From Bits to Atoms: 3D Printing, Physical Validation, and Firm Growth

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Abstract

This paper investigates whether and how the adoption of 3D printing affected the growth rate of manufacturing firms in France. Using microdata from 2017 and 2019, we document a robust and positive relationship between 3D printing use and firm growth. To shed light on the underlying mechanisms, we distinguish between innovation-focused and production-focused applications of 3D printing. Our results show that the positive association is primarily driven by the use of 3D printing for internal prototyping, underscoring its role in enabling rapid experimentation and validation of design ideas in physical space. Using matched employer-employee data, we find evidence that firms using 3D printing for prototyping exhibit greater hiring of specialized R&D workers, consistent with the innovation-focused channel. Matching to the community innovation survey (CIS) reveals direct evidence of greater and more-novel product innovation in a large subsample of firms. Overall, our findings highlight that the use of 3D printing enables rapid experimentation and operates as an "invention of a method of invention."

Keywords: 3D printing, additive manufacturing, firm growth rate, innovation, R&D.
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1 Introduction

Growing literatures in economics and management examine how digital technologies reshape innovation by lowering the costs of search, experimentation, and recombination (e.g., Goldfarb and Tucker, 2019; Nambisan et al., 2019). The implications for firm and economic growth have attracted particular attention in the case of artificial intelligence (AI), where recent work suggests AI's primary contribution lies not in productive efficiency but in augmented idea generation—functioning as an "invention of a method of invention" (Griliches, 1957) that accelerates the discovery of new products and processes (Cockburn et al., 2018; Agrawal et al., 2018; Babina et al., 2024). Yet this focus on *digital* generation of ideas overlooks a critical constraint in many innovation processes: the *physical* verification of those ideas. Even when prediction—be it AI-assisted or purely human—identifies a promising design, the cost of testing it in the physical world remains a significant bottleneck (Thomke, 1998; Contigiani and Levinthal, 2019; Agrawal et al., 2025).

Many digital technologies also reduce testing and validation costs when evaluation itself can be digitized (as in software or simulated environments). In contrast, for innovations whose performance must be established in the physical world, verification still hinges on fabricating and testing material artifacts. Additive manufacturing (AM), or 3D printing, specifically addresses the digital-to-physical transition by making physical instantiation cheaper and faster (Beltagui et al., 2020; Candi and Beltagui, 2019). Understanding how this translates into firm performance—as well as how it shapes complementary labor market and technology choices—is the focus of this paper.

Addressing these questions requires confronting competing views on what remains an emerging technology with evolving applications and economic potential. A popular view frames 3D printing as a flexible production technology that drives growth by reducing the minimum efficient scale of manufacturing. This view predicts shifts in global value chains (Laplume et al., 2016), reduced reliance on external suppliers (Andrenelli and González, 2021), and the direct sale of highly customized goods (Freund et al., 2022). If this mechanism dominates, the technology's value will be realized through substitution of manufacturing capital in the production of final goods.

An alternative view——which we develop and test in depth——frames 3D printing as an innovation-focused technology that primarily accelerates the validation of ideas. This perspective need not rule out the possibility that firms—particularly smaller firms in highly differentiated markets—will be able to leverage 3D printing in final goods production. Rather, it draws focus to a less-studied and potentially higher-impact channel with distinct implications for firm growth, labor demand, and innovation outcomes in the aggregate.

The core contribution of this paper is to draw out this alternative understanding of AM and empirically test these competing predictions and implications. We first step back to ask whether 3D printing adoption is significantly associated with firm growth, and if so, whether that relationship operates primarily through prototyping or production applications. We then examine the labor market implications to further probe mechanisms. If 3D printing functions as an innovation technology, it should complement R&D workers who design and interpret experiments rather than substitute for production labor. Finally, we directly investigate innovation outcomes—–whether 3D printing enables novel-to-market product innovation—and conduct a "correlation test" for complementarities with AI adoption, which would be consistent with the two technologies addressing different bottlenecks in the innovation process.

Disentangling distinct mechanisms by which flexible technologies may impact firm performance is challenging because standard measurement approaches often treat technology adoption as a binary variable, confounding specific use-cases that may have contrasting economic implications (e.g., Forman et al., 2005; McElheran, 2015). To overcome this challenge, we exploit a unique feature of French ICT survey data that distinguishes between distinct applications of 3D printing: prototypes for internal use, prototypes for sale, goods for internal use, and goods for sale. This allows us to test directly whether growth is achieved through prototyping or production channels. Our matched dataset covers more than 3,700 manufacturing firms observed in 2017 and 2019, linked to administrative records on firm performance and workforce composition. We further link to the Community Innovation Survey (CIS) to observe innovation outcomes for a sizeable subsample of firms.

Our analysis yields four sets of findings. First, 3D printing use is significantly associated with firm sales growth—approximately 7% over a five-year period. Critically, this relationship is driven entirely by the use of 3D printing for internal prototyping; coefficients on production applications are consistently insignificant. This "null result" on production-focused applications suggests that, at the stage of diffusion we observe, the innovation channel is the key driver of 3D printing's economic benefits.

