# Online Appendix (For Online Publication Only)

**The Innovation Race: Experimental Evidence on Advanced Technologies**

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## A More Details about the INVIND Survey

The Bank of Italy has conducted the INVIND survey since 1972. Initially, the survey included only industrial processing firms with at least 50 employees. In 1999 the scope was extended to all manufacturing firms and those in the energy and extractive industries. In 2001, it was broadened to include firms with 20–49 employees, and in 2002 it was further expanded to non-financial private service firms with 20 or more employees.

The survey employs a one-stage stratified sampling method, with strata defined by industry branch, firm size (based on employee count), and the region of the head office. The sample size is determined in two steps: first, size classes are selected using optimal allocation to minimize variance in key variables (employment, turnover, investment); second, these classes are proportionally distributed across regions and industries. Firms are drawn from the Social Security Institute (INPS), the Italian Business Register (Infocamere), and other sources to reduce under-coverage. Firms from previous waves are recontacted if still eligible, and those unwilling to participate are replaced with comparable firms.

The data for a survey referring to a given year are collected through interviews conducted by the Bank of Italy's branches between February and May of the following year. Contrary to other official surveys that are outsourced to external private companies, the interviews are conducted with the assistance of the officers of the Bank of Italy's branches, making less likely that answers are fabricated or haphazard. The officers assigned to each province have often had long term relations with the respondents, providing a guarantee of consistency in the history of the answers. The INVIND data then undergo a system of quality checks. These include verifying that responses to closed questions fall within the allowed ranges, ensuring time consistency in panel data and identifying outliers. Questionnaires are first reviewed by Bank of Italy officers drawing on their expertise and local knowledge. The data-entry system

automatically rejects values outside defined ranges or inconsistent with the questionnaire. Suspicious data within acceptable ranges are flagged for review, and firms may be contacted for clarification. Additional checks use statistical editing techniques to detect outliers based on distribution patterns. A selective editing process then ranks firms by the potential impact of their data on final estimates, prioritizing verification only for high-impact cases. This approach improves estimate quality while minimizing the burden on respondents.

In the case of employment, investment and turnover, information is requested for three periods: the year just ended (preliminary results), the previous year (final results), and the following year (expected values).

The survey data also include sampling weights to account for selection probabilities. The weights are also post-stratified to the distributions of firms by geographical location, number of employees and sector of activity.

Validation checks have been done on the INVIND data and samples in the past. Caprara et al. (2024) show that the variables collected through INVIND (e.g., turnover, investment, employment) are broadly consistent with the aggregates reported in national accounts, despite some definitional and conceptual differences.

D'Aurizio and Papadia (2016) highlight the high degree of integration between INVIND data and external sources such as Cerved, a dataset which collects firms' balance sheet data. Over 90% of firms in the INVIND survey were successfully matched with Cerved records. Moreover, for nearly 80% of matched firms, the difference in reported turnover is less than 5%. The correlation coefficients for employment and turnover between the two datasets are both around 0.98, indicating a very strong alignment. This will become important for us, since in future steps of the analysis we plan to link the survey experiment responses to administrative data on firms' balance sheet (CERVED), employee data from the Social Security Institute (INPS), custom and VAT data and credit registry data. The goal will be to examine the impact of our treatments on an array of variables related to firms' decisions.

# B More Details about the Imputation of Prior Beliefs

Figure B.1 shows the distribution of prior gaps, broken down by individuals in the treatment and control groups. Panel (a) uses the raw prior beliefs. Whether prior beliefs were contaminated is straightforward to test empirically. Under no contamination, the distribution of prior beliefs should be indistinguishable between treatment and control groups. By contrast, if treated subjects revised their prior beliefs after seeing the information, we would expect the treatment group's prior beliefs to be more accurate than those in the control group. Panel (a) shows evidence of some contamination of prior beliefs. Relative to the control group, in the treatment group the distribution of prior gaps is shifted to zero, that is, towards more accuracy. In particular, there is bunching near 0%, suggesting that a minority—but non-negligible—share of firms after seeing the treatment message they went back and edited their prior beliefs to match the information exactly.

For a more formal assessment, panel (a) shows the p-value of the Epps-Singleton two-sample test of the equality of the distributions between the treatment and control groups. This tests uses the empirical characteristic function, which is a version of the Kolmogorov-Smirnov test of equality of distributions that is valid for discrete data (Goerg and Kaiser, 2009). The p-value$<$0.001 indicates that the difference between the two distributions is statistically significant. In particular, the differences are more notable as a higher probability of reporting a prior exactly equal to the signal, and a lower probability of reporting a prior that is well below it. One simple interpretation is that a small but non-negligible share of individuals who entered a prior that saw later that it was well below the signal went back and changed their prior response to match the signal exactly.

