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Predictive AI and productivity growth dynamics: evidence from French firms

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Abstract

While artificial intelligence (AI) adoption holds the potential to enhance business operations through improved forecasting and automation, its relation with average productivity growth remain highly heterogeneous across firms. This paper shifts the focus and investigates the impact of predictive artificial intelligence (AI) on the volatility of firms' productivity growth rates. Using firm-level data from the 2019 French ICT survey, we provide robust evidence that AI use is associated with increased volatility. This relationship persists across multiple robustness checks, including analyses addressing causality concerns. To propose a possible mechanisms underlying this effect, we compare firms that purchase AI from external providers ("AI buyers") and those that develop AI in-house ("AI developers"). Our results show that heightened volatility is concentrated among AI buyers, whereas firms that develop AI internally experience no such effect. Finally, we find that AI-induced volatility among "AI buyers" is mitigated in firms with a higher share of ICT engineers and technicians, suggesting that AI's successful integration requires complementary human capital.

Keywords: Artificial intelligence, productivity growth volatility, coarsened exact matching.

JEL Codes: D20, O14, O33.

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1 Introduction

Adopting new technologies has long posed significant challenges for businesses, especially when it comes to general-purpose technologies (GPTs) such as computers, information and communication technologies (ICT). The adoption of GPTs typically requires substantial complementary investments in organizational restructuring, workforce upskilling, and new business processes (David, 1990; Brynjolfsson and Hitt, 2003). The extent of these transformations is so profound that scholars have described them as coinvention, emphasizing the need for firms not only to adopt new technologies but also to innovate in how they are integrated and utilized (Bresnahan et al., 1996). Institutional inertia may further complicate the integration of GPTs, creating mismatches between technological potential and existing organization practices.[1] These complementary changes have been shown to evolve incrementally and unevenly across firms and industries, resulting in significant heterogeneity in productivity impacts (Dosi, 2023). For these reasons, when these technologies hold transformative potential their productivity benefits often take years to materialize.[2]

Artificial intelligence (AI) is no exception to this pattern. The adoption of AI has shown great promise for transforming business operations through predictive analytics and automation, yet its impact on productivity growth remains uncertain (Agrawal et al., 2022; Brynjolfsson et al., 2021; Acemoglu et al., 2022). Recent studies have also identified substantial heterogeneity in firms' ability to leverage AI (Calvino and Fontanelli, 2023; Czarnitzki et al., 2023), in line with the idea that complementary assets such as advanced digital capabilities and highly skilled workforces are key for returns to AI use (Brynjolfsson et al., 2018). Firms that develop their own AI systems in-house (Calvino and Fontanelli, 2024), as well as those patenting AI-related innovations (see, e.g., Marioni et al., 2024; Damioli et al., 2021; Alderucci et al., 2021), tend to benefit the most. Further, AI has been shown to impact firms not only through operational efficiency but also via product innovations (Babina et al., 2024).[3] All together these evidences underscore the inherent complexities in integrating AI, as with earlier GPTs, into existing organizational systems as well as the challenges in predicting how AI will impact productivity growth dynamics within firms.

In contributing to this literature, our work is the first to shift attention away from expected productivity gains and focus on how the integration of AI systems alters the variability in productivity growth dynamics within firms. While its commercial use dates back to 2012, AI remains in its early stages of development, exhibiting strong technological dynamism and a steep learning curve, which is expected to amplify fluctuations in firms' performance (Bresnahan et al., 2002). Such heightened volatility can deter investment by increasing uncertainty, disrupt workforce stability by making employment cycles more erratic, and create barriers to AI adoption by

[1] Dosi et al. (2021), for example, highlight that the absence of hierarchical structures in organizations can hinder coordination and distort knowledge flows impeding full integration of GPTs.

[2] Robert Solow provocatively observed already in 1987 that "You [could] see the computer age everywhere but in the productivity statistics". See "We'd Better Watch Out" published in The New York Times Book Review on July 12.

[3] Recent analyses estimating a positive impact of generative AI use on the productivity of certain categories of workers (see also Brynjolfsson et al., 2023; Noy and Zhang, 2023; Peng et al., 2023; Eloundou et al., 2023; Kreitmeir and Raschky, 2023) complements the firm-level evidence discussed above. First, generative AI was unlikely to be widely used by the firms before 2023. Also, these studies primarily focus on specific worker categories and this relationship may depend on whether tasks fall within the current capabilities of AI systems (Dell'Acqua et al., 2023). Lastly, whether AI-driven gains in worker productivity translate into overall firm productivity remains an open question, specially in light of the task-specific use made of generative AI by workers (Handa et al., 2025). For instance, Dell'Acqua et al. (2023) provide experimental evidence suggesting that AI adoption may reduce team performance and increase coordination failures.

raising the costs of integration and organizational adaptation. This, in turn, would slow the diffusion of AI technologies across firms and limit their long-term transformative potential (Rosenberg, 2009; Acemoglu, 2024).

Leveraging data from an ICT survey distributed to French firms with 10 or more employees, we find robust correlational evidence that the use of predictive AI is associated with an increase in the volatility of a firm's productivity growth rates. This relationship persists across a range of robustness checks and alternative specifications, including variations in the computation of the dependent variable, the choice of productivity index, and adjustments for sectoral composition. Furthermore, we conduct more rigorous identification tests to address key endogeneity concerns. While not fully definitive, the results strengthen the case that our main finding reflects more than a simple correlation. First, we account for differences in firm characteristics by employing a Coarsened Exact Matching (CEM) approach, which balances AI users and non-users ex-ante based on characteristics such as size, age, productivity, industry, and digitalization measures. We then estimate the effect of AI on volatility using the matched sample of AI users and non-users. Second, larger, more productive, and more digitized firms are known to self-select into AI adoption (Calvino and Fontanelli, 2023; Alekseeva et al., 2021; Calvino and Fontanelli, 2024). We address this potential sample selection pre-trends by showing that the AI-volatility relationship did not exist during a period when AI adoption was not yet possible. Our results confirm the OLS findings, suggesting that AI use positively affects the volatility of firms' productivity growth rates.[4] This difference is found in the range between 6% and 10% depending on the specification.

Building on this result, we extend our analysis to examine how firms source AI. As with other GPTs, firms may develop AI in-house, purchase AI solutions from external providers, or adopt a hybrid approach that integrates both strategies (Hoffreumon et al., 2024). This "make-or-buy" decision presents a key trade-off: in-house development enables firms to tailor AI to their specific needs, but demands substantial investment in technical expertise and organizational adaptation. In contrast, purchased AI solutions can deliver benefit from economies of scale, lower upfront costs, and embedded best practices but may lack flexibility and require complementary adjustments for effective integration. Some firms, recognizing these trade-offs, pursue a mixed strategy to combine the advantages of internal development with external procurement (Arora and Gambardella, 1994). Indeed firms with in-house AI expertise can better integrate, customize, and extend third-party solutions, aligning them with business needs. Moreover, internal capabilities improve firms' ability to evaluate external technologies, absorb new knowledge, and implement hybrid solutions that blend proprietary innovations with best-in-class third-party tools.

Rather than focusing on the determinants of the make-or-buy decision, we investigate its implications.[5] Leveraging a unique feature of the French ICT survey, we classify firms into three categories: those that purchase AI externally ("AI buyers"), those that develop AI in-house ("AI developers"), and those that combine both approaches. We then assess how these sourcing strategies influence the volatility of firms' productivity growth trajectories. Using our preferred specification to account for this heterogeneity, we find that higher volatility in productivity growth is observed only among AI buyers, whereas firms that develop AI in-house or use an hybrid

[4]Close to our work, but with a different perspective, Bianchini et al. (2022) analyse research activities and show that the impact of AI use on output quality is highly uncertain.

[5]Determinants and consequences of decisions of make-or-buy AI systems have been studies in Hoffreumon et al. (2024) and Calvino and Fontanelli (2024).

strategy do not exhibit this effect. This divergence suggests that firms' ability to integrate and leverage AI effectively depends not only on access to the technology *per se*, but also on their internal capacity to absorb and apply it productively. Absorptive capacities have been shown to play a crucial role in determining how firms assimilate, activate, and exploit new knowledge thereby shaping its complementarities with existing firm-specific assets (Cohen and Levinthal, 1990). In line with the concept of absorptive capacity, firms that develop AI in-house are likely better equipped to internalize and refine AI-driven processes, aligning them with existing workflows and minimizing disruptive fluctuations. In contrast, AI buyers seem to struggle to assimilate and optimize externally sourced AI, leading to greater instability in productivity growth.

To operationalize one important dimension of absorptive capacity in our context and explore its role in shaping firms' ability to integrate AI without destabilizing productivity growth, we conclude our investigations turning our attention to the presence of ICT specialists within AI users. Leveraging a feature of our dataset – the matching of employer data with employee information –, we calculate for each firm the share of hours worked by ICT engineers and technicians and investigate whether their presence is able to mitigate the volatility effects associated with AI adoption. Our analysis reveals that the effect of AI on productivity growth volatility among AI buyers is reduced when firms have a higher proportion of workers with ICT expertise. These new results corroborates the intuition that a workforce with strong AI expertise is a critical precondition for stabilizing productivity growth dynamics. Firms that source AI solutions externally, but have a workforce equipped with ICT knowledge, are better positioned to integrate AI effectively. This finding contributes to the literature highlighting the importance of complementing AI adoption with ICT- and STEM-specialized human capital (Calvino and Fontanelli, 2023; Babina et al., 2023; Harrigan et al., 2023; Acemoglu et al., 2022; McElheran et al., 2023; Fontanelli et al., 2024). We extend this body of work by showing that the risks of inadequate AI integration go beyond limiting productivity gains, they also introduce greater instability, potentially deterring firms from adopting AI in the first place.

From a policy perspective, our findings support the case for industrial policies to mitigate the technological uncertainty associated with the early adoption of general-purpose technologies (GPTs) such as AI systems (see Bresnahan et al., 2002). Specifically, they highlight that the impact of AI on productivity growth volatility depends on the type of AI user and the characteristics of firms. Policies aimed at facilitating firms' access to essential complementary assets during the AI adoption process could yield a double benefit: smoothing productivity growth dynamics and lowering barriers to AI adoption, thereby fostering further digital investment.

The remainder of the paper is organised as follows. In Section 2 we discuss the theoretical framework, methodology, data and identification structure that we aim at using for studying the research question at stake. In Section 3 and 4 we discuss the main results and the mechanism mediating the positive effect of AI on the volatility of productivity growth rates. In Section 5 we draw the conclusions. Four appendices complete the paper with more details about descriptive statistics (Appendix A), robustness check of the baseline OLS models (Appendix B), of the CEM models (Appendix C), and of the models accounting for heterogeneity in the AI adoption strategies (Appendix D).