Second, we examine the relationship between 3D printing adoption and labor demand in firms. We find that firms employing 3D printing for prototyping display higher R&D intensity and a stronger association with R&D technical workers, but not general technical staff. This mirrors the findings of Aghion et al. (2025a) regarding AI, suggesting that 3D printing is also is a skill-biased technology that augments the productivity of high-human-capital workers.

Third, we link these mechanisms directly to innovation outcomes. Using the Community Innovation Survey (CIS) data, we show that the use of 3D printing for prototyping is significantly associated with a higher probability of introducing new products to the market.

Finally, we provide high-level insights into how 3D printing and AI adoption interact, a topic of increasing interest as AI diffusion increases across all sectors of economic activity (McElheran et al., 2024; Calvino and Fontanelli, 2024). If, as predicted, AI will augment the generation of new ideas, this has immediate implications for where the bottleneck will arise in search and innovation: testing and validation (Knudsen and Levinthal, 2007; Agrawal et al., 2025). Recognizing this, firms should seek out digital tools for easing the next step in the innovation value chain—and vice versa. The testable implication is that we should observe a high correlation between AI and 3D printing use in the ICT adoption data, which is indeed what we find. The highly correlated adoption is further driven primarily by prototyping applications, again consistent with the innovation channel we hypothesize.

Collectively, these findings suggest that 3D printing serves as a critical but less-studied input to the "innovation flywheel" anticipated from other, purely-digital technologies, like AI. As such, managers and policymakers should be warned that the R&D gains from the digital revolution will not be realized by merely automating the generation of ideas. Rather, inventive processes encompass both the creation of ideas and the experimentation needed to refine them. Investments in complementary methods of invention that accelerate the testing and validation of ideas are crucial for successful innovation.

This paper contributes to a few growing streams of research in economics and management. First, it adds to the burgeoning literature on how digitization shapes innovation processes and outcomes. By lowing the costs of search, experimentation, coordination, and recombination, digital technologies and data have been credited with changing the rate and direction of innovation in both scientific research (Agrawal and Goldfarb, 2008; Ding et al., 2010; Furman and Teodoridis, 2020) and in firms (Forman and Zeebroeck, 2012; Nagaraj et al., 2020; Hoelzemann et al., 2024; Tranchero, 2025; Besiroglu et al., 2024, with profound impacts on performance (Ewens et al. (2018); Wu et al. (2020); Koning et al. (2022); Jin and McElheran (2024)). This paper zeroes in on the "bits-to-atoms" transition when digital inputs require physical instantiation to understand what easing this bottleneck implies for firm performance, labor market choices, and the adoption of potentially complementary technologies like AI.

A key concern with the rise of so many digital technologies has been the broader labor market implications, particularly for those that could substitute for human labor in key production activities (Felten et al., 2021; Eloundou et al., 2023; Autor, 2022). AM is no exception (Felice et al., 2022). This paper contributes to a small but growing stream of work seeking to determine the implications for high-skill workers, finding complementarity with high-skilled cognitive work, rather than substitution (**?**Aghion et al., 2025a).

Finally, we contribute to small but growth literature focused on the human and technological complements to frontier technology adoption. Evidence is increasing that the impact of frontier digital tools is significantly shaped by other investments in human capital, organizational design, other elements of the technology stack, and firm strategic decisions (Bresnahan et al., 2002; Brynjolfsson and Milgrom, 2013; Tambe et al., 2011, 2020,?; Brynjolfsson et al., 2021; McElheran et al., 2025; Calvino and Fontanelli, 2025). Our finding that 3D printing and AI adoption are positively correlated—and that the former robustly correlates with high-skilled human capital—–suggests these complementarities extend across the innovation pipeline, from digital idea generation to physical validation.

More broadly, this paper revitalizes evergreen insights that "methods of invention" (Griliches, 1957) are not confined to the digital realm, and that even promising technologies like AI must operate in broader systems of constraints and complements (Agrawal et al., 2021; McElheran et al., 2025). For firms producing physical goods—–from manufacturing to pharmaceuticals to advanced materials——technologies that ease the testing and validation bottleneck may prove increasingly essential in a world where idea generation becomes cheap.

2 Literature and Motivation

2.1 Digitization, Verification, and Firm Growth

A robust literature in economics and management links the adoption of digital technologies to firm performance (e.g., Brynjolfsson and Hitt, 2003; Tambe and Hitt, 2012; Wu et al., 2020). The advantage of digital tools stems from their ability to reduce fundamental information frictions such as search, replication, transporation, tracking, and verification (Goldfarb and Tucker, 2019). As these frictions decline, firms can identify opportunities faster, scale solutions more cheaply, and coordinate activities more effectively.

A core question in the strategic management of technology is whether these advantages manifest primarily as operational efficiency (cost reduction, higher total factor productivity) or growth (revenue expansion, increased size). While early research viewed IT primarily as a tool for automating routine tasks, a converging body of work emphasizes the growth channel.

In the information systems literature, Mithas et al. (2012) provide evidence that digital investments have a larger impact on revenue growth than on cost reduction, primarily by enabling firms to improve product quality and customer satisfaction. Yoo et al. (2012) conceptualize digital technologies as "generative" resources. Unlike specific-purpose manufacturing assets which are constrained by their physical form, digital tools are characterized by reprogrammability and data homogenization. This grants firms the capacity for "digital recombination"—–the ability to rapidly reconfigure existing designs and data into new products and services at near-zero marginal cost.