For additional evidence, the two panels of Figure B.2 breaks down panel (a) of Figure B.1 in two groups, based on the response mode. Panel (a) of Figure B.2 corresponds to the individuals who received an in-person visit from an interviewer, for whom we would not expect any contamination. In turn, panel (b) of Figure B.2 corresponds to the rest of the response mode, such as downloading a PDF to fill it out on their own, for whom contamination is possible. As expected, panel (a) shows no no significant evidence of contamination for individuals who received an in-person visit. The difference in the distribution of prior beliefs

is statistically indistinguishable (p=0.546) between the treatment and control groups, and we do not observe any bunching near 0%. By contrast, panel (b) shows evidence that a minority, but non-negligible of subjects in the treatment group went back to revise their perception gaps: there is a significant difference (p<0.001) in the distribution of prior beliefs between treatment and control groups, manifested mostly as excess bunching around 0%.

Note that while prior beliefs seem to be contaminated for some subjects, it is far from being an issue for all subjects. Even in the treatment group (who saw the signal) only a minority (less than 10%) end up reporting exactly the value of the signal received, and most of them still report a prior that is far below it. However, for the heterogeneity analysis and the 2SLS model, we would like to use prior beliefs that are not subject to any contamination concerns at all. For that, we use the imputation method.

To predict prior beliefs, we estimate a linear regression model that incorporates several controls from the same survey wave, along with sector-size fixed effects. The estimation is carried out on the sample of control firms, whose prior beliefs are not subject to contamination.[34] The results, reported in Table B.2, show that exporting firms, firms with higher turnover, firms already using AI or robotics, and firms that invest more heavily in advanced technologies tend to report higher prior beliefs. Importantly, in a context where the overall tendency is to underestimate the true share of competitors adopting advanced technologies, holding higher prior beliefs corresponds to being more accurate. Taken together, these findings suggest that firms with these characteristics are better informed about the actual extent of advanced technology adoption among their peers.

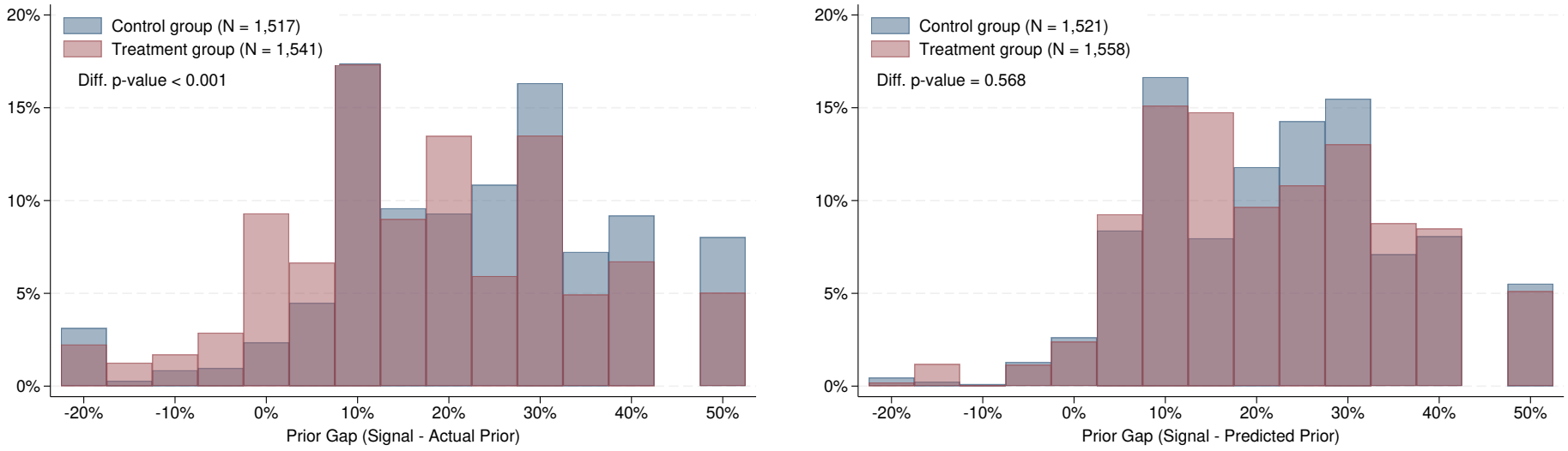
As a sanity check, we can assess whether the imputed prior beliefs are truly free from any contamination. For consistency with the measurement of raw prior beliefs (defined as the midpoints of ten bins), we round the imputed prior beliefs to the midpoint of the corresponding decile. Recall that Figure B.1 shows the distribution of prior gaps. Panel (b) is identical to panel (a), except that it uses the imputed prior beliefs instead of the raw prior beliefs. In panel (b), the distribution of prior gaps is almost identical between treatment and control groups. Indeed, according to the Epps-Singleton test, the difference between the distributions of the treatment and control groups is not statistically significant (p=0.542).

[34] The dependent variable (raw prior belief) is winsorized at the 1st and 99th percentiles.