2 Data, empirical framework and identification strategy

2.1 Data

In this work we make use of an ICT representative survey distributed to about 9,000 French firms with 10 or more employees in 2019. We complement information provided by the survey with administrative data from balance-sheets and income statements and with employers-employees matched data. All data sources are provided by the French National Institute of Statistics and Economic Studies (INSEE).[6] Below we describe the basic features of these data in presenting the way we define our empirical proxies.

AI use. Our variable of interest is a dummy that proxies the use of predictive AI. To build this proxy we leverage the French ICT survey distributed in 2019 encompassing a representative sample of approximately 9,000 firms with a workforce of 10 employees or more and spanning the manufacturing and non-financial services sectors. This sample contains firms with on average 50 employees and 20 years of age. Our data exhibits an exceptional degree of detail in contrast to alternative commercial surveys and enables a comprehensive exploration of the patterns of AI adoption among firms.[7] We define a dummy variable AI_i that takes the value 1 if firm i reports using predictive AI technologies as of 2018.

Figure 1: Computing volatility of productivity growth rates.

	2012	2013	2014	2015	2016	2017	**2018**	2019
Firm 1	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	**0**	0 (0)
Firm 2	0 (1)	0 (1)	0 (1)	0 (1)	0 (1)	0 (0)	**0**	0 (0)
Firm 3	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)	**1**	1 (1)
Firm 4	1 (0)	1 (0)	1 (0)	1 (0)	1 (1)	1 (1)	**1**	1 (1)

Notes: AI 'users' (1) and 'non-user' (0) status over 2012-2019 for four hypothetical firms. ICT survey provides factual information on their status of users in 2018. Since in other years this information is not available, we propagate it backward and forward to cover the entire time span 2012-2019. Then, in the baseline model the volatility of productivity growth rates σ_i is computed only over the time window 2014-2019 (dashed green border). Firms are assumed to have at most one switch from 'non-user' to 'user'. To illustrate misclassification mistakes we report in parenthesis the hypothetical true status. If the two indicators within a cell match, our procedure correctly classifies the firm as a user or non-user (cells with black numbers); if they do not match, the classification contains some measurement error (cells with red numbers).

Volatility of productivity growth rates. The dependent variable in all the empirical investigations below is the volatility of the productivity growth rates of the French firms in our sample. To build this measure we first link to our sample balance-sheet information (sourced in the FICUS/FARE data-sets over the $2007-2019$ period) needed to estimate different indexes of productivity, encompassing both single-factor (value added over labour ratio) and multi-factor alternatives estimated using the single-stage GMM procedure described in Wooldridge (2009). We denote a firm's i productivity level in year t with $A_{i,t}$ and define its logarithmic growth rate as

[6] Access to some confidential data, on which is based this work, has been made possible within a secure environment offered by CASD (Centre d'acces securise aux donnees, Ref. 10.34724/CASD).

[7] Our data is referred to as the "Enquete sur les Technologies de l'Information et de la Communication (TIC)". Further information at this link.

$\omega_{i,t} = \ln A_{i,t} - \ln A_{i,t-1}$.

Deciding over which time window computing the volatility of the firms' growth rates $\omega_{i,t}$ is challenging due to a data limitation. Specifically, while we know which firms reported using AI in 2018, we lack information on the timing of their AI adoption or whether they opted in and out in previous years. This information would indeed be crucial to identify the correct number of times a firm has truly been an adopter during the considered window. To address this challenge we adopt the following procedure. First, we make the conservative hypothesis that the surge in firms' adoption of AI started only after 2011. This hypothesis is justified on the fact that key advancements in predictive AI applications and technologies, such that the "AlexNet" neural network, marking the onset of superior performance of deep learning and artificial neural networks compared to prevailing non-AI methodologies in statistical analyses, took place around that year (see Babina et al., 2024; Engberg et al., 2024). Next, we consider 2012 as the earliest adoption year for all firms declaring to be AI users in 2018. Second, we restrict our time horizon up to 2019 to avoid the Covid-19 crisis. Third, we reasonably assume that firms do not transition in and out of AI technologies more than once over the period $2012 - 2019$. Finally, in selecting the year range $[t_0, t_1]$ to compute σ_i, we balance concerns about noise in volatility estimates against potential biases due to misclassifications and fix as a baseline the interval $2014 - 2019$ including in the computation five growth rates.

Advantages and disadvantages of this procedure are illustrated using Figure 1 which presents the case of four hypothetical firms: non-user ("Firm 1" and "Firm 2") and users ("Firm 3" and "Firm 4"). On the one hand, for firms like "Firm 1" and "Firm 3", our procedure correctly classifies the two firms, although only partially exploiting the sample size of available growth rates. On the other hand, for firms like "Firm 2" and "Firm 4", the partial exploitation of the sample helps us mitigating the bias that could arise from incorrect firm classification when comparing AI users and non-users. In case AI users indeed do exhibit a more volatile productivity growth profile, our approach seems in a first approximation conservative. By extending firm status over the period, we introduce a potential bias that overestimates volatility for non-AI users and underestimates it for AI users. This bias makes it more challenging to detect differences in volatility between the two groups, meaning that any significant difference we do observe is likely a lower bound of the true effect. In any case, recognizing the arbitrariness of our classification procedure, we conduct robustness checks in our empirical analysis by computing σ_i over different time windows.

Firm-level controls. We build two sets of control variables. First, we consider firmographics – including variables such as size, age, industrial sector, geographical localization – come from balance-sheet data.[8] To simplify the notation, we collectively represent them as $FGP_{i,t}$ where t spans the entire time window 2012-2019. Second, leveraging again the ICT survey, we build proxies capturing the extent to which a firm uses digital technologies other than AI. In particular, we build a a categorical variable accounting for the number of other than AI digital technologies in use at the same firm and a dummy capturing the presence of a fast broadband connection.[9] We collectively represent these variables with ICT_i, that do not present any time index since they are all observed only in 2018.

[8]Firmographics, also known as firm demographics, represents are sets of characteristics to segment organizations.

[9]The survey asks explicit questions on the use of Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) software, and involvement in e-commerce activities.

2.2 Empirical framework and identification strategy

Let $A_{i,t}$ represents a multi-factor productivity index of a Hicks-neutral technology. Following the well-established literature (see e.g. Jovanovic, 1982; Hopenhayn, 1992; Luttmer, 2007; Dosi et al., 2016; Fontanelli et al., 2023), we assume that a firm's productivity evolves in time as a simple multiplicative process $A_{i,t} = A_{i,t-1}e^{\omega_{i,t}}$ where $\omega_{i,t}$ represents a firm-specific idiosyncratic term capturing capital deepening, institutional factors or learning dynamics in our productivity measure.

We characterize the vector of firm-specific productivity growth shocks in terms of a density function $\mathcal{G}$. We assume that such a distribution is determined by some firm characteristics $FGP_{i,t}$ as well as by the firm decisions to use predictive artificial intelligence $AI_{i,t}$ or other ICT technologies $ICT_{i,t}$. Formally, we can write:

$$\omega_{i,t} \sim \mathcal{G}(\mu_i, \sigma_i) \text{ with } \begin{cases} \mu_i = \mathcal{F}_\mu(FGP_{i,t}, AI_i, ICT_i) \\ \sigma_i = \mathcal{F}_\sigma(FGP_{i,t}, AI_i, ICT_i) \end{cases}$$

where μ_i and σ_i denote the location and scale parameters of the distribution allowed to be heterogeneous across firms. The functional form $\mathcal{F}$ is assumed instead identical across firms. While hyper-simplified, this framework has the merit to provide a simple representation of the impact of diverse firm characteristics, including the use of AI and of other technologies, on the productivity growth distribution $\mathcal{G}$, in terms of partial derivatives of the functions $\mathcal{F}_\mu$ and $\mathcal{F}_\sigma$ with respect to X, AI and ICT respectively.

This paper is interested in studying $\dfrac{\partial \mathcal{F}_\sigma}{\partial AI_i}$ when AI_i represents the use of predictive AI technologies. As discussed in the Introduction firms may use AI and machine learning to improve the quality of forecasts for sales, inventory, and supply chain management hence moderating productivity growth volatility. However, without proper capabilities to master AI and interpret its outcomes firms may also face an exacerbation of fluctuations in productivity dynamics. To resolve this ambiguity we take $\dfrac{\partial \mathcal{F}_\sigma}{\partial AI_i}$ to the data. Our paper is the first tackling this issue. To carry out this task, we regress the (log) volatility computed over the time span 2014-2019 on an AI adoption indicator while controlling for other ICT technologies adoption, firm characteristics, and sector (2-digit) and region fixed effects

$$\ln \sigma_i = \alpha + \beta AI_i + \gamma_1 \ln FGP_{i,2014} + \gamma_2 ICT_i + \delta_s + \delta_r + \epsilon_i \ , \tag{1}$$

where $FGP_{i,2014}$ includes a firm's size, age and productivity, ICT_i a categorical variable capturing the number of ICT technologies other than AI and a dummy for fast broadband use, and δ_s and δ_r represent sector and region fixed effects. Firmographics are measured in 2014 to alleviate reverse-causality concerns. The identification of β, our parameter of interest, relies on variation in AI adoption across firms within the same sector and region that is not systematically related to unobserved determinants of volatility. Specifically, β is identified from differences in AI adoption among firms with similar pre-existing characteristics, conditional on other ICT usage and fixed effects. While in equation (1) we control for several firm characteristics and for two different sources of unobserved heterogeneity, OLS estimates may be biased for reasons we discuss in the remaining of this section, where we also propose a matching procedure to alleviate endogeneity concerns threatening our identification strategy.

To refine the credibility of our estimation strategy, we implement a Coarsened Exact Matching (CEM) estimator following the approach in Iacus et al. (2012, 2011). CEM is a matching method that reduces model dependence and imbalance between treated and control groups by coarsening the covariates into discrete strata and then performing exact matching within these strata. Unlike OLS, CEM improves covariate balance ex ante, ensuring that treated and control groups are comparable in terms of observable characteristics before estimating the effect of AI adoption. By reducing potential bias from systematic differences between AI adopters and non-adopters, CEM is aimed at strengthening the credibility of the comparison between the treated (AI users) and control (non AI users) groups.