This generative capability provides a theoretical micro-foundation for the returns to scale observed in recent economics research. For example, Hottman et al. (2016) provide structural evidence that such improvements in product quality and variety—–rather than simple price reductions—–are the primary drivers of firm growth and heterogeneity. Lashkari et al. (2024) connect this explicitly to digitization by demonstrating structurally that, because digital technologies reduce the organizational costs of managing complexity, they allow firms to expand their product variety and scale of operations. Furthermore, pure efficiency gains can ultimately lead to growth. Acemoglu et al. (2020) find that adoption of advanced technologies (specifically, robots) induces a“ scale effect" where firms *leverage* efficiency gains to expand market share rather than simply reducing inputs.

Additive manufacturing (AM) combines the economic properties of both digital and physical automation technologies. As a digital technology, AM reduces the costs of replication and search: designs can be modified, recombined, and reproduced at near-zero marginal cost (Goldfarb and Tucker, 2019). As a physical automation technology, AM reduces the fixed costs associated with tooling and setup that traditionally constrain manufacturing flexibility (Baumers et al., 2016).

More deeply, AM further addresses a core, often-overlooked friction that *neither* conventional IT nor industrial robotics directly targets: the high cost of translating digital designs into initial physical prototypes. While digital tools allow for the costless iteration of designs ("bits"), the translation of those designs into material form ("atoms") has traditionally been constrained by the rigidity of physical manufacturing capital. Traditional methods of physical prototyping—–injection molding, CNC machining, casting—–require significant tooling and setup, creating a bottleneck between digital ideation and physical validation (Thomke, 2003). This gap between idea generation and validation is argued to be a rising concern in the age of AI (Agrawal et al., 2024).

AM fundamentally alters this cost structure by enabling **direct digital manufacturing**. By fabricating objects layer-by-layer directly from code, it eliminates the need for intermediate tooling. This uncouples the cost of *instantiation* from the complexity of the design.

This uncoupling effectively releases the firm from the traditional trade-off between variation and cost. By allowing for the rapid physical realization of digital designs, AM grants manufacturing firms the capacity to accelerate product development (time-to-market) as well as facilitate the direct manufacturing of complex geometries (product variety). The removal of these frictions predicts an expansion in the firm's effective scale of operations relative to non-adopting competitors. We therefore establish a baseline prediction regarding the technology's net impact on firm performance:

Hypothesis 1 (Baseline): *The use of 3D printing is positively associated with firm* *growth.*

2.2 Mechanism 1: Flexible Production and Asset Substitution

While Hypothesis 1 predicts a positive aggregate effect, the specific economic mechanism driving this growth remains theoretically ambiguous. The first possibility is that AM operates primarily as a production technology that substitutes for traditional manufacturing assets.

In standard production economics, traditional manufacturing is characterized by high fixed costs and significant economies of scale. These constraints dictate firm boundaries: firms often outsource the production of intermediate goods to specialized suppliers to avoid the high transaction costs of internalizing specialized capital (Williamson, 1985). However, technological shifts frequently force firms to redraw these boundaries to capture value (Kapoor and Adner, 2012). Proponents of the "flexible production" hypothesis argue that AM effectively reduces the minimum efficient scale of production to a single unit (d'Aveni, 2015). By eliminating the need for tooling and molds, the technology theoretically allows firms to re-integrate their supply chains, internalizing the production of final goods or intermediate inputs that were previously outsourced (Laplume et al., 2016).

If this mechanism dominates, the economic value of AM arises from asset substitution: the firm replaces external suppliers or capital-intensive internal machinery with digital fabrication tools to reduce inventory costs and increase responsiveness. In this scenario, firm growth is driven by price competitiveness and vertical supply chain reintegration. We would therefore expect growth to be associated with the use of the technology for the production of final goods, independent of R&D activities.

Hypothesis 2 (Production Substitution): *Firm growth is positively associated with the use of 3D printing specifically for the production of final goods or intermediate inputs.*

2.3 Mechanism 2: Invention in the Method of Invention (IMI)

While the production substitution argument is intuitive, we argue that it is unlikely to be the primary driver of performance gains at this stage of AM's diffusion. We do not dispute that such applications exist. However, the realization of a new technology's potential often depends on the development of complementary assets—materials, equipment, skills, and standards—that constitute an industrial ecosystem (Adner and Kapoor, 2016). For AM, this ecosystem remains immature: available materials lack the performance characteristics required for many production applications; post-processing capabilities are limited; and certification standards for quality assurance have not yet been established in most industries

(Baumers et al., 2016). These ecosystem limitations impose binding constraints on production applications, limiting AM's viability as a substitute for traditional manufacturing at scale.

An alternative framework locates the primary value of AM not in manufacturing execution, but in the innovation process that precedes it. We ground this mechanism in the concept of an "invention of a method of invention" (IMI). Introduced by Griliches (1957) and recently formalized in the context of AI by Cockburn et al. (2018), an IMI is a technology that fundamentally alters the "playbook" of how new ideas are discovered and validated. We argue that AM operates as a distinct IMI for the physical domain. By fundamentally altering the cost structure of validating designs in physical space, it serves as a critical complement to the discovery process, increasing the efficiency of R&D rather than production.