The imputation method is useful depending on the model's predictive power. At one extreme, if the model had perfect predictive power, the imputed values would be equivalent to observing the true (uncontaminated) prior beliefs. At the other extreme, if the model had no predictive power, the imputed priors would be pure noise. The lower the predictive power, the noisier the imputed prior beliefs and thus the larger the attenuation bias—working against us. Indeed, one must keep in mind that even when using the prior beliefs, due to its subjective nature, they are still measured with noise and thus introduce attenuation bias—some respondents may not pay enough attention, may round up or down strongly, make typos, etc. It is just that the imputation adds even more noise and thus increases the attenuation bias. Table B.2 shows the out-of-sample $R^2$ is 0.28, which is fairly decent, implying that while our imputed measure of prior beliefs is not perfect, it contains substantial signal relative to the noise.

Figure B.1: Distribution of Gaps in Prior Beliefs, Before and After the Imputation

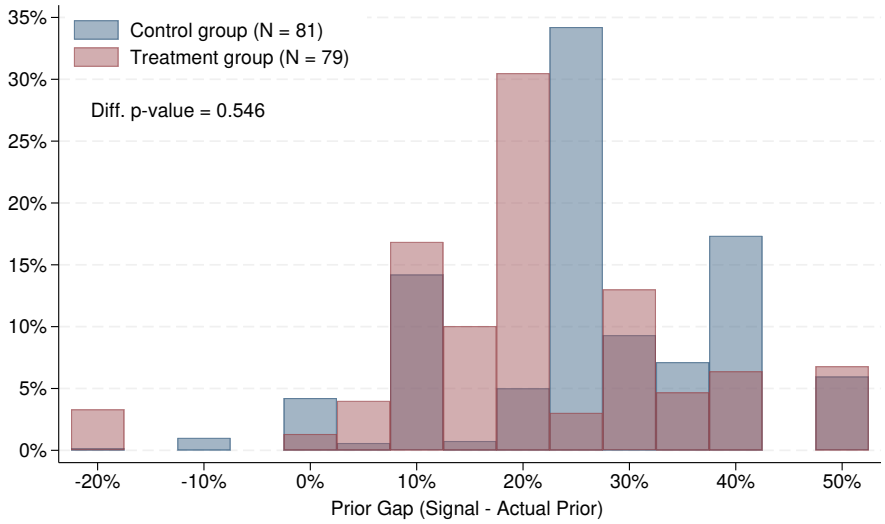
(a) Raw Priors (b) Imputed Priors



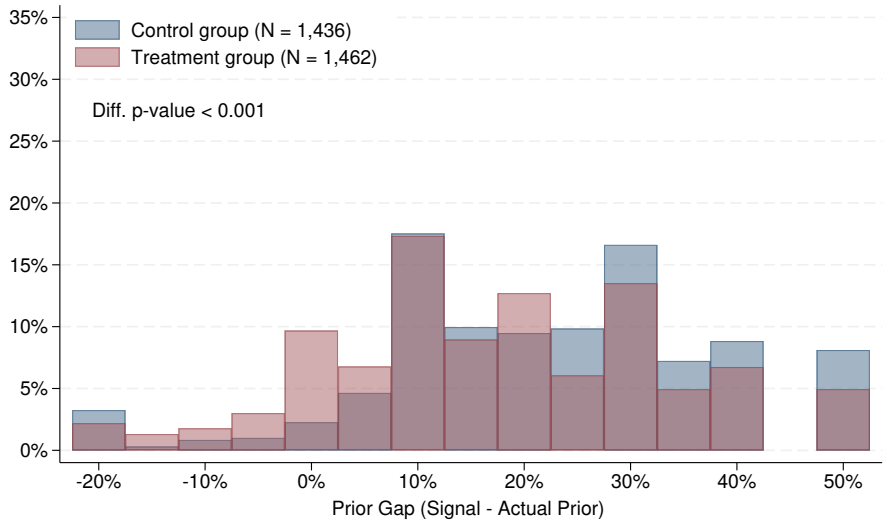

Notes: The Figure is based on the 2025 INVIND survey. Panel (a) shows the empirical distribution of the gap between prior beliefs and the information that would be shown if treated, displayed for control and treated firms. Panel (b) shows the empirical distributions of the imputed prior gap, where the imputation of the prior is based on Table B.2. In both panels the first and the last bins group observations with prior gaps below -15 and above 45, respectively. The difference in p-value refers to the Epps-Singleton test of the null hypothesis that the distribution of the prior gap in the control and in the treated group are identical. The imputation method allows us to impute priors for some firms whose raw prior is missing: for this reason the number of firms in panel (b) exceeds the number of firms in panel (a).

Figure B.2: Distribution of Gaps in Raw Prior Beliefs, by Mode of Interview

(a) Raw Priors: Personal Visit




(b) Raw Priors: Other than personal visit




Notes: The Figure is based on the 2025 INVIND survey. Panel (a) shows the empirical distribution of the gap between prior beliefs and the information that would be shown if treated, displayed for control and treated firms interviewed with a personal visit or a teleconference. Panel (b) shows the empirical distribution of the the same gap for control and treated firms interviewed by telephone or through a remote self-administered questionnaire or through a web self-administered questionnaire. In both panels the first and the last bins group observations with prior gaps below -15 and above 45, respectively. The difference in p-value refers to the Epps-Singleton test of the null hypothesis that the distribution of the prior gap in the control and in the treated group are identical.