Building CEM estimators entails a two-step procedure. The first step involves coarsening the continuous and categorical covariates into discrete intervals or bins. In implementing CEM, the choice of coarsening levels is crucial: too coarse a classification may lead to poor balance, while too fine a classification may result in excessive pruning of observations, reducing statistical power. The goal is to group observations into strata, where treated and control units belong to the same strata in each coarsened covariate. In our baseline, we build strata using a firm's age, size, productivity, ICT technologies other than AI and industrial sector. For age and size we classify firms using $[5, 10, 20]$ and $[10, 20, 50, 100, 250, 500]$ as break points. The logarithmic transformation of productivity is divided based on 15 equidistant cutpoints, ensuring that the bin distances in levels correspond to fixed percentage differences. ICT technologies and fast broadband are summarized in a single dummy equal one if at least one of them is available to the firm. For sectors, we use the 29 survey classes used in the ICT survey.[10] Note that the choice to prioritize firmographics over the intensity of ICT use (excluding AI) is intentional and reflects the apparent strong complementarity between AI and other digital technologies.

In the second step, we compare AI users and AI non-users in the matched sample estimating an average treatment effect. Unlike other matching estimators, like the Propensity Score Matching, in CEM observations in this second step are weighted based on the number of treated and control units within each stratum. While CEM increases the credibility of our identification strategy, it assumes that firms with identical coarsened covariates are comparable. In practice, some selection bias may remain if other determinants of AI adoption are omitted from the stratification. This is why we add other controls, not used in the matching procedure. Furthermore we control for productivity level at the start of the period and 2019 to at least limit possible reverse causality. Indeed CEM, while effective in addresses selection on observables, does not solve concerns regarding firms adopting AI in response to volatility shocks. Finally, we also explore different approaches to define strata in the matching procedure and we test our results against the use of an alternative matching technique.

3 AI-volatility link

This section presents our empirical results, progressing from descriptive evidence to robust OLS results and concluding with a more credible identification strategy based on a coarsend exact matching (CEM). We complement baseline results with a series of robusteness checks to address the main threats to our identification. Our findings robustly indicate that predictive AI use is associated with greater volatility in productivity growth and provide

[10] Classes are based on the 3-digit NAF classification: 100-129, 130-159, 160-189, 190-239, 240-259, 265-267, 261-264 + 268, 270-289, 290-309, 310-339, 350-399, 410-439, 450-459, 460-469 (excluding 465), 465, 47, 49-53, 55, 56, 582, 58-61 (excluded 582), 61, 62 and 631, 639, 68, 69-74, 77-78 joint to 80-82, 79, 951.

support that this link goes beyond a simple correlation.

3.1 Descriptive evidence

From the representative sample of about 9,000 firms with 10 or more employees used in the 2019 French ICT survey we extract 7,915 firms for which we can build the variables needed in our investigations.[11] As reported in Table 1, in 2018 these firms are, on average, around 22 years old and primarily medium to large-sized enterprises, with a mean of approximately 50 employees. They operate across a diverse range of 61 sectors ranging from manufacturing of food products (#10) to services like the repair of computers (#95), reflecting a broad industrial coverage. Consistent with the existing literature, we observe substantial heterogeneity in productivity across firms. Even within narrowly defined sectors, the ratio between the top and bottom 5% of firms' productivity is of the order of 40 when we use a multi-factor productivity index.[12]

Table 1: Comparing AI users and non AI users.

	Full sample	**Non AI users**	**AI users**
Age	21.7	21.8	22.2
Size	52.3	43.3	121.4***
Productivity	203.0	195.0	263.5***
Fast Broadband	0.13	0.12	0.20***
# other digital technologies	0.90	0.87	1.15***
Volatility of prod. growth rates (σ_i)	0.20	0.20	0.23***
Obs.	7,915	6,715	1,200

Notes: Volatility of productivity growth rates is computed over the time span 2014 − 2019, demographic variables ('Age', 'Size', 'Productivity') are measured in 2014 while ICT technological variables in 2018 where the 'user' and 'non-user' status is recorded. Means are computed using survey weights as well as the corresponding t-tests.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Among the 7,915 firms, 1,200 (approximately 15% unweighted and 11.13% when using sample weights) reported using predictive AI technologies. As shown in Table 1, AI users tend to be significantly larger and more productive than their non-user counterparts. They are also more likely to adopt other digital technologies, such as fast broadband, reinforcing the notion that AI adoption is part of a broader technological transformation. Our key empirical question concerns whether AI use is associated with differences in the volatility of productivity growth trajectories. The unconditional figures in Table 1 suggest that AI users exhibit significantly higher volatility compared to non-users. While still based on preliminary evidence, this result already reveals a somewhat unexpected pattern at least within industrial dynamics. Indeed, prior literature indicates that larger firms typically exhibit less volatile growth trajectories in terms of size (see Stanley et al., 1996; Bottazzi and Secchi, 2006; Calvino et al., 2018, among others). However, our findings points in the direction that this relationship does not extend to productivity growth, as AI-adopting firms, despite being larger on average, experience greater volatility in their productivity growth trajectories. This divergence may well hint at the possibility that AI adoption introduces firm-level dynamics that are specific to productivity rather than overall growth stability.

[11] See Table A.1 in Appendix A for details about the sample size and its composition.

[12] Reassuring on the quality of our data, similar patterns emerge analysing data in other from other surveys (Zolas et al., 2020; McElheran et al., 2023; Calvino and Fontanelli, 2023).

In any case this raw comparison of volatilities in Table 1 does not account for potential composition effects that would indicate that the difference of volatilities between groups are due to differences in firm size, sector composition, or other technological investments. To address these and other concerns, we next turn to a regression framework and estimate the relationship between AI adoption and productivity growth volatility using OLS specification with extensive controls for observable firm characteristics and other unobservable sources of heterogeneity.

3.2 OLS estimates

Table 2 reports these OLS estimates. In the first two columns we focus on the volatility of productivity growth computed over 2014-2019 and progressively add controls, starting with only industry and region fixed effects in Column (1) and then adding firmographics and ICT controls in Column (2). To reduce reverse causality concerns, firm characteristics are measured in 2014, the initial year of the window used to compute volatilities. Across these two specifications, the coefficient on the AI User dummy is positive and statistically significant indicating that firms adopting AI exhibit higher productivity growth volatility than non-AI users even after accounting for multiple sources of omitted variable bias. Although narrowing from a difference of about 15% (computed from the unconditional comparison in Table 1), the difference of about 11% highlighted in Column (2)remains economic seizable. Column (3) shows that the result does not change if we introduce the (log) productivity in 2019 thus controlling for the total 2014-2019 productivity growth. Table B.1 in the appendix reports results tables including estimates for control variables. Estimates for controls are in line with expectations. Reconciling with existing literature older and larger firms are associated with a less turbulent productivity dynamics. The existence of a fast broadband connection with a higher volatility.

Table 2: OLS estimates of Equation (1).

	σ_i **(2014-2019)**			σ_i **(2015-2019)**	σ_i **(2012-2019)**	σ_i **(2007-2012)**
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.083***	0.940***	0.098***	0.057**	0.090***	0.079
	(0.025)	(0.024)	(0.023)	(0.025)	(0.022)	(0.049)
log Productivity (2019)			-0.152***	-0.199***	-0.132***	
			(0.049)	(0.044)	(0.034)	
Controls X_{i,t_0}	No	Yes	Yes	Yes	Yes	Yes
Controls ICT_i	No	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,915	7,915	7,915	7,879	7,462	6,379
Adj. R^2	0.051	0.099	0.108	0.095	0.119	0.112
Clustered SE	Industry	Industry	Industry	Industry	Industry	Industry

Notes: Volatility of productivity growth rates σ_i is computed over the time span $2014-2019$ in columns (1)-(3), and over $2015-2019$, $2012-2019$ and $2007-2012$ in columns (4), (5), and (6) respectively. Firmographics variables ('Age', 'Size', 'Productivity') are measured at t_0, the initial year of the span over which volatility are computed, that is 2014 for the first three columns and 2015, 2012, 2007 for the last three columns. ICT technological variables are measured in 2018, the year in which the AI-related status is recorded. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. All the specifications are estimated using survey weights. The complete table is reported on Table B.1 in Appendix B.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Given our data limitations, one might be concerned that measurement error affects our estimates of productivity growth volatility, particularly due to potential misclassification of AI adoption timing. As discussed above, our approach seeks to balance the trade-off between minimizing noise in volatility estimates and reducing bias from firm misclassification. To assess the robustness of our findings in this regard, we examine how our results change when varying the time window used to compute volatilities. Specifically, we extend the window backward to incorporate earlier growth rates and, also, restrict it forward to focus on more recent periods. Columns (4) and (5) present results of this investigation, using our preferred specification, which includes all controls, fixed-effects and accounts for productivity level in 2019. When we shorten the time window to $2015 - 2019$ in Column (5), our coefficient of interest remains statistically significant, but nearly halves in magnitude, suggesting a smaller gap, around 6%, in volatility between AI users and non-users. Conversely, when we extend the window to its maximum span of $2012 - 2019$ in Column (5), the estimated coefficient β remains very close to our baseline specification and highly statistically significant. These results confirms that the procedure for computing σ_i performs as expected based on our working hypothesis. The potential bias introduced by firm misclassification does not appear to materially affect our findings, suggesting that our approach remains a valid and conservative strategy. At the same time, when we reduce the number of growth rates involved in the computation of σ_i, the associated coefficient attenuates, but this effect aligns with our expectations in case of a greater measurement error.

A second concern is selection bias: if firms with inherently more volatile productivity growth are more likely to adopt AI, our results could be driven by pre-existing differences rather than being the effect of predictive AI use itself. To address this, we conduct a placebo-style exercise using the period $2007 - 2012$, a time frame of the same length as our baseline window, but before AI adoption could have spread. If our findings were purely the result of firms with more volatile productivity growth self-selecting into AI use, we would expect to see a similar association between AI user status (as recorded in 2018) and productivity volatility in this earlier period. Column (6) presents the results, showing no significant relationship between AI user status and volatility in 2007˘2012 and suggesting that our main findings do not seem imputable to pre-existing differences between firms.

Finally we conduct three tests to check that our results are not driven by the specific way we compute the productivity index or by sectoral composition. We first evaluate whether our findings hold when employing a different proxy for productivity (namely labour productivity instead of MFP); second, when a different functional form for volatility is employed (namely the mean absolute deviation); third, when we exclude firms operating in sectors that primarily declare an ICT-related main activity (NACE 58-63). Results of these tests are aligned with those presented in this section and reported in Table B.2 in Appendix B.

