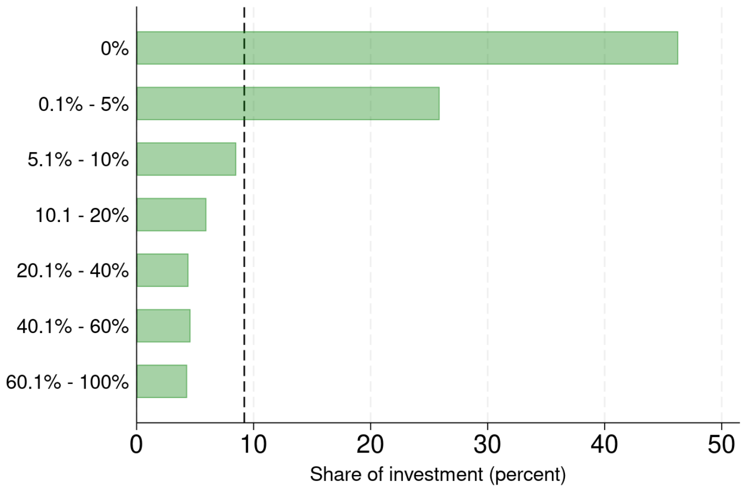
These descriptive patterns help interpret the results in the main text. Given the limited intensity of use and the relatively small investment shares observed during this period, it is not surprising that AI adoption is not associated with a pronounced acceleration in aggregate investment among adopters relative to non-adopters in Italy. Rather, the evidence is consistent with AI being deployed primarily through incremental, targeted applications – often complementary to existing capital – whose aggregate investment implications may materialize only gradually as adoption deepens and scales over time.

Figure A3: Intensity of Use of AI and Investment in Advanced Technologies

(a) Intensity of use of AI technologies



(b) Share of investment devoted to advanced technologies



Notes: The figure reports evidence from the Bank of Italy's INVIND survey (2024 wave, conducted in spring 2025) for firms with at least 50 employees in industry and services. Panel (a) shows firms' self-reported intensity of use of predictive AI, generative AI, and robotics, based on the definitions provided in the survey questionnaire. Panel (b) displays the distribution of the share of total investment devoted to advanced technologies. The vertical dashed line indicates the average investment share. All statistics are weighted using survey sampling weights.