Table B.1: Information Treatments

| Sector | Firm Size (1) | Signal (2) | Observations (3) |
|---|---|---|---|
| Food and Beverages | 20–49 | 43% | 163 |
| | 50+ | 58% | 213 |
| Textiles, Clothing and Footwear | 20–49 | 16% | 79 |
| | 50+ | 33% | 133 |
| Chemical, Rubber and Plastics | 20–49 | 35% | 76 |
| | 50+ | 55% | 208 |
| Nonmetallic Minerals | 20–49 | 33% | 51 |
| | 50+ | 53% | 64 |
| Basic Metals and Engineering | 20–49 | 49% | 257 |
| | 50+ | 59% | 659 |
| Other Manufacturing | 20–49 | 39% | 85 |
| | 50+ | 61% | 163 |
| Extractive and Energy | 20–49 | 39% | 41 |
| | 50+ | 40% | 116 |
| Trade | 20–49 | 17% | 139 |
| | 50+ | 38% | 276 |
| Lodging and Catering | 20–49 | 25% | 34 |
| | 50+ | 13% | 42 |
| Transport, Storage and Communication | 20–49 | 23% | 92 |
| | 50+ | 38% | 269 |
| Real estate and Other Services | 20–49 | 33% | 56 |
| | 50+ | 40% | 171 |

Notes: The Table shows the information treatments provided to treated firms in the INVIND Survey module 2025 (TEC25). Firm size refers to the number of employees. The information treatment is calculated as the share of firms in each sector-size cell that replied that they were currently using or expected to introduce by the end of 2024 any technology among Pred.-AI, Gen.-AI or robotics (questions TEC5N and TEC11N in the Survey Module 2024). Column (3) corresponds to the number of firms who responded to the question on AT adoption from the 2024 survey.

Table B.2: Prediction Model for Prior Beliefs Imputation (Control Group Only)

| | Prior Belief |
|---|---|
| | (1) |
| Current Use of Pred.-AI | 0.035** |
| | (0.014) |
| Current Use of Gen.-AI | 0.028** |
| | (0.012) |
| Current Use of Robotics | 0.038*** |
| | (0.010) |
| Share of Investment in Advanced Technologies in 2024 | 0.403*** |
| | (0.039) |
| Exporter | 0.019** |
| | (0.008) |
| Turnover (standardized within sector/size) | 0.759** |
| | (0.353) |
| Number of employees (standardized within sector/size) | -0.157 |
| | (0.209) |
| Share of investment over turnover | -1.231 |
| | (1.845) |
| People involved in the compilation of the questionnaire | 0.494 |
| | (0.402) |
| Managers involved in the compilation of the questionnaire | -0.036 |
| | (0.762) |
| Observations | 1,517 |
| Mean of Dep. Var. | 13.36 |
| Sector-size Fixed Effects | Yes |
| R2 | 0.30 |
| R2 Out-Of-Sample | 0.28 |

Notes: The dependent variable is the firm's raw prior belief about competitors' adoption rates of advanced technologies elicited in the INVIND survey conducted in 2025. More specifically, we define the prior belief as midpoints of the ten bins in the answering options to question TEC24. The estimation sample includes only firms in the control group.

# C Additional Results and Robustness Checks

## C.1 Additional Details on the Usage of Artificial Intelligence

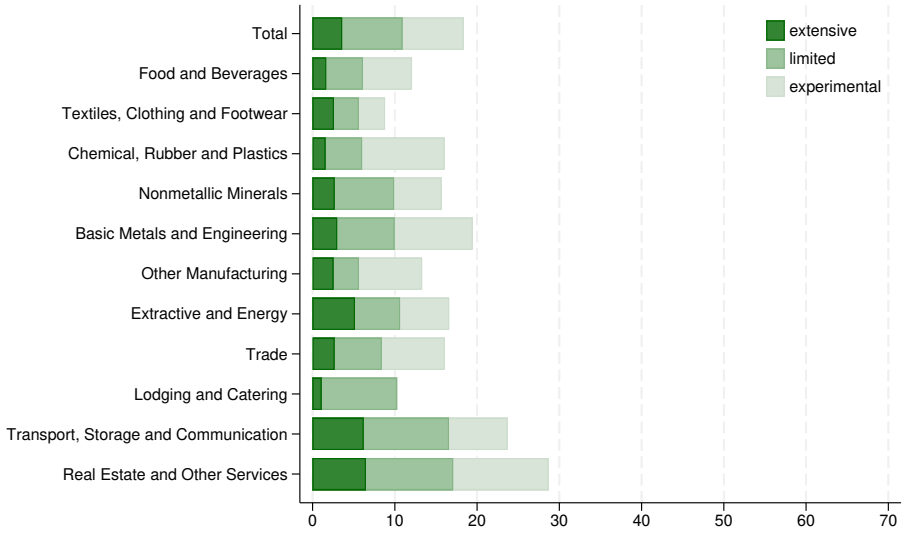
Figure C.1 replicates Panel A of Figure 1, but broken down by generative versus predictive AI. In 2025, around 72% of firms used neither predictive nor generative AI tools, about 15% used both predictive and generative AI, 10% used only generative AI and 3% only predictive AI.