In summary, the key insight from OLS estimates is that difference in volatility between AI users and non-users is robust and does not disappear when we condition on firmographic and technological factors, as well as industry and region fixed effects. This difference in volatilities, estimated to be around 10%, holds true when we address potential measurement issues with our dependent variable but disappears in a placebo test further reducing concerns that our result is purely driven by self-selection. Notwithstanding these tests, our evidence remains largely correlational, and identification persists to be a challenge. In the next section, we employ a matching estimator to improve our empirical strategy and move closer to causal inference.

3.3 Refining identification: OLS estimates after CEM balancing

In this section we implement a Coarsened Exact Matching (CEM) estimator. This estimator improves identification by explicitly balancing the distribution of observed covariates between AI users and non-users before estimation. CEM ensures that treated and control firms are more comparable ex ante by pruning observations that lack suitable matches. This matching process improves internal validity, particularly when the overlap between treated and control groups is limited or when nonlinearities in the relationship between controls and outcomes may bias OLS estimates.

Table 3: Comparing AI users and non AI users after CEM balance.

	Non AI users	**AI users**
log Age	3.06	3.08
log Size	4.78	4.82
log Productivity	5.78	5.80
Fast Broadband	0.34	0.41^{***}
# other digital technologies	1.52	1.69^{***}
Obs.	3,897	1,031

Notes: Volatility of productivity growth rates is computed over the time span $2014 - 2019$, demographic variables ('Age', 'Size', 'Productivity') are measured in 2014 while ICT technological variables in 2018 where the 'user' and 'non-user' status is recorded. Strata are built following Section 2.2 generating 1,885 strata, 503 of which are matched reducing the sample size to 4,928 observations. Means are computed using CEM weights as well as the corresponding t-tests.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The first step in our CEM implementation involves constructing strata that group firms into comparable categories based on some observable characteristics. The trade-off here is between using overly fine categories, in turn reducing sample size and statistical power, and coarsening too much, weakening the balance between treated and control groups. As discussed in Section 2.2, in the baseline specification of the CEM, we consider 5 dimensions: size, age, productivity, ICT use and industrial activity. Specifically, we classify firm age using three breakpoints $[5, 10, 20]$, dividing firms into start-ups, young, mature and old ones; firm size is coarsened by means of 6 breakpoints $[10, 20, 50, 100, 250, 500]$, which is equivalent to the sampling structure of the ICT survey ($\leq$20, 20-49, 50-249, 250-499, 500+) except for the fact that we also account for micro-firms with less than 10 employees. The logarithmic transformation of productivity is divided based on 15 equidistant cutpoints, ensuring that the bin distances in levels correspond to fixed percentage differences. We then use a binary classification to separate firms using fast broadband services or other ICT technologies (different from AI) and 29 classes for industrial sectors. CEM generates 1,885 strata, 503 of which are matched, reducing the sample size to 4,928 observations. As a consequence, about 3k firms are lost in the matching process. Table 3 presents the covariates balance between AI users and non-users after implementing CEM. Given our choice to allow finer classification for firm characteristics, the distributions of firm age, size, and productivity are now closely aligned between the two groups. The gap in digital technology adoption remains statistically significant, but it is now smaller than in the original sample. Overall, the balancing process effectively enhances the credibility of our comparisons by making AI users and non-users more similar in observable characteristics.

After preprocessing data with CEM, we compare AI users and non AI reverting to regression analysis. As baseline, we consider the specification used in OLS with controls for firm characteristics, industry and region fixed-effects and a control for productivity measured in 2019 – i.e., Table 2, column (3). Estimates for this baseline are reported in Table 4, column (1). The estimated effect of AI adoption on productivity growth volatility remains positive and statistically significant even under the more rigorous identification strategy of the CEM estimator, reinforcing the idea that the relationship between AI adoption and increased volatility extends beyond a simple correlation. The magnitude of the effect decreases compared to 0.098 in the OLS estimates, suggesting that part of the initial effect was driven by ex ante differences between firm characteristics that CEM helps to balance. Nonetheless, the difference remains of the order of about 6%. As for the OLS, controls enter the regression with the expected sign (cfr. Table C.1 in Appendix C).

Table 4: OLS estimates of Equation (1) after CEM balancing.

	σ_i **(2014-2019)**	σ_i **(2015-2019)**	σ_i **(2012-2019)**	σ_i **(2014-2019)**		**PSM**
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.057**	0.056*	0.098***	0.065**	0.061**	0.104***
	(0.027)	(0.031)	(0.033)	(0.027)	(0.027)	(0.033)
log Productivity (2019)	-0.234***	-0.319***	-0.104*	-0.176***	-0.212**	-0.203**
	(0.070)	(0.067)	(0.055)	(0.067)	(0.075)	(0.060)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,928	4,833	4,585	5,462	6,000	2,399
Adj. R^2	0.192	0.188	0.204	0.182	0.188	0.164
Starting Imbalance	0.811	0.825	0.805	0.811	0.811	
Ending Imbalance	0.712	0.724	0.690	0.721	0.756	
Number Strata	1,885	2,139	1,877	1,530	1,201	
Number Matched Strata	503	518	502	460	376	
Clustered SE	CEM bin	CEM bin	CEM bin	CEM bin	CEM bin	

Notes: Volatility of productivity growth rates σ_i is computed over the time span $2014-2019$ in columns (1) and (4)-(6), and over $2015-2019$, $2012-2019$ in columns (2), (3) respectively. Firmographics variables ('Age', 'Size', 'Productivity') are measured at t_0, the initial year of the span over which volatility are computed. ICT technological variables are measured in 2018 where the 'user' and 'non-user' status is recorded. Industry are defined at 2-digit level and all the specifications are estimated using CEM weights. CEM balancing is performed using baseline classification described in Section 2.2 in columns (1)-(3), with only 10 productivity bins in column (4), with broader classes for age and size in column (5). Column (6) reports results of a PSM estimator. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. All the specifications are estimated using CEM weights. The complete table is reported on Table C.1 in Appendix C.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, in column (2) and (3) we evaluate whether our findings hold adjusting the time window used to compute volatility by both restricting and expanding $(2012-2019)$ the period. Reducing the time window to $2015-2019$ leads to a further decline in the estimated effect with respect to the corresponding baseline, mirroring the pattern observed in OLS (cfr. Table 2). However, with CEM this reduction also results in a loss of statistical significance, making it the first and only case in our analysis where the AI-volatility relationship is no longer significant at the 5% level. In contrast, expanding the time window to $2012-2019$ generates a positive and significant point estimate almost 10% larger than in the baseline. Although directly assessing the significance of this difference is challenging, the direction of the change in both the estimate and its standard error appears consistent. Expanding the time window allows for the inclusion of more treated growth rates in the computation, but may also introduce additional noise.

Proceeding to columns (4) and (5), we explore the sensitivity of our results to alternative coarsening choices in the CEM matching procedure. In particular, we broaden the stratification strategy. First, by reducing the number of productivity bins from 15 to 10 (column 4). Secondly, by reducing the number of break points for age and size (column 5).[13] The AI User coefficient β remains positive and statistically significant in both the specifications with no relevant changes in its magnitude and in the corresponding standard errors. This suggests that the overall relationship is not highly sensitive to changes in stratification, and that the change in sample size does not impact too much on the precision of the estimator.

Finally, in column (6) we further validate our identification strategy by presenting the results derived from an estimator adopting a different matching strategy, namely the Propensity Score Matching (PSM) estimator. While CEM (ex-ante) coarsens covariates into discrete bins before matching and discards observations that do not find a match, PSM estimates the probability of treatment assignment given observed covariates and matches (ex-post) treated and control units based on their similarity in propensity scores. In terms of sample construction, the PSM results to be much more restrictive than CEM, with only 2399 observations preserved, against 4928 with CEM. Compared to CEM, PSM produces a larger point estimate for β (0.117 vs. 0.057), with a slightly larger standard error and a smaller matched sample. Nonetheless, the effect remains positive and statistically significant across both approaches, providing reassuring evidence that the association between AI adoption and productivity growth volatility is robust also across different matching designs.

As with the OLS estimates, we also conduct a battery of robustness tests to ensure that our results are not driven by specific modelling choices or sectoral composition. Once again, we evaluate whether our findings hold when employing a different proxy for productivity (labour productivity instead of MFP), when using an alternative measure of volatility (mean absolute deviation instead of standard deviation), and when excluding firms operating in sectors that primarily declare an ICT-related main activity. Results adhere to the findings reported in the main text and are collected in Table C.2 of Appendix C.

Overall, this section confirms that the observed positive relationship between AI adoption and productivity growth volatility persists even under stricter identification strategies, suggesting that it goes beyond a simple correlation. Having established this pattern, we now turn to investigating a potential mechanism that could explain why AI adoption leads to greater volatility in productivity growth.

4 Unpacking the AI-volatility link

Our empirical findings so far indicate that predictive AI use is associated with increased volatility in firms' productivity growth rates. However, they provide little insight into the economic mechanisms through which AI adoption influences firms' productivity growth and the factors that shape its impact. In this section, we examine whether the impact of AI use depends on how firms source AI. We then assess to what extent differences across

[13] Precisely in column (5) we use, $[5, 10]$ and $[10, 50, 250, 500]$ as break points for age and size respectively.

AI sourcing strategies are mediated by firms' absorptive capacities making them better able to assimilate and exploit new knowledge embedded in AI.

As discussed in the Introduction, the impact of AI on productivity growth volatility is likely to vary across firms depending on their AI sourcing strategy (Arora and Gambardella, 1994; Hoffreumon et al., 2024). Yet the direction of this effect is not obvious ex-ante. Developing AI in-house enables greater customization and integration with existing workflows, potentially reducing volatility. However, it also requires significant investment in technical expertise and organizational adaptation, the absence of which could instead increase volatility. Similarly, purchasing AI solutions generate benefits in terms of economies of scale and lowers upfront costs, which may stabilize operations. At the same time, integration challenges and dependence on external providers could introduce uncertainties, pushing volatility in the opposite direction. To empirically assess how these trade-offs impact volatility, we exploit a key feature of our dataset: the ability to distinguish firms that purchase AI externally, develop it in-house, or do both.

Table 5: Comparing AI buyers, AI developers and AI buyer-developers with non AI users.