To link this explicitly to growth, we rely on the economics of experimentation (Thomke, 2003) that treats innovation as a search process constrained by the cost and fidelity of testing. Knudsen and Levinthal (2007) decompose search into *discovery* (generating options) and *evaluation* (testing options). While digital simulation has reduced the cost of discovery, physical evaluation remains a bottleneck, as discussed above.

In more detail, AM addresses this bottleneck by changing the economics of iteration, enabling what Thomke (2003) defines as *"Front-Loading."* This operates through two channels:

- **Frequency (The Cost Channel):** By reducing the marginal cost of a prototype, AM allows firms to run *more* experiments per unit of time. This increases the probability of finding a high-value outlier design.

- **Fidelity (The Information Channel):** By allowing for physical testing earlier in the design cycle, AM improves the signal quality of early evaluations. This allows firms to "fail fast"—identifying and discarding technical flaws when they are cheap to fix, rather than discovering them during expensive production ramp-up.

This logic of rapid experimentation extends beyond the product itself to the production process. Just as AM allows firms to prototype a new widget, it allows them to prototype the *tools and fixtures* required to manufacture that widget efficiently. By iterating on the design of jigs, clamps, and assembly aids, firms can optimize their conventional production lines before a single unit is sold. Thus, this enhanced "Method of Invention' generates value not only through superior products (product innovation) but through the development of more efficient manufacturing routines (process innovation).

Under this view, the technology's value is realized not through the sale of the printed object, but through the *information generated by the prototype(s).* Unlike Mechanism 1, where AM replaces the production line, here AM improves the product and its production process.

Hypothesis 3 (IMI):*Firm growth is positively associated with the use of 3D printing specifically for prototyping (not for the production of final goods).*

2.4 Labor Complements to 3D Printing

If AM operates as an IMI, its impact on labor demand should be distinct from traditional automation. We focus specifically on R&D human capital, a choice motivated by recent empirical work measuring occupational exposure to digital technologies.

Scholars have recently argued that highly skilled, creative professions exhibit the highest "exposure" to new technologies. Felten et al. (2021) document this link for AI generally, while Eloundou et al. (2023) find an even stronger correlation for generative AI, noting that jobs with higher barriers to entry—such as engineering and science—face the highest degree of task overlap. While such exposure is frequently interpreted as a signal of potential displacement (raising alarm about the automation of cognitive tasks), we argue that in the context of an IMI exposure effectively signals **complementarity** rather than substitution. This is a major departure from how mainstream media has interpreted "AI exposure."

Yet the literature on skill-biased technological change supports this view. Aghion et al. (2025b) demonstrate that AI augments the productivity of workers engaged in ideation and creative tasks. Similarly, Rock (2019) shows that returns to AI investments are highest when combined with technical talent capable of leveraging these tools.

We extend this logic to AM, arguing that realizing productivity gains requires complementary investments in human capital. As McElheran et al. (2025) argue, firms cannot simply purchase digital technologies and expect automatic benefits; they require skilled workers to integrate these tools into experimental workflows. Consistent with this view, evidence shows that firms developing digital technologies internally achieve higher productivity gains (Calvino and Fontanelli, 2024), suggesting that in-house specialized ICT capabilities are crucial for AI (Fontanelli et al., 2025a). Conversely, firms lacking such complementary human capital tend to experience more volatile productivity returns (Fontanelli et al., 2025b). Consequently, if the technology's primary value comes from enabling rapid physical experimentation, it should complement workers who design experiments and interpret results—that is, R&D personnel with the technical expertise to translate ideas into prototypes and iterate based on testing outcome.

The theoretical prediction for ultimate employment *levels* is less straightforward. When the cost of experimentation falls, the quantity of experimentation should increase. However, whether this translates into greater demand for R&D workers depends on the elasticity of substitution between labor and the technology. If AM primarily makes existing R&D workers more productive, firms might maintain employment levels while increasing output. Alternatively, if the marginal return to R&D labor increases sufficiently, firms may expand R&D employment.

We do not resolve this ambiguity theoretically. However, we can make a sharper prediction about the *type* of labor affected. The "method of invention" framing implies that AM should complement cognitive labor engaged in innovation rather than production labor. If AM's value lies in prototyping, we should observe associations with R&D workers, specifically, not with general technical staff.

Hypothesis 4 (Labor Complementarity): *The use of 3D printing for prototyping is positively associated with the demand for R&D technical workers, but not general (non-R&D) technical workers.*

2.5 Innovation Outcomes

The method-of-invention framework generates specific predictions about the types of innovation AM should enable. If AM reduces the cost of physical validation, and if this constraint is most binding when firms pursue designs that differ substantially from existing products, then AM should disproportionately enable novel-to-market product innovations rather than incremental improvements.

The logic follows directly from the limitations of data analytics identified by Wu et al. (2020). Analytics capabilities are most valuable when firms can leverage existing data to identify promising combinations of known technologies. But for radical innovations—products that differ substantially from the firm's existing offerings or from competitors' products—the relevant data does not exist. No amount of analytics can validate a design for which there is no historical performance information. In such cases, the only path to validation is through physical experimentation: building prototypes, testing them, and learning from the results. By reducing the cost of this experimentation, AM enables firms to explore more radical design spaces that would be prohibitively expensive to validate using traditional methods.