## C.2 Correlation Between Perceived Competitor's Adoption on Own Intention to Adopt

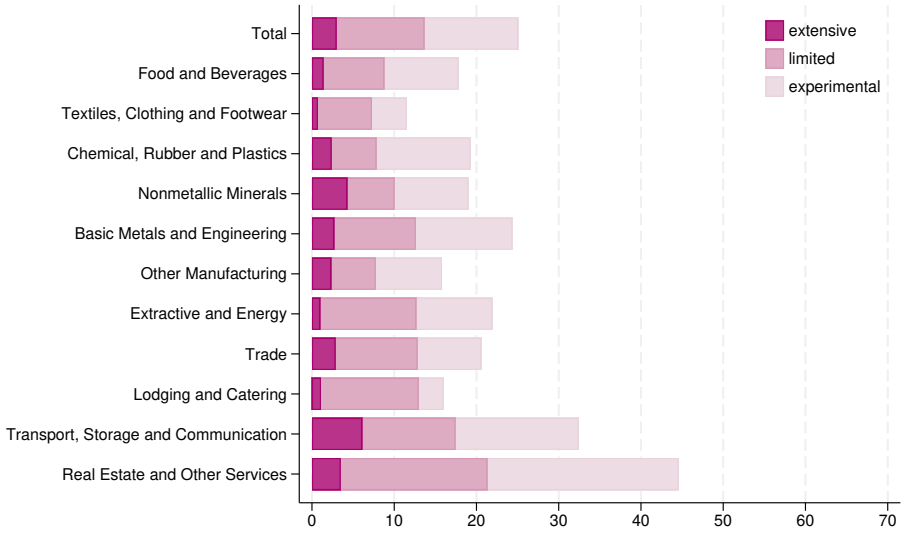
Figure C.2 shows that, in the control group, there is a significant correlation between the expected competitors' adoption and the firm's own adoption plan. However, these correlations suggest that non-experimental estimates can be misleading. In this correlational analysis, there is a significant correlation between the expected competitors' adoption of advanced technologies and the probability that the firm adopts each of the three technologies. In the experimental analysis, however, the correlation is significant for the adoption of robotics technologies, but not for either of the two AI technologies.

Figure C.1: Usage of Artificial Intelligence Separately for Predictive AI and Generative AI