	AI non users	**AI buyers**	**AI developers**	**AI buyer-developers**
Age	21.7	22.4	19.8	21.1
Size	45.5	82.4**	259.4***	220.8***
Productivity	195.3	238.4***	293.7***	381.3***
Fast Broadband	0.12	0.15*	0.41***	0.33***
# other digital technologies	0.87	1.0***	1.59***	1.55***
Volatility of prod. growth rates (σ_i)	0.20	0.24**	0.21	0.24*
Obs.	6,603	686	230	266

Notes: Volatility of productivity growth rates is computed over the time span 2014 − 2019, demographic variables ('Age', 'Size', 'Productivity') are measured in 2014 while ICT technological variables in 2018 where the 'buyer' or 'developer' status is recorded. Means are computed using survey weights as well as the corresponding t-tests run against non AI users. The difference of the sample size here with respect to that in Table 1 is due to the loss of 130 firms declaring in the survey to be both buyers and developers or for which we do not have information on workforce.

Table 5 presents descriptive evidence comparing these three groups of AI users with the control group of non-AI users. Among the 1182 firms reporting the use of predictive AI solutions, 686 (approximately 58%) classify themselves as pure buyers, 230 (approximately 20%) as pure developers, and 266 (approximately 22%) as both buyers and developers. As expected, all AI users tend to be larger, more productive, and more intensive users of other ICT technologies comparad to non-AI users. However, when focusing only on AI users, non-trivial differences emerge between groups. AI developers stand out as a distinct group: they are larger, more productive, and significantly more engaged in other ICT technologies than AI buyers, suggesting the presence of a group of AI 'super-users' deeply embedded in digital transformation. Among these super-user firms, those being pure developers looks larger, significantly less productive and slightly younger than firms adopting an hybrid sourcing strategy.[14] More importantly for our analysis, while both AI buyers and AI buyer-developers exhibit significantly higher unconditional volatility in productivity growth compared to non-users, this is not the case for pure AI developers. This preliminary evidence clearly warrants further investigation into whether the volatility-inducing effect of AI adoption is primarily concentrated among firms relying on external AI solutions rather than those

[14]When comparing with a t-test pure developers and buyer-developers among AI users they significantly differ only in their productivity averages.

developing AI in-house.

With this aim we turn to regression analysis and present the results in Table 6. We begin by replicating our preferred specification, including firmographic and ICT intensity controls, as well as region and industry fixed effects, while adding dummies for the three AI user groups. Non-AI users serve as the baseline category. Consistent with our preliminary statistics, the OLS estimates in column (1) indicate that AI adoption is strongly associated with increased productivity growth volatility among AI buyers. For firms adopting a hybrid sourcing strategy, the effect remains positive but is less statistically significant, while for pure AI developers, it disappears. The magnitude of the coefficient for AI buyers is comparable with that found in the OLS estimates for generic AI users (Table 2, column 3), corresponding to an elasticity of about 11%. As above the full set of estimated parameters is reported in Table D.4 of Appendix D, suggesting that controls enter the regression with expected signs.

Table 6: OLS estimates of Equation (1) for different categories of AI users.

	AI users	**AI buyers**		**AI developers**		**AI buyer-developers**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI buyers	0.106***	0.107***	0.055*				
	(0.030)	(0.030)	(0.033)				
AI developers	0.068			0.050	0.064		
	(0.057)			(0.058)	(0.057)		
AI buyer-developers	0.123*					0.109	0.073
	(0.067)					(0.067)	(0.063)
log Productivity (2019)	-0.152***	-0.158***	-0.188***	-0.157***	-0.210	-0.155***	-0.404***
	(0.042)	(0.043)	(0.060)	(0.043)	(0.126)	(0.043)	(0.128)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,785	7,289	3,929	6,833	1,253	6,869	1,738
Adj. R^2	0.110	0.107	0.190	0.116	0.235	0.116	0.278
Starting Imbalance			0.86		0.96		0.95
Ending Imbalance			0.71		0.70		0.83
Number Strata			1,805		1,764		1,768
Number Matched Strata			366		145		152
Clustered SE	Industry	Industry	CEM bin	Industry	CEM bin	Industry	CEM bin

Notes: Column (1) reports the results of OLS estimation on the full sample when AI users are unpacked into different categories. Columns (2) and (3) report the OLS estimation results before and after CEM for AI buyers, columns (4) and (5) for AI developers and (6) and (7) for AI buyer-developers. Volatility of productivity growth rates is computed over the time span $2014-2019$, demographic variables ('Age', 'Size', 'Productivity') are measured in 2014 while ICT technological variables in 2018 where the AI-related status is recorded.The specifications in columns (3), (5) and (7) are estimated using CEM weights, the ones in columns (1), (2), (4) and (6) with survey weights. Strata are built following Section 2.2. Industry are defined at 2-digit level. Regions correspond to 11 French administrative regions. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches.

While these initial OLS estimates are in line with unconditional comparisons, a more robust identification strategy is needed to address potential endogeneity concerns, as done in the previous section. However, with multiple AI user groups, applying CEM balancing is not straightforward, as achieving a well-balanced match across all categories simultaneously is data demanding. Implementing CEM with three treatment groups and jointly balancing all groups ensures the best comparability across treatments, but may significantly reduce the matched sample size due to the need for common support across all groups. The alternative of conducting pairwise matching between each treatment and the control separately, maximizes sample retention for each comparison with the potential cost of leading to different control group compositions, complicating cross-treatment comparisons. Given the size and composition of our sample, we opt for the second strategy. We split the sample, keeping non-AI users as the control group while varying the treated group across the three AI user types. This strategy ensures comparability within each pairwise comparison, while preserving the structure of the original identification framework. A key advantage is that it allows us to maintain well-balanced samples, improving internal validity. The limitation is that it does not allow for direct statistical testing of differences across AI user groups, requiring caution when comparing effect sizes across specifications.

Columns (3), (5), and (7) present OLS estimates after applying CEM balancing.[15] The results show that for AI buyers, the coefficient remains positive and statistically significant, but is nearly halved compared to the OLS estimate in column (1). This mirrors the pattern observed in the previous section, suggesting that part of the initial effect stems from firm characteristics rather than AI adoption per se, though a meaningful association with volatility persists. For AI developers, the coefficient remains unchanged from the simple OLS estimate and is still not statistically different from zero. Finally, for buyer-developers, the coefficient declines and loses statistical significance. For comparison, columns (2), (4), and (6) report OLS estimates for the split samples. The sign and magnitude of the coefficient remain consistent with the patterns observed when using the full sample, as in column (1). Furthermore, we propose specific robustness checks wherein we couple AI buyer-developers either with AI buyers or developers. Results are reported on Table D.3 and broadly confirms the results: differently from AI developers, AI buyers are more volatile.

Overall, these results support the idea that buyers, developers, and buyer-developers represent distinct types of firms in terms of how AI integration affects their production and organizational routines. Specifically, firms that rely on purchased AI solutions tend to face greater uncertainty when incorporating these technologies into their workflows. Several factors may contribute to these difficulties. First, externally sourced AI solutions, designed for broad applicability, may not fully align with a firm's specific business processes. Second, dependence on external providers for updates, maintenance, and troubleshooting can make AI integration more time-consuming, complex, and uncertain. Third, the lack of full control over the technology means that employees, especially those unfamiliar with AI-driven processes, are more prone to misinterpret AI outputs, potentially overreacting to signals they receive. In contrast, firms that develop AI in-house seems to experience a smoother integration process, as they are likely to engage with the technology from its inception. Beyond the ability to fine-tune models to their needs, results suggest that these firms are more likely to foster an internal culture of technological understanding and development, where AI is not just a tool, but an evolving component of the decision-making framework. Employees, whether technical experts or not, are exposed to AI-driven insights early on, facilitating a learning process that reduces uncertainty. As a result, their productivity trajectories may reflect a more deliberate and controlled adoption process, rather than abrupt adjustments driven by external factors. Hybrid firms that both develop AI in-house and purchase external solutions likely fall somewhere between these two extremes.

[15] Table D.1 in Appendix D reports descriptive statistics on comparisons between groups of AI users after CEM balance.

While they rely on external AI solutions, they also benefit from the flexibility and customization of internal development. This combination looks enough to mitigate some of the integration challenges faced by pure AI buyers. Our preferred estimates, after CEM balancing, suggest that hybrid firms do not experience the same increase in productivity growth volatility observed for firms that rely solely on external off-the-shelf AI solutions.

We interpret these findings as suggesting that differences in firms' absorptive capacity, that is in their ability to internalize, adapt, and effectively use new technology, drive the heterogeneous effects of AI on productivity growth volatility (Cohen and Levinthal, 1990). In the remainder of this section, we focus on one key determinant of absorptive capacity: workforce composition. Specifically, we posit that firms developing AI in-house are inherently better equipped to integrate AI into their operations. Their strategic approach to AI adoption necessitates employing ICT technicians and engineers from the outset, ensuring a smoother transition and minimizing disruptions to productivity growth. In contrast, AI buyers may or may not have the requisite digital competencies to integrate AI effectively. If the tacit knowledge embedded in technically skilled workers plays a crucial role in facilitating AI adoption, we should observe that among AI buyers, firms with a higher share of ICT engineers and technicians experience a more moderated impact of AI on productivity growth volatility.

To conduct this analysis, we focus on firms that source AI externally (i.e., pure buyers or hybrid buyer-developers), for which we have estimated at last one statisticall significant effect in Tables 3 and 7. We leverage an additional dataset containing French matched employer-employee data (DADS) and link it to our sample of firms. DADS provides detailed information on the occupations and work hours of employees in French firms, allowing us to identify ICT engineers and technicians and measure their total hours worked in a given year.[16] Using this information, we compute the share of hours worked by ICT engineers and technicians within each firm, denoted as $ICTW_{i,t_0}$ where t_0 is 2014, the first year of calculation of our dependend variable. To incorporate this dimension, we extend our baseline specification (1) as follows:

$$\ln \sigma_i = \beta_0 + \beta AI_i + \beta_w AI_i \times ICTW_{i,2014} + \gamma_1 ICTW_{i,2014} + \gamma_3 \ln FGP_{i,2014} + \gamma_4 ICT_i + \delta_s + \delta_r + \epsilon_i \ , \qquad (2)$$

where the interaction term captures the extent to which the impact of externally acquired AI solutions on MFP growth volatility is dampened by a firm's ability to rely upon a technically competent workforce. Our specification also directly controls for the share of hours worked by ICT engineers and technicians. We estimate β_w, our parameter of interest, following the same identification strategy as before, starting with OLS for comparability before applying the CEM estimator. From a purely descriptive viewpoint, we record that companies classified as non users and pure buyers are characterized by very low shares of ICT hours worked (respectively 2.89% and 2.76%), while a substantially larger share of ICT hours worked is instead achieved by companies with a hybrid AI adoption strategy (17.03%) and by the AI developers (23.08%).