This reasoning suggests a clear prediction: AM use for prototyping should be associated with a higher probability of introducing products that are *new to the market*, not merely incremental improvements or imitations of existing offerings.

The prediction for process innovation is less clear. AM can certainly be used to produce tooling, jigs, fixtures, and other process aids, potentially enabling experimentation with production workflows. However, the comparative advantage of AM lies in design flexibility and rapid iteration—attributes that are more valuable for product innovation than for optimizing established production processes. We therefore expect AM's impact to be concentrated in product innovation, with weaker or null effects on process innovation

Hypothesis 5 (Innovation Outcomes): *The use of 3D printing for prototyping is positively associated with the introduction of new-to-market products, but has a weaker or null association with process innovation.*

2.6 Complementarity with Artificial Intelligence

Finally, our framework suggests a potential complementarity between AM and artificial intelligence (AI), which is a topic of high current interest across digitization, strategy, and economics research. If AI accelerates the generation and prioritization of ideas, while AM accelerates the physical validation of those ideas, then the two technologies address different bottlenecks in the innovation process. Firms adopting both technologies may be positioned to realize gains that neither technology could deliver alone.

The logic follows directly from the search framework established in Section 2.3. AI expands the set of candidate solutions a firm can consider by reducing the cost of prediction and enabling search over larger design spaces (Agrawal et al., 2018). But as the set of candidates expands, the validation bottleneck becomes more binding: more ideas require more testing. AM relieves precisely this constraint by enabling rapid physical prototyping. Together, the technologies accelerate the full innovation cycle—from ideation (discovery) through validation (evaluation)—in ways that depend on their joint deployment.

We do not attempt a full causal test of complementarity, which would require exogenous variation in the adoption of both technologies. However, we can examine whether the adoption of AI and AM is positively correlated across firms. As Brynjolfsson and Milgrom (2013) note, while correlation cannot establish causal complementarity, it provides suggestive evidence when combined with a coherent theoretical rationale. If firms recognize the value in deploying these technologies together to balance the discovery and evaluation distinct costs, we should observe a clustering of adoption.

Hypothesis 6 (AI Complementarity): *Firms using 3D printing are more likely to use AI systems, particularly when 3D printing is used for prototyping.*

3 Data

We test our set of hypotheses relying on firm-level data for France. France offers an ideal setting for this study primarily due to its data granularity. Unlike typical firm-level datasets, French matched employer-employee records (DADS) allow us to distinguish specific occupations within the firm. This is essential for testing our labor complementarity hypothesis (H4), which requires separating R&D technical staff from general production labor. Additionally, France's diversified industrial base (aerospace, automotive) and active "Industry of the Future" policy environment ensure our sample captures meaningful variation in advanced technology adoption relevant to other developed economies. Specifically, we rely on four sources of government-collected microdata.

ICT Surveys. The first is the 2018 and 2020 versions of the French ICT survey (*"Enquête sur les Technologies de l'Information et de la Communication (TIC)"*), which is managed by the INSEE (the French statistical office).[1] Each wave of the survey includes a rotating sample counting approximately 9000 firms from both manufacturing and non-financial market-services sectors. The sample is representative for firms with 10 or more employees and is exhaustive for those with over 500 employees.[2] We focus on firms belonging to the manufacturing sectors (approximately 2000 per year), and exclude ones belonging to tobacco and petroleum products.[3,4]

In the ICT Surveys, *"the use of three-dimensional (3D) printing, or additive manufacturing, refers to the use of special printers to create three-dimensional physical objects through digital technology, either by the company itself or through a service provided by another company."*. Questions on 3D printing technologies focus on the purchase of 3D printing services in 2017 and 2019.[5] Importantly, the survey provides information on the different functions and use of 3D printed objects developed or purchased by firms, distinguishing them into four non-exclusive categories: prototypes for internal use, prototypes for sales, goods for internal use, and goods for sales. In our context, we define a 3D printing user as a firm that uses 3D printed objects in at least one of these four categories. Our main 3D printing use variable thus takes the form of a dummy, indicating whether firms use 3D printing technologies or not.

The ICT survey also collects information on firms' use of other digital technologies. Specifically, in both the 2018 and 2020 waves, firms are asked about engagement in e-commerce

[1]Further information about each ICT survey can be found here for 2018 https://www.insee.fr/fr/metadonnees/source/operation/s1062/presentation and here for 2020 https://www.insee.fr/fr/metadonnees/source/operation/s1391/presentation

[2]It is therefore challenging to exploit the panel dimension of these datasets.

[3]The use of 3D printing outside of the manufacturing sector is very rare, with rate of use generally around or below 5% in 1-digit industries. The highest rate is recorded Professional, Scientific and Technical sector (NAF 68-73), where firms provide 3D printing services. This sector has not been included in the analysis because we are interested in studying how 3D printers boost growth by speeding up innovation processes.

[4]The number of firms in NAF 12 and 19 amounts to 2 and 12 respectively in the two years considered.

[5]The survey is distributed in the early months of the reference year. The questions about advanced digital technologies are updated annually, and the ICT surveys run in different years may not include questions about the same technologies.

activities, purchase of cloud services (mail excluded), use of Big Data analytics and presence of robots. Moreover, the survey includes questions on broadband connectivity, specifying whether the firm has no broadband access or a connection speed of less than 2, between 2 and 10, between 10 and 30, between 30 and 100, or 100 Mbit/s and above.