(a) Use of Predictive AI, by Intensity



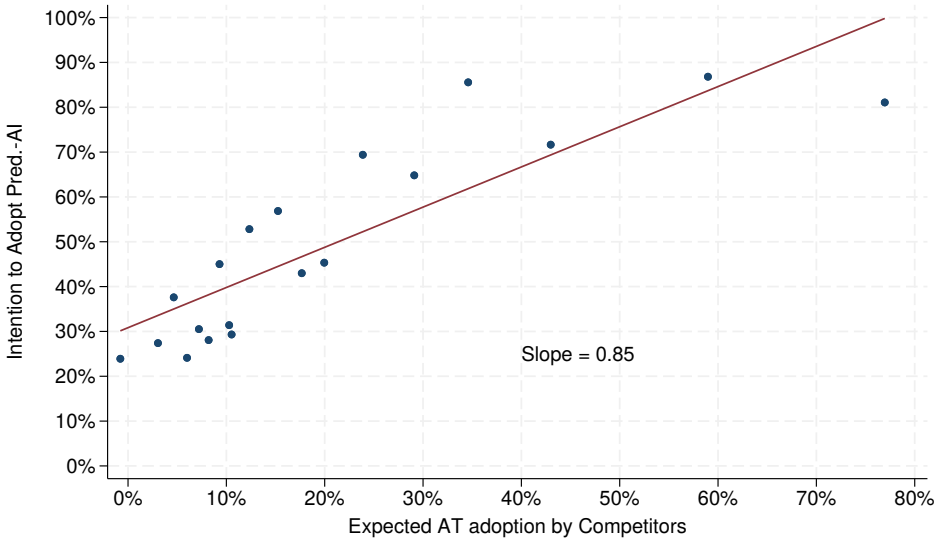

(b) Use of Generative AI, by Intensity



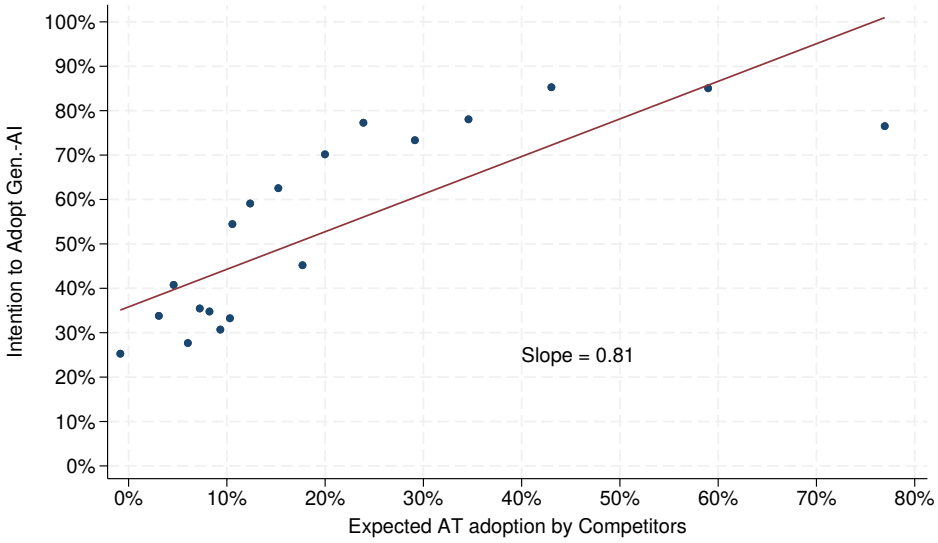

Notes: The Figure is based on the INVIND survey conducted in 2025 and splits Figure 1, panel (a). It separately shows the intensity in the use of predictive AI (panel a) and generative AI (panel b) at the moment of the interview (survey questions TEC5N1 and TEC5N2).

Figure C.2: Effects of Expected Competitors' Adoption on Own Future Adoption: OLS estimates in the Control Group

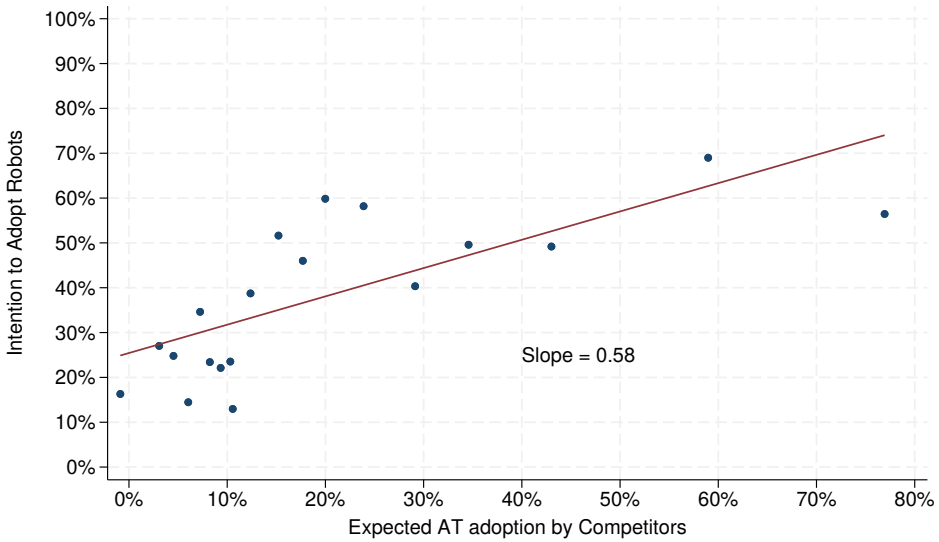
(a) Intention to Adopt Pred.-AI



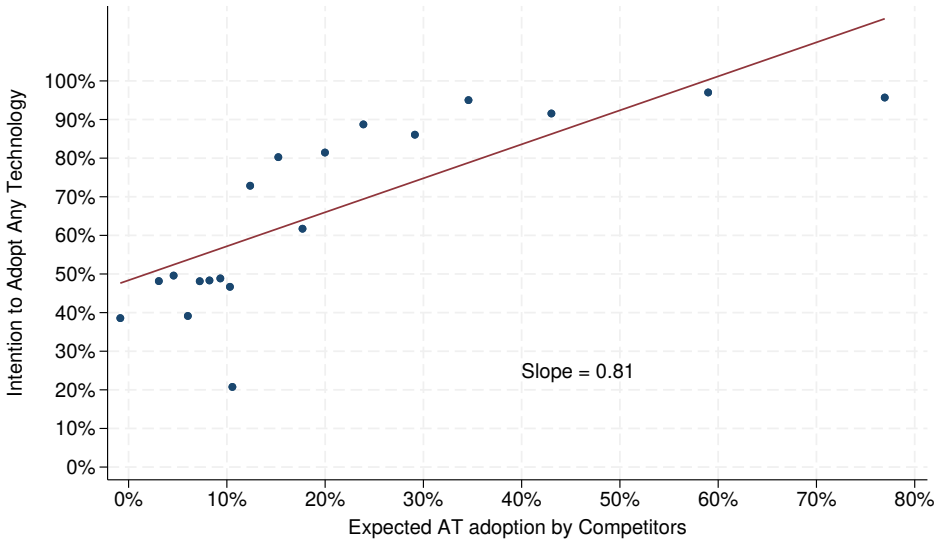

(b) Intention to Adopt Gen.-AI




(c) Intention to Adopt Robots




(d) Intention to Adopt Any Technology




Notes: The Figure is based on the INVIND survey conducted in 2025. The graph is a binscatter of the relationship between the intention to adopt a given technology by 2027 (questions TEC27A, TEC27B and TEC27C) and the expected competitors' adoption (question TEC26) in the control group. It represents the OLS counterpart of equation (5) estimated on the control group, accounting only for sector-size fixed effects.