Table 7 presents the OLS estimates of Equation (2) for AI buyers (colums 1 and 2) and for AI buyers or AI buyer-developers (columns 3 and 4).The estimates confirm the previous result that AI adoption is associated with higher productivity growth volatility, but crucially, this effect depends on the presence of ICT specialists within the firm. In column (1), before CEM balancing, the coefficient on AI buyers is significant and found equal to 0.132, reaffirming that firms relying on externally sourced AI experience significantly greater volatility. However, the

[16] Details can be found [here]. We define ICT engineers using occupation codes [388a, 388b, 388c, 388d, 388e] and ICT technicians using codes [478a, 478b, 478c, 478d] according to the 2003 PCS classification.

Table 7: OLS estimates of Equation (2) for AI buyers without and with buyer-developers only before and after the CEM balance.

	AI buyers		**AI buyers and AI buyer-developers**	
	(1)	(2)	(3)	(4)
AI	0.132***	0.075**	0.137***	0.083***
	(0.029)	(0.034)	(0.027)	(0.031)
$ICTW_{i,t_0}$	0.090	0.254	0.041	-0.107
	(0.153)	(0.164)	(0.158)	(0.161)
AI$\times ICTW_{i,t_0}$	-0.911***	-0.404**	-0.588***	-0.266*
	(0.252)	(0.180)	(0.082)	(0.160)
log Productivity (2019)	-0.158***	-0.191***	-0.155***	-0.236***
	(0.043)	(0.060)	(0.041)	(0.069)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes
Observations	7,289	3,929	7,555	4,422
Adj. R^2	0.108	0.191	0.114	0.197
Starting Imbalance		0.86		0.86
Ending Imbalance		0.71		0.71
Number Strata		1,805		1,842
Number Matched Strata		366		437
Clustered SE	Industry	CEM bin	Industry	CEM bin

Notes:
Notes: Columns (1) and (2) report the OLS estimation results before and after CEM for non-users and AI buyers, and columns (3) and (4) report the OLS estimation results before and after CEM for non-users, AI buyers and buyer-developers. Volatility of productivity growth rates is computed over the time span $2014 - 2019$, demographic variables ('Age', 'Size', 'Productivity') and the share of hours worked by ICT technicians and engineers are measured in 2014 while ICT technological variables in 2018 where the AI-related status is recorded. Industry are defined at 2-digit level.Regions correspond to administrative regions of metropolitan France. Strata are built following Section 2.2. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. The specifications in columns (2), and (4) are estimated using CEM weights, the ones in columns (1) and (3) with survey weights.

interaction term between AI buyers and ICT share is negative, significant and large enough to indicate that firms with a higher intensity of ICT workers experience a substantially weaker volatility effect. After CEM balancing (column 2), which ensures a more comparable set of AI buyers and non-users, the story does not change. The coefficient on AI buyers decreases by nearly half to 0.075 remaining significant in large part following the same pattern observed in previous sections. Also, the same is true for the interaction term which remains negative and significant halving in size even in the context of CEM-based identification.

Interestingly, these new point estimates suggest the presence of a threshold effect. Our estimates in column (2), for example, indicate that the marginal impact of AI technologies on the volatility of MFP growth ($\frac{\partial \sigma}{\partial AI}$ can be cancelled only by buyers that have a share of ICT working hours of about 18%. This threshold is approximately 6 times larger than the average share of ICT working hours displayed by AI buyer. Hence, our estimates align well with the absorptive capacity framework, indicating that what matters is not merely the presence of a few highly skilled experts, potentially confined to specialized research units, but rather a critical mass of ICT competence diffused across the organization, ensuring AI technologies are effectively integrated into firm-wide processes.

We report robustness checks in Table D.5 in Appendix D. We explore a different specification augmented with a quadratic term for $ICTW$, and report results for the sample of developers, including their interaction with ICT workers, which is not significantly different from 0.

Taking stock of these evidence leads to the important conclusion that the first waves of predictive AI technologies, developed and adopted between 2012 and 2018, were not meant for "dilettantes", and only firms with a widespread absortive capacity have been able to unleash the potential of these technologies without the perils derived from higher risk.

5 Conclusion

With this study, we provide novel insights into the relationship between AI use and the volatility of firms' productivity growth rates in the early stages of predictive AI diffusion, an aspect largely unexplored by the emerging literature on AI's impact. Our main finding indicates that AI adoption increases the volatility of productivity growth, highlighting the challenges that firms face when integrating predictive AI technologies into their processes. In particular, we find that firms that develop AI systems in-house do not experience this volatility surge, unlike firms that procure AI from external providers. This suggests that firms with established AI capabilities that tailor AI technologies to their specific needs, do not experience drawbacks from AI use. Conversely, AI buyers that purchase predictive AI systems from third parties may lack flexibility and require complementary adjustments for effective integration. Corroborating this interpretation, we find that AI-buying firms endowed with a larger share of ICT workers exhibit lower volatility in productivity growth. This points to the critical role of ICT-related complementary assets in mitigating AI-induced volatility.

Our contribution is twofold. First, we provide empirical evidence on AI adoption's effect on firm-level productivity growth volatility, addressing a gap in the literature. Because prior research has mostly focused on AI's impact on productivity levels, our study underscores the importance of volatility as a key dimension for understanding AI's broader implications. Second, we extend the literature on complementary assets for AI adoption, demonstrating that firms with stronger ICT capabilities and with more absortive capacity are better equipped to manage AI-induced disruptions. These findings align with past experiences with other GPTs (David, 1990; Bresnahan et al., 1996; Brynjolfsson and Hitt, 2003).

Reducing the negative effects of AI-driven volatility could be a relevant policy target, as more uncertainty may deter firms from investing in AI, ultimately limiting its diffusion. Our findings suggest that policymakers can support firms by promoting investments in AI capabilities and ICT human capital, facilitating smoother AI integration.

This study can be extended in several directions. First, a more granular analysis of AI technologies could reveal whether certain AI applications contribute more than others to volatility in productivity growth. Second, future research could examine the long-term effects of AI adoption on volatility. While our study focuses on AI's early diffusion, as firms refine their AI integration strategies, volatility patterns may reverse, with AI users eventually becoming less volatile due to AI-driven improvements in data analytics and predictive capabilities.

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A Descriptive evidence

Table A.1: Samples size and composition.

	Full sample (n. obs.)	Non AI users (n. obs.)	AI buyers (n. obs.)	AI developers (n. firms)	AI buyer-developers (n. firms)
no controls	8,877	7,514	769	280	314
adding FGP_{i,t_0} and ICT_i controls	7,915	6,715	700	232	268
adding also $ICTW_{i,t_0}$	7,785	6,603	686	230	266

B OLS estimates

Table B.1: OLS estimates of Equation (1).

	σ_i **(2014-2019)**			σ_i **(2015-2019)**	σ_i **(2012-2019)**	σ_i **(2007-2012)**
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.083***	0.094***	0.098***	0.057**	0.090***	0.079
	(0.025)	(0.024)	(0.023)	(0.025)	(0.027)	(0.049)
log Productivity (2019)			-0.152***	-0.199***	-0.132***	
			(0.041)	(0.044)	(0.034)	
log Productivity (2014)		-0.151***	-0.049			
		(0.052)	(0.060)			
log Size (2014)		-0.093***	-0.079***			
		(0.021)	(0.024)			
log Age (2014)		-0.049***	-0.052***			
		(0.016)	(0.016)			
log Productivity (2015)				-0.005		
				(0.059)		
log Size (2015)				-0.085***		
				(0.027)		
log Age (2015)				-0.041*		
				(0.022)		
log Productivity (2012)					-0.032	0.005
					(0.060)	(0.067)
log Size (2012)					-0.084***	
					(0.019)	
log Age (2012)					-0.046**	
					(0.019)	
log Productivity (2007)						-0.007
						(0.049)
log Size (2007)						-0.096***
						(0.018)
log Age (2007)						-0.033***
						(0.011)
Fast Broadband		0.053***	0.066***	0.057**	0.079***	0.106***
		(0.019)	(0.019)	(0.022)	(0.020)	(0.026)
Number of Other Digital Technologies = 1		0.031	0.034	0.031	0.015	0.063*
		(0.033)	(0.034)	(0.035)	(0.032)	(0.037)
Number of Other Digital Technologies = 2		0.058	0.063	0.069*	0.024	0.062
		(0.037)	(0.038)	(0.039)	(0.035)	(0.058)
Number of Other Digital Technologies = 3		0.037	0.039	0.040	0.039	0.099
		(0.059)	(0.059)	(0.058)	(0.062)	(0.093)
Constant	-1.913***	-0.783***	-0.565**	-0.589**	-0.707***	-1.538***
	(0.003)	(0.213)	(0.237)	(0.244)	(0.210)	(0.278)
Controls X_{i,t_0}	No	Yes	Yes	Yes	Yes	Yes
Controls ICT_i	No	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,915	7,915	7,915	7,879	7,462	6,379
Adj. R^2	0.051	0.099	0.108	0.095	0.119	0.112
Clustered SE	Industry	Ind. 2d	Ind. 2d	Ind. 2d	Ind. 2d	Ind. 2d

Notes: Volatility of productivity growth rates σ_i is computed over the time span $2014-2019$ in columns (1)-(3), and over $2015-2019$, $2012-2019$ and $2007-2012$ in columns (4), (5), and (6) respectively. Firmographics variables ('Age', 'Size', 'Productivity') are measured at t_0, the initial year of the span over which volatility are computed, that is 2014 for the first three columns and 2015, 2012, 2007 for the last three columns. ICT technological variables are measured in 2018, the year in which the AI-related status is recorded. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. All the specifications are estimated using survey weights.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Robustness checks - OLS estimates of Equation (1).