Growth rates and firmographics. We match the ICT survey with the administrative data from French firms' balance sheets (FARE) covering the 2004–2019 period.[6] This dataset provides information on firm sales, age, employment, geographical location, as well as physical and intangible capital.[7] These variables allow us to provide a complete picture of firms using 3D printing technologies, and to control for potential links between size growth and firm characteristics.

R&D workers. We match the ICT survey with French employer-employee data (DADS).[8] These data allow us to build the firm-level share of hours worked by, wages paid to, and presence of technical workers (engineers and technicians), disentangling ones specialized in R&D or other technical tasks, and the average hourly wage of managers and engineers in a firm.[9] In line with suggestions from the classification of occupations into functions provided by the French National Statistical Institute, [10] we consider R&D technical workers to be employees falling within the 4-digit classes 383a, 384a, 385a, 386a, 388a, 473a, 473b, 474a, 474b, 475a, and 478a of the 2003 French PCS classification (*Nomenclature des professions et catégories socioprofessionnelles*). Conversely, non-R&D technical workers include the classes within the 2-digit classes 38 and 47 different from the 4-digit classes characterizing R&D technical workers and mentioned above.

Innovation performance. We source information on innovation performance from the CIS survey (2018).[11] The CIS survey is exhaustive for firms with more than 250 employees (500 employees in the ICT survey) and covers a rotating sample of smaller firms. Therefore,

[6] Additional details about this dataset can be accessed here: https://www.casd.eu/en/source/annual-structural-statistics-of-companies-from-the-esane-scheme/.

[7] All nominal variables are deflated using the SNA A38 industry specific price deflators provided by INSEE, the French National Statistical Office, with the exception of intangible capital, which is deflated using deflators from the EUKLEMS & INTANProd database (Bontadini et al., 2023).

[8] Further information about DADS here https://www.casd.eu/en/source/all-employees-databases-business-data.

[9] It is worth noting that R&D workers are part of the 'techies' definition used in Harrigan et al. (2021). The 'techies' definition encompasses all occupations within the 2-digit classes 38 (executives and engineers) and 47 (Technicians) of the 2003 French PCS classification. Further details and information on the PCS classification can be found here https://www.insee.fr/fr/statistiques/fichier/2401328/Brochure_PCS_ESE_2003.pdf.

[10] The classification can be found here https://www.insee.fr/fr/statistiques/1893116.

[11] We focus on the 2018 CIS survey. More information can be found at this link: https://www.insee.fr/fr/metadonnees/source/operation/s1477/presentation. We cannot rely on the 2020 CIS survey because it is sampled on "enterprises profilées", whereas the 2018 CIS is sampled on legal units, consistent with the ICT surveys (https://www.insee.fr/fr/metadonnees/definition/c1665).

our baseline results focus on large firms (more than 250 employees), for which we can use the weighted ICT survey sample. We extract information from questions referring to the 2016-2018 period, coding responses as binary variables. Specifically, we consider whether firms introduced a new or improved product/service and whether it was new or similar to competitors' offerings, as well as whether firms introduced new or improved processes in areas such as organization of processes/external relations, ICT processing, logistics, marketing, accounting and administration, production methods, and organization of work/decision processes/human resources.

Table 1: Averages for the sample, also divided into firms using or not 3D Printed products.

	All Firms	Using 3D Printers	Not Using 3D Printers
3D Printing User	12,79%		
Physical Capital	5256,1 k€	13939,34 k€	3982,76 k€
Intangible Capital	60,64 k€	177,19 k€	43,55 k€
Employees	65,71	168,04	50,7
Sales	21792,41 k€	60131,72 k€	16170,23 k€
Intermediate Costs	15955,99 k€	42864,75 k€	12010,01 k€
Age	29,83	32,03	29,5
Cloud	14,07%	27,13%	12,15%
Fast Broadband	25,03%	31,29%	24,12%
Robot	24,91%	42,55%	22,33%
E-commerce	9,99%	12,32%	9,65%
Big Data Analysis	13,23%	18,40%	12,47%
Share of R&D Techn. Workers	3,49%	7,42%	2,92%
Share of Non-R&D Techn. Workers	11,21%	17,26%	10,32%
Wage of R&D Techn. Workers	460,02 k€	2239,95 k€	199,00 k€
Wage of Non-R&D Techn. Workers	886,66 k€	3157,87 k€	553,60 k€
Share of Firms with R&D Techn. Workers	37,51%	63,64%	33,68%
Share of Firms with Non-R&D Techn. Workers	67,96%	85,59%	65,37%
Innovation	86,42%	92,80%	83,50%
Product Innovation	77,78%	85,77%	74,11%
Process Innovation	76,78%	81,23%	74,74%

Note: The averages are estimated using survey weights.

Summary statistics. Table 1 provides a snapshot of the French firms using 3D printers in our sample, amounting to 12.79 percent of manufacturing firms. These firms tend to be more capital intensive (both in physical and intangible assets), larger in terms of employment and sales, and slightly older than non-users. 3D printing users are also more digitally advanced than their counterparts, showing more frequent use of other digital technologies such as cloud computing, fast broadband, robots, e-commerce, and big data analytics.

Focusing on the different functions for which AM is used, we note substantial heterogeneity. Consistent with our hypotheses 2 and 3, production of 3D printed prototypes is the most widespread 3D printing application, with 41.7% of firms selling prototypes and 73.1% using them internally.[12] Looking at goods production, only about 20.4% of firms report using 3D printers to print goods to be sold, while internal use of 3D printed products is

[12] The shares do not sum up to 100% because some firms use 3D printing for multiple functions.

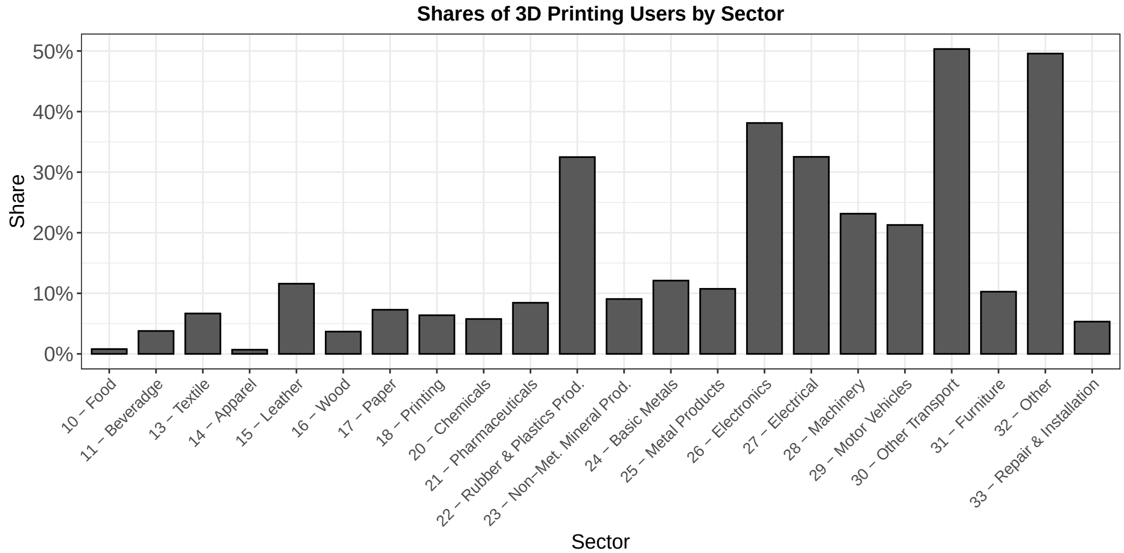

Figure 1: Percentage of firms using 3D printing by 2-digit manufacturing sector.

more common, at 38.7%. These patterns suggest that 3D printing is primarily employed for internal experimentation and product development – a method of invention – whereas the commercialization of 3D printed final or intermediate goods remains relatively limited.

Shifting our attention to complementarities, Table 1 indicates that firms that use 3D printing have a higher share of technical workers, including both R&D and non-R&D staff. They are also more likely to employ technical personnel in general and pay higher wage bills to technical workers. Furthermore, firms using 3D printing technologies are more likely to participate in innovation activities.

Figure 1 reports the share of firms using 3D printing across 2-digit NAF manufacturing sectors, highlighting substantial heterogeneity in use.[13] The highest rates of use are observed in medium- and high-tech industries, where demand for product customization is strong (NAF 32) and design complexity and innovation intensity is high (NAF 22, 26–30), with the exception of the chemical and pharmaceutical sectors (NAF 20–21), where usage remains below 10%. Use is comparatively low in more traditional sectors, such as metal and non-metallic mineral products (NAF 23–25), reflecting the early stage of 3D printing diffusion at the time of the survey, as well as in food, beverage, textile, paper, wood, and printing industries (NAF 10–18), where usage likely relates to niche applications.

[13]The *Nomenclature d'activités française* (NAF) is the French classification system for identifying sectoral activities. The first two digits correspond to the ISIC and NACE classifications.

4 The relationship between 3D printing and growth

This section presents the empirical model linking growth rate and 3D printing in Section 4.1 and discusses the estimation results in Section 4.2.

4.1 The empirical framework

We estimate the relationship between 3D printing use and growth by relying on long-term growth rates. Using short-term growth rates is not good for three key reasons. First, a vast body of research shows that short-term firm growth rates often conform to Gibrat's Law (Gibrat, 1931), especially among more mature surviving firms (Santarelli et al., 2006; Lotti et al., 2003, 2009; Fontanelli, 2024).[14] This suggests that short-run variations in firm size are largely stochastic and therefore ill-suited to capture structural growth determinants that emerge over longer horizons.

Second, prior studies have shown that the performance effects of digital technologies often take time to materialize (Brynjolfsson and Hitt, 2003; Tambe and Hitt, 2012; Brynjolfsson et al., 2018; Acemoglu and Restrepo, 2020; Babina et al., 2024; McElheran et al., 2025). This lag is typically attributed to the substantial organizational transformations required to integrate new technologies effectively. Such reasoning likely extends to 3D printing, where identifying an appropriate internal use case, iterating through prototype development, and embedding the resulting tool into regular operations are processes that unfold over time.