# D Survey Module 2025

| Please indicate your main source of funding for investment in 2023-24. | V240 |
|---|---|
| 1 Self-financing or intra-group funding<br>2 Banks and other financial intermediaries<br>3 Risk or equity capital (including venture capital)<br>4 Bond issuance<br>5 Public funding and/or tax credit<br>6 Other | |

| Have you used the following incentives for new investment in capital goods in 2024, or do you plan to use them in 2025?: | 2024 | 2025 |
|---|---|---|
| Tax credit for capital goods under the **Transition 4.0** programme *(new tangible and intangible capital goods for the technological and digital transformation of production processes).* | SAM23A | SAM23B |
| Tax credit for capital goods under the **Transition 5.0** programme *(investments to reduce the energy consumption of production facilities by at least 3 per cent or, alternatively, to reduce the energy consumption of the processes involved in the investment by at least 5 per cent).* | SAM26A | SAM26B |

***Legend**: 1 = yes; 2 = no, we do/did not know about this incentive; 3 = (only for Transition 5.0) no, because the investment did not meet the energy saving requirements to receive this incentive; 4 = no, because the incentive application procedure is unclear/complicated; 5 = no, for other reasons; 8 = not applicable to our company.*

**'Transition 4.0' tax incentives:** Tax incentives are available until 2025 for investments in tangible and intangible assets for technological transition according to the Transition 4.0 model (formerly Industry 4.0). The tax credit is available to all resident companies regardless of their legal form, economic sector or size. The tax credit can be used to offset tax liabilities without limit and in three equal annual instalments, starting from the year in which the assets are integrated into the company's interconnection system. The tax credit is available for investment in new technologically advanced tangible assets – for production facilities located in Italy – included in Annex A to the 2017 Budget Law (i. capital goods operated by computerized systems or managed by special sensors and drives; ii. quality and sustainability assurance systems; iii. devices for human-machine interaction and for improving ergonomics and safety in the workplace under the 4.0 model) and in intangible assets (software, systems and system integration, platforms and applications) in connection with the above-mentioned investments in tangible assets, included in Annex B to the same Budget Law.
**'Transition 5.0' tax incentives:** The Transition 5.0 plan was included in Decree Law 19/2024 (the NRRP Decree), with the aim of supporting the digital and energy transition. The tax incentives are available to all resident companies that make investments during the two-year period 2024-25, as part of innovation projects that result in energy savings. The new tangible and intangible assets listed in Annexes A and B to Law 232/2016 (i.e. Industry 4.0 investment assets) are eligible for the incentives provided that they are used in innovation projects that achieve a reduction in energy consumption for production of at least 3 per cent or a reduction in energy consumption of the processes affected by the investments of at least 5 per cent.

## Advanced technologies

**Advanced technologies**: those included in Italy's Firm 4.0 plan and already included in the Industry 4.0 plan. The technologies must possess the technical characteristics necessary for their inclusion in the lists presented as an annex to the Budget Law 2017. Such technologies include, but are not limited to, a) mobile Internet and cloud computing (e.g. wireless technology, apps, smartphones, tablets, high-speed Internet networks and cloud management services); b) artificial intelligence and big data (e.g. the collection and utilization of high volumes of data which, also through the use of machine learning algorithms, can support decisionmaking in fields such as telemedicine, the construction of algorithms for financial investments, and patent or legal research); c) Internet of Things (e.g. the use of technologies which, by means of advanced sensors, enable communication between the different devices used in production and business processes by facilitating their integration); d) advanced robotics (the robotics utilized in industrial processes using artificial intelligence); e) 3D printing; f) capital goods whose functioning is controlled by computerized systems or through sensors and mechanism, including links with plant-level IT systems where the relevant instructions are provided remotely.

| **Looking at the advanced technology listed below: how much is it used at your firm in the production process and/or in support activities?** | |
|---|---|
| **A Predictive artificial intelligence** (such as text mining, voice and image recognition or machine learning) | TEC5N1 |
| **B Generative artificial intelligence** (such as chatbots, virtual assistants and tools for the autonomous production of original texts, codes, images, and audio and video clips) | TEC5N2 |
| **C Robotics** (machines that are automatically controlled, reprogrammable and multipurpose) | TEC11N |

***Legend**: 1 = extensive use; 2 = limited use; 3 = only experimental uses; 4 = we do not currently use this technology.*

**Out of the total investment carried out by your firm in 2024, what was the approximate share of investment in advanced technologies*?** — TEC16N

0 No investment in advanced technologies
1 Between 0,1% and 5%
2 Between 5,1% and 10%
3 Between 10,1% and 20%
4 Between 20,1% and 40%
5 Between 40,1% and 60%
6 More than 60%

**In your opinion, what is the share of companies similar to yours in terms of sector and size, potentially your competitors, that are currently using robotics and/or artificial intelligence (generative and/or predictive AI)?:** — TEC24

1 Less than 10%
2 Between 10.1% and 20%
3 Between 20.1% and 30%
4 Between 30.1% and 40%
5 Between 40.1% and 50%
6 Between 50.1% and 60%
7 Between 60.1% and 70%
8 Between 70.1% and 80%
9 Between 80.1% and 90%
10 More than 90%