	Lab. Productivity (1)	Excluding NACE 62-63 (2)	Excluding NACE 58-63 (3)	MAD (4)
AI	0.073***	0.105***	0.111***	0.087***
	(0.021)	(0.023)	(0.023)	(0.023)
log Productivity (2019)	-0.043	-0.157***	-0.157***	-0.131***
	(0.045)	(0.041)	(0.043)	(0.042)
log Productivity (2014)	-0.110*	-0.046	-0.045	-0.061
	(0.059)	(0.062)	(0.067)	(0.049)
log Size (2014)	-0.181***	-0.076***	-0.076***	-0.077***
	(0.013)	(0.024)	(0.026)	(0.022)
log Age (2014)	-0.035**	-0.050***	-0.049***	-0.047***
	(0.016)	(0.016)	(0.017)	(0.014)
Fast Broadband	0.057***	0.075***	0.071***	0.068***
	(0.018)	(0.019)	(0.020)	(0.018)
Number of Other Digital Technologies = 1	-0.006	0.031	0.034	0.042
	(0.031)	(0.034)	(0.034)	(0.031)
Number of Other Digital Technologies = 2	0.036	0.057	0.065*	0.053
	(0.029)	(0.038)	(0.038)	(0.036)
Number of Other Digital Technologies = 3	0.026	0.037	0.043	0.054
	(0.046)	(0.060)	(0.061)	(0.057)
Constant	-0.935***	-0.571**	-0.591**	-0.843***
	(0.075)	(0.244)	(0.256)	(0.225)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes
Controls ICT_i	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	7,915	7,691	7,346	7,915
Adj. R^2	0.108	0.106	0.0962	0.116
Clustered SE	Industry	Industry	Industry	Industry

Notes: Volatility of productivity growth rates σ_i is computed using the ratio of value addded to total employees over the time span $2014 - 2019$ in column (1). Columns (2) and (3) exclude forms with main activity in the ICT service sectors NACE 62-63 and NACE 58-63. Column (4) employes the Mean Absolute Deviation in place of the standard deviation to compute the volatility of productivity growth rates. Firmographics variables ('Age', 'Size', 'Productivity') are measured at t_0, the initial year of the span over which volatility are computed, that is 2014 for the first three columns and 2015, 2012, 2007 for the last three columns. ICT technological variables are measured in 2018, the year in which the 'user' and 'non-user' status is recorded. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. All the specifications are estimated using survey weights.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C CEM estimates

Table C.1: OLS estimates of Equation (1) after CEM balancing.

	σ_i (2014-2019)	σ_i (2012-2019)		σ_i (2014-2019)		PSM
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.057**	0.056*	0.098***	0.065**	0.061**	0.104***
	(0.027)	(0.031)	(0.033)	(0.027)	(0.027)	(0.033)
log Productivity (2019)	-0.234***	-0.319***	-0.104*	-0.186***	-0.212***	-0.203***
	(0.070)	(0.067)	(0.055)	(0.061)	(0.075)	(0.060)
log Productivity (2014)	0.289***			0.213***	0.235***	0.184***
	(0.081)			(0.074)	(0.087)	(0.063)
log Size (2014)	-0.163***			-0.166***	-0.154***	-0.156***
	(0.019)			(0.020)	(0.020)	(0.015)
log Age (2014)	-0.077***			-0.064***	-0.061**	-0.102***
	(0.023)			(0.021)	(0.024)	(0.020)
log Productivity (2015)		0.327***				
		(0.080)				
log Size (2015)		-0.132***				
		(0.026)				
log Age (2015)		-0.090***				
		(0.027)				
log Productivity (2012)			0.163***			
			(0.062)			
log Size (2012)			-0.174***			
			(0.022)			
log Age (2012)			-0.048**			
			(0.024)			
Fast Broadband	0.051	0.103**	0.079**	0.058	0.063*	0.060
	(0.035)	(0.044)	(0.039)	(0.038)	(0.035)	(0.040)
Number of Other Digital Technologies = 1	0.018	0.034	0.024	0.067	-0.002	0.056
	(0.051)	(0.056)	(0.048)	(0.042)	(0.051)	(0.053)
Number of Other Digital Technologies = 2	0.006	-0.029	0.026	0.052	-0.021	0.052
	(0.057)	(0.058)	(0.052)	(0.047)	(0.057)	(0.055)
Number of Other Digital Technologies = 3	-0.015	-0.042	0.071	0.037	-0.005	0.062
	(0.071)	(0.081)	(0.064)	(0.060)	(0.078)	(0.069)
Constant	-1.269***	-1.234***	-1.360***	-1.135***	-1.186***	
	(0.284)	(0.307)	(0.242)	(0.283)	(0.277)	
Controls X_{i,t_0}	Yes	Yes	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,928	4,833	4,585	5,462	6,000	2,399
Adj. R^2	0.192	0.188	0.204	0.182	0.188	0.164
Starting Imbalance	0.811	0.825	0.805	0.811	0.811	
Ending Imbalance	0.712	0.724	0.690	0.721	0.756	
Number Strata	1,885	2,139	1,877	1,530	1,201	
Number Matched Strata	503	518	502	460	376	
Clustered SE	CEM bin	CEM bin	CEM bin	CEM bin	CEM bin	

Notes: Volatility of productivity growth rates σ_i is computed over the time span $2014-2019$ in columns (1) and (4)-(6), and over $2015-2019$, $2012-2019$ in columns (2), (3) respectively. Firmographics variables ('Age', 'Size', 'Productivity') are measured at t_0, the initial year of the span over which volatility are computed. ICT technological variables are measured in 2018 where the 'user' and 'non-user' status is recorded. Industry are defined at 2-digit level and all the specifications are estimated using CEM weights. CEM balancing is performed using baseline classification described in Section 2.2 in columns (1)-(3), with only 10 productivity bins in column (4), with broader classes for age and size in column (5). Column (6) reports results of a PSM estimator. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. All the specifications are estimated using CEM weights. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Robustness checks - OLS estimates of Equation (1) after CEM balancing.

	Lab. Productivity (1)	Excluding NACE 62-63 (2)	Excluding NACE 58-63 (3)	MAD (4)
AI	0.057**	0.068**	0.074**	0.048*
	(0.028)	(0.028)	(0.029)	(0.025)
log Productivity (2019)	-0.096*	-0.228***	-0.224***	-0.200***
	(0.057)	(0.082)	(0.081)	(0.066)
log Productivity (2014)	0.107	0.262***	0.251***	0.267***
	(0.073)	(0.091)	(0.092)	(0.075)
log Size (2014)	-0.169***	-0.142***	-0.141***	-0.163***
	(0.010)	(0.022)	(0.024)	(0.017)
log Age (2014)	-0.074***	-0.079***	-0.069***	-0.073***
	(0.023)	(0.025)	(0.026)	(0.021)
Fast Broadband	0.050	0.065*	0.066*	0.057*
	(0.033)	(0.039)	(0.040)	(0.031)
Number of Other Digital Technologies = 1	0.075*	0.010	0.010	0.018
	(0.040)	(0.053)	(0.054)	(0.046)
Number of Other Digital Technologies = 2	0.055	-0.018	-0.025	0.006
	(0.044)	(0.058)	(0.058)	(0.050)
Number of Other Digital Technologies = 3	-0.014	-0.041	-0.030	0.001
	(0.057)	(0.080)	(0.082)	(0.062)
Constant	-0.873***	-1.235***	-1.226***	-1.548***
	(0.141)	(0.310)	(0.315)	(0.244)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes
Controls ICT_i	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	7,915	7,691	7,346	7,915
Adj. R^2	0.215	0.171	0.159	0.205
Starting Imbalance	0.821	0.809	0.793	0.811
Ending Imbalance	0.770	0.688	0.683	0.712
Number Strata	1,804	1,897	1,783	1,885
Number Matched Strata	481	489	461	503
Clustered SE	CEM bin	CEM bin	CEM bin	CEM bin

Notes: Volatility of productivity growth rates σ_i is computed using the ratio of value addded to total employees over the time span $2014 - 2019$ in column (1). Columns (2) and (3) exclude forms with main activity in the ICT service sectors NACE 62-63 and NACE 58-63. Column (4) employes the Mean Absolute Deviation in place of the standard deviation to compute the volatility of productivity growth rates. Firmographics variables ('Age', 'Size', 'Productivity') are measured at t_0, the initial year of the span over which volatility are computed. ICT technological variables are measured in 2018 where the 'user' and 'non-user' status is recorded. Strata are built following Section 2.2. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. All the specifications are estimated using CEM weights.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D Unpacking the AI-volatility link

Table D.1: Comparing AI buyers, AI developers and AI buyer-developers with non AI users after CEM balance.

	Non AI users	**AI buyers**	**Non AI users**	**AI developers**	**Non AI users**	**AI buyer-developers**
log Age	3.03	3.07	3.01	3.05	3.12	3.12
log Size	4.37	4.41*	5.31	5.36	5.50	5.56*
log Productivity	5.65	5.65	5.84	5.84	6.11	6.17
Fast Broadband	0.27	0.33***	0.46	0.52	0.46	0.53*
# other digital technologies	1.42	1.54***	1.73	1.93***	1.66	1.95***
Obs.	3,243	686	1,023	230	1472	266

Notes: Volatility of productivity growth rates is computed over the time span $2014 - 2019$, demographic variables ('Age', 'Size', 'Productivity') are measured in 2014 while ICT technological variables in 2018 where the AI-related status is recorded. Strata are built following Section 2.2. Means are computed using CEM weights as well as the corresponding t-tests.

Table D.2: OLS estimates of Equation (1) for different categories of AI users.

	AI users	AI buyers		AI developers		AI buyer-developers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AI buyers	0.106***	0.107***	0.055*				
	(0.030)	(0.030)	(0.033)				
AI developers	0.068			0.050	0.064		
	(0.057)			(0.058)	(0.057)		
AI buyer-developers	0.123*					0.109	0.073
	(0.067)					(0.067)	(0.063)
log Productivity (2019)	-0.152***	-0.158***	-0.188***	-0.157***	-0.210	-0.159***	-0.404***
	(0.041)	(0.043)	(0.060)	(0.044)	(0.148)	(0.043)	(0.138)
log Productivity (2014)	-0.054	-0.050	0.129	-0.049	0.374***	-0.047	0.554***
	(0.060)	(0.063)	(0.086)	(0.060)	(0.142)	(0.062)	(0.151)
log Size (2014)	-0.075***	-0.074***	-0.126***	-0.071***	-0.181***	-0.072***	-0.202***
	(0.024)	(0.025)	(0.023)	(0.024)	(0.031)	(0.023)	(0.031)
log Age (2014)	-0.055***	-0.054***	-0.086***	-0.053***	-0.094**	-0.054***	-0.053
	(0.016)	(0.016)	(0.026)	(0.016)	(0.047)	(0.017)	(0.048)
Fast Broadband	0.069***	0.076***	0.091**	0.076***	0.006	0.071***	0.078
	(0.020)	(0.021)	(0.041)	(0.021)	(0.059)	(0.022)	(0.062)
Number of Other Digital Technologies = 1	0.039	0.040	0.021	0.046	0.161	0.045	-0.024
	(0.034)	(0.034)	(0.051)	(0.032)	(0.125)	(0.032)	(0.189)
Number of Other Digital Technologies = 2	0.062	0.057	0.005	0.066	0.096	0.074*	0.033
	(0.039)	(0.041)	(0.060)	(0.040)	(0.132)	(0.038)	(0.197)
Number of Other Digital Technologies = 3	0.040	0.022	0.022	0.033	0.089	0.052	-0.117
	(0.058)	(0.060)	(0.074)	(0.063)	(0.147)	(0.064)	(0.198)
Constant	-0.549**	-0.550**	-0.747**	-0.568**	-2.120***	-0.566**	-1.729***
	(0.240)	(0.251)	(0.366)	(0.238)	(0.502)	(0.244)	(0.471)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,785	7,289	3,929	6,833	1,253	6,869	1,738
Adj. R^2	0.110	0.107	0.190	0.116	0.235	0.116	0.278
Starting Imbalance			0.86		0.96		0.95
Ending Imbalance			0.71		0.70		0.83
Number Strata			1,805		1,764		1,768
Number Matched Strata			366		145		152
Clustered SE	Industry	Industry	CEM bin	Industry	CEM bin	Industry	CEM bin