Finally, focusing on short-term growth risks conflating firms that have long used 3D printing with those that only recently adopted it. For early adopters, annual growth captures only the marginal effect of continued use, while for recent adopters, the benefits may not yet have materialized. Consequently, an analysis based on long-term growth rates provides a more accurate picture of the cumulative impact of 3D printing adoption on firm performance.

Empirical model. Our baseline estimation tests the relationship between 3D printing use and firms' sales growth defined as 5-year logarithmic difference in sales. Our baseline regression model reads as follows:

$$\begin{aligned}\text{Growth Rate}_{i,t,t-5} =& a + \beta_1 \text{3D Printing}_{i,t} + \beta_{xt}\textbf{ICT Controls}_{i,t} + \\ &+ \beta_{xt0}\textbf{Controls}_{i,t-5} + \textbf{FE}_s + \textbf{FE}_t + \text{FE}_{Ile} + \epsilon_{i,t}.\end{aligned} \tag{1}$$

For each firm i and year t, the dependent variable Growth $\text{Rate}_{i,t,t-5}$ measures the sales growth rate over the previous five-year period, measured as the logarithmic difference between

[14] According to Gibrat's framework, firm size evolves as $\log s_{i,t} = \log s_{i,0} + \sum_{\tau=1}^{t} \epsilon_\tau$, where ϵ_τ is an independently and identically distributed random variable.

sales. The key explanatory variable, 3D $\text{Printing}_{i,t}$, is a dummy equal to one if the firm reports using 3D printing technology. Following the empirical strategy by Forman and McElheran (2025), we include a vector of controls $\text{X}_{i,t-5}$ measured at the beginning of the period in $t-5$, which includes the logarithms of sales, intermediate goods expenditure, firm age, employment, physical capital, and intangible capital, all measured at the beginning of the period. The vector $\textbf{ICT Controls}_{i,t}$ captures dummies for other digital technologies – robots, big data, e-commerce, and cloud computing – as well as for access to fast broadband. The model further includes vectors of fixed effects $\mathbf{FE}_s$, $\mathbf{FE}_t$, and $\mathbf{FE}_{Ile}$, which account for unobserved heterogeneity across 2-digit industries, years, and main office locations in the Île-de-France region, respectively. Standard errors are clustered at the survey strata level, defined by firm size and industry bins.[15] Growth rates are trimmed at the top and bottom 1% by year to mitigate the influence of outliers[16]

Measuring 3D printing in t. The coefficient associated with the variable 3D $\text{Printing}_{i,t}$ provides an estimate of the average long-term differential in sales growth rates attributable to the use of 3D printing technologies, conditional upon the inclusion of control variables. The ICT survey data only indicates whether a firm employed or developed a 3D-printed object during a specific year, lacking supplementary information regarding the precise year of initial adoption. This introduces a substantial measurement challenge, as firms may have implemented 3D printing prior to the observed period t.

To maintain methodological consistency and address this temporal issue, we adhere to the established empirical strategies prevalent in the literature concerning the effects of ICT adoption on firms (Forman et al., 2012; Forman and McElheran, 2025; Babina et al., 2024). Consequently, we measure 3D printing use at time t rather than at a significantly lagged period (e.g., $t-5$) for the following three primary reasons:

First, employing a significantly lagged measure (e.g., $t-5$) increases the probability that the econometric specification described by Equation 1 conflates users and non-users. Part of firms classified as non-users at $t-5$ may have adopted in subsequent years, which would introduce attenuation bias in the estimated coefficient.

Second, measuring 3D printing use at $t-5$ would prematurely censor the critical early diffusion phase of these technologies, thereby neglecting the initial effects of 3D printing use on growth rates, which are particularly salient to our inquiry. Indeed, historical evidence suggests that the adoption of 3D printing technologies prior to 2009 was highly improbable

[15] Firm bins are based on employment (20-49, 50-99, 100-249, 250-499, and more than 500). Industry bins 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.

[16] Baseline results remain robust to alternative trimming specifications, e.g. trimming the top and bottom 0.5% by year and SNA38 industry.

due to the high cost associated with 3D printing services until the early 2010s (Andrenelli and González, 2021). This implies that the French firms in our sample, observed in 2017 and 2019, likely adopted 3D printing after 2010. Measuring use at t more effectively captures these initial phases of use and, consequently, is expected to absorb the dominant share of performance gains attributable to 3D printing. Furthermore, measuring 3D printing at $t-5$ risks conflating the effects of 3D printing with the dynamics induced by the COVID-19 pandemic in post-2019 data. The pandemic not only accelerated general digital adoption (Avalos et al., 2024; Calvino et al., 2024), but may also have differentially influenced sales disparities between users and non-users through resilience mechanisms associated with broader digitalization rather than 3D printing per se.

Finally, measuring the control variables prior to the widespread diffusion of 3D printing adoption (specifically at $t-5$ in our case) serves to mitigate the risk of "bad control" bias in the estimation of the 3D printing-growth relationship (Angrist and Pischke, 2008). Controls measured in 2012 or 2014 are less likely to have been endogenously influenced by the firm's 3D printing diffusion process, which was generally in its early stages during those earlier periods.

Control variables. The vector of control variables, denoted $\mathrm{X}_{i,t-5}$, encompasses a comprehensive set of time-varying firm characteristics measured five years prior to the observation period. Specifically, this vector includes the logarithm of