A

The findings of the last survey showed that the share of companies similar to yours in terms of sector and size, potentially your competitors, that were using or planning to use robotics and/or artificial intelligence (generative and/or predictive AI) was: — TEC25

**What do you think will be the share of companies similar to yours in terms of sector and size, potentially your competitors, using these advanced technologies in 2027?** — TEC26A

1 Less than 10%
2 Between 10.1% and 20%
3 Between 20.1% and 30%
4 Between 30.1% and 40%
5 Between 40.1% and 50%
6 Between 50.1% and 60%
7 Between 60.1% and 70%
8 Between 70.1% and 80%
9 Between 80.1% and 90%
10 More than 90%

B

**What do you think will be the share of companies similar to yours in terms of sector and size, potentially your competitors, using these advanced technologies in 2027?** — TEC26B

1 Less than 10%
2 Between 10.1% and 20%
3 Between 20.1% and 30%
4 Between 30.1% and 40%
5 Between 40.1% and 50%
6 Between 50.1% and 60%
7 Between 60.1% and 70%
8 Between 70.1% and 80%
9 Between 80.1% and 90%
10 More than 90%

**Please take a look at the advanced technologies listed below. How do you plan to use them in your company, as part of your production process and/or support activities, by 2027?**

| | |
|---|---|
| **A Predictive artificial intelligence** (such as text mining, voice and image recognition or machine learning) | TEC27A |
| **B Generative artificial intelligence** (such as chatbots, virtual assistants and tools for the autonomous production of original texts, codes, images, and audio and video clips) | TEC27B |
| **C Robotics** (machines that are automatically controlled, reprogrammable and multipurpose) | TEC27C |

***Legend**: 1 = extensive use; 2 = limited use; 3 = only experimental uses; 4 = we do not currently use this technology.*

# E Survey Module 2024

## Advanced technologies

**Advanced technologies**: those included in Italy's Firm 4.0 plan and already included in the Industry 4.0 plan. The technologies must possess the technical characteristics necessary for their inclusion in the lists presented as an annex to the Budget Law 2017. Such technologies include, but are not limited to, a) mobile Internet and cloud computing (e.g. wireless technology, apps, smartphones, tablets, high-speed Internet networks and cloud management services); b) artificial intelligence and big data (e.g. the collection and utilization of high volumes of data which, also through the use of machine learning algorithms, can support decisionmaking in fields such as telemedicine, the construction of algorithms for financial investments, and patent or legal research); c) Internet of Things (e.g. the use of technologies which, by means of advanced sensors, enable communication between the different devices used in production and business processes by facilitating their integration); d) advanced robotics (the robotics utilized in industrial processes using artificial intelligence); e) 3D printing; f) capital goods whose functioning is

| **Out of the total investment carried out by your firm in 2023, what was the approximate share of investment in advanced technologies*?** | TEC16 |
|---|---|

0 No investment in advanced technologies
1 Between 0,1% and 5%
2 Between 5,1% and 20%
3 Between 20,1% and 40%
4 More than 40%

* Consider as advanced technologies those included in Italy's Firm 4.0 plan and already included in the Industry 4.0 plan.

| **Looking at the advanced technology listed below: how much is it used at your firm in the production process and/or in support activities?** | |
|---|---|
| **A Cloud computing** (set of hardware and software resources for processing and storing network data) | TEC2N |
| **B Predictive** (such as text mining, voice and image recognition or machine learning) **and/or generative artificial intelligence** (such as chatbots, virtual assistants and tools for the autonomous production of original texts, codes, images, and audio and video clips) | TEC5N |
| **C Robotics** (machines that are automatically controlled, reprogrammable and multipurpose) | TEC11N |
| **D Interconnection in the production process** (e.g. the Internet of Things and radio frequency identification) | TEC8N |

***Legend***: *1 = extensive use; 2 = limited use; 3 = only experimental uses; 4 = not currently used but expected to be introduced by December 2024; 5 = not currently used and not expected to be introduced by December 2024.*

*If you use Artificial Intelligence (1, 2 or 3 for question B):*

| **Does your firm use generative tools as part of its artificial intelligence technology?** | TEC22 |
|---|---|

1 Yes, more than it uses predictive tools
2 Yes, to the same extent that it uses predictive tools
3 Yes, less than it uses predictive tools
4 No

*If your answers to the previous **B** or **C** questions are from 1 to 4:*

| **How important are the following objectives when choosing to use Artificial Intelligence and/or robotics?** | Artificial Intelligence | Robotics |
|---|---|---|
| Automation of tasks previously done by workers | TEC23AA | TEC23AB |
| Improvement of methods and/or production processes among those previously automated | TEC23BA | TEC23BB |
| Enhancement of the qualities and reliability of work support processes | TEC23CA | TEC23CB |
| Broadening the range of goods and/or services produced | TEC23DA | TEC23DB |

***Legend***: *1 = not important; 2 = not very important; 3 = somewhat important; 4 = very important.*