Notes: Column (1) reports the results of OLS estimation on the full sample when AI users are unpacked into different categories. Columns (2) and (3) report the OLS estimation results before and after CEM for AI buyers, columns (4) and (5) for AI developers and (6) and (7) for AI buyer-developers. Volatility of productivity growth rates is computed over the time span 2014 − 2019, demographic variables ('Age', 'Size', 'Productivity') are measured in 2014 while ICT technological variables in 2018 where the AI-related status is recorded.The specifications in columns (3), (5) and (7) are estimated using CEM weights, the ones in columns (1), (2), (4) and (6) with survey weights. Strata are built following Section 2.2. Industry are defined at 2-digit level. Regions correspond to 11 French administrative regions. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches.

Table D.3: OLS estimates of Equation (2) for AI buyers only before and after the CEM balance.

	AI developers and buyer-developers (1)	(2)	**AI buyers and buyer-developers** (3)	(4)
AI developers and buyer-developers	0.083**	0.058		
	(0.037)	(0.044)		
AI buyers and buyer-developers			0.109***	0.064**
			(0.027)	(0.030)
log Productivity (2019)	-0.155***	-0.295**	-0.156***	-0.238***
	(0.043)	(0.126)	(0.041)	(0.070)
log Productivity (2014)	-0.050	0.461***	-0.051	0.251***
	(0.059)	(0.131)	(0.063)	(0.087)
log Size (2014)	-0.072***	-0.194***	-0.074***	-0.151***
	(0.023)	(0.024)	(0.024)	(0.021)
log Age (2014)	-0.054***	-0.062*	-0.055***	-0.079***
	(0.017)	(0.035)	(0.016)	(0.024)
Fast Broadband	0.069***	0.026	0.070***	0.087**
	(0.021)	(0.047)	(0.020)	(0.038)
Number of Other Digital Technologies = 1	0.045	0.059	0.039	-0.002
	(0.032)	(0.132)	(0.034)	(0.053)
Number of Other Digital Technologies = 2	0.072*	0.076	0.064	0.013
	(0.038)	(0.136)	(0.039)	(0.059)
Number of Other Digital Technologies = 3	0.052	0.000	0.040	-0.021
	(0.062)	(0.144)	(0.059)	(0.075)
Constant	-0.567**	-1.993***	-0.548**	-1.087***
	(0.235)	(0.395)	(0.248)	(0.322)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes
Observations	7,099	2,364	7,555	4,422
Adj. R^2	0.107	0.206	0.108	0.192
Starting Imbalance		0.83		0.86
Ending Imbalance		0.72		0.71
Number Strata		1,800		1,842
Number Matched Strata		242		437
Clustered SE	Industry	CEM bin	Industry	CEM bin

Notes: Columns (1) and (2) reports the OLS estimation results before and after CEM for non-users, AI developers and buyer-developers, columns (3) and (4) for non-users, AI buyers and buyer-developers. Volatility of productivity growth rates is computed over the time span 2014 − 2019, demographic variables ('Age', 'Size', 'Productivity') and the share of hours worked by ICT technicians and engineers are measured in 2014 while ICT technological variables in 2018 where AI-releated status is recorded. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. Strata are built following Section 2.2. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. The specifications in columns (2), and (4) are estimated using CEM weights, the ones in columns (1) and (3) with survey weights.

Table D.4: OLS estimates of Equation (2) for AI buyers without and with buyer-developers only before and after the CEM balance.

	AI buyers		**AI buyers and AI buyer-developers**	
	(1)	(2)	(3)	(4)
AI	0.132***	0.075**	0.137***	0.083***
	(0.029)	(0.034)	(0.027)	(0.031)
$ICTW_{i,t_0}$	0.090	0.254	0.041	-0.107
	(0.153)	(0.164)	(0.158)	(0.161)
AI$\times ICTW_{i,t_0}$	-0.911***	-0.404**	-0.588***	-0.266*
	(0.252)	(0.180)	(0.082)	(0.160)
log Productivity (2019)	-0.158***	-0.191***	-0.155***	-0.236***
	(0.043)	(0.060)	(0.041)	(0.069)
log Productivity (2014)	-0.048	0.130	-0.050	0.251***
	(0.064)	(0.086)	(0.063)	(0.087)
log Size (2014)	-0.073***	-0.125***	-0.074***	-0.151***
	(0.024)	(0.023)	(0.024)	(0.021)
log Age (2014)	-0.054***	-0.085***	-0.056***	-0.080***
	(0.016)	(0.026)	(0.016)	(0.024)
Fast Broadband	0.079***	0.089**	0.074***	0.090**
	(0.020)	(0.041)	(0.020)	(0.038)
Number of Other Digital Technologies = 1	0.039	0.017	0.039	0.001
	(0.034)	(0.052)	(0.034)	(0.053)
Number of Other Digital Technologies = 2	0.057	0.001	0.065	0.016
	(0.041)	(0.060)	(0.039)	(0.060)
Number of Other Digital Technologies = 3	0.022	0.019	0.039	-0.020
	(0.060)	(0.074)	(0.059)	(0.075)
Constant	-0.559**	-0.750**	-0.555**	-1.096***
	(0.252)	(0.366)	(0.249)	(0.322)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes
Observations	7,289	3,929	7,555	4,422
Adj. R^2	0.108	0.191	0.114	0.197
Starting Imbalance		0.86		0.86
Ending Imbalance		0.71		0.71
Number Strata		1,805		1,842
Number Matched Strata		366		437
Clustered SE	Industry	CEM bin	Industry	CEM bin

Notes: Columns (1) and (2) report the OLS estimation results before and after CEM for non-users and AI buyers, and columns (3) and (4) report the OLS estimation results before and after CEM for non-users, AI buyers and buyer-developers. Volatility of productivity growth rates is computed over the time span 2014 − 2019, demographic variables ('Age', 'Size', 'Productivity') and the share of hours worked by ICT technicians and engineers are measured in 2014 while ICT technological variables in 2018 where the AI-related status is recorded. Industry are defined at 2-digit level.Regions correspond to administrative regions of metropolitan France. Strata are built following Section 2.2. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. The specifications in columns (2), and (4) are estimated using CEM weights, the ones in columns (1) and (3) with survey weights.

Table D.5: OLS estimates of Equation (2) for AI buyers, buyers and buyer-developers, and developers only.

	AI buyers	**AI buyers and buyer-developers**	**AI developers**	
	(1)	(2)	(3)	(4)
AI buyers	0.071**			
	(0.034)			
AI buyers and buyer-developers		0.082***		
		(0.031)		
AI developers			0.114	0.034
			(0.090)	(0.069)
$ICTW_{i,t_0}$	1.601***	1.281***	0.024	-0.100
	(0.424)	(0.400)	(0.180)	(0.243)
AI$\times ICTW_{i,t_0}$	-0.389**	-0.295*	-0.293*	0.162
	(0.184)	(0.157)	(0.169)	(0.153)
${ICTW_{i,t_0}}^2$	-1.775***	-1.720***		
	(0.493)	(0.449)		
log Productivity (2019)	-0.195***	-0.242***	-0.157***	-0.211
	(0.060)	(0.069)	(0.044)	(0.148)
log Productivity (2014)	0.127	0.250***	-0.050	0.374***
	(0.085)	(0.086)	(0.061)	(0.141)
log Size (2014)	-0.122***	-0.147***	-0.071***	-0.180***
	(0.023)	(0.021)	(0.024)	(0.031)
log Age (2014)	-0.088***	-0.082***	-0.053***	-0.093*
	(0.026)	(0.024)	(0.017)	(0.047)
Fast Broadband	0.086**	0.080**	0.077***	0.008
	(0.041)	(0.038)	(0.021)	(0.059)
Number of Other Digital Technologies = 1	0.012	-0.006	0.046	0.159
	(0.052)	(0.053)	(0.032)	(0.125)
Number of Other Digital Technologies = 2	-0.007	0.005	0.065	0.096
	(0.060)	(0.059)	(0.040)	(0.132)
Number of Other Digital Technologies = 3	0.002	-0.038	0.032	0.088
	(0.074)	(0.074)	(0.064)	(0.147)
Constant	-0.707*	-1.059***	-0.569**	-2.109***
	(0.366)	(0.321)	(0.238)	(0.502)
Controls X_{i,t_0}	Yes	Yes	Yes	Yes
Controls $ICT_{i,2018}$	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Reg. FE	Yes	Yes	Yes	Yes
Observations	3,929	4,422	6,833	1,253
Adj. R^2	0.194	0.197	0.106	0.190
Starting Imbalance	0.86	0.86		0.964
Ending Imbalance	0.71	0.71		0.696
Number Strata	1,805	1,842		1764
Number Matched Strata	366	437		145
Clustered SE	CEM bin	CEM bin	Industry	CEM bin

Notes: Columns (1) and (2) report the OLS estimation results after CEM for non-users and AI buyers without and with AI buyer-developers respectively. Columns (3) and (4) report the OLS estimation results before and after CEM for non-users, AI developers. Volatility of productivity growth rates is computed over the time span 2014 − 2019, demographic variables ('Age', 'Size', 'Productivity', ICTW) are measured in 2014, while ICT technological variables in 2018 where the AI-releated status is recorded. Industry are defined at 2-digit level. Regions correspond to administrative regions of metropolitan France. Strata are built following Section 2.2. Number Strata and Number Matched Strata are the total number of strata in total and the one with matches. The specifications in columns (2), and (4) are estimated using CEM weights, the one in column (3) with survey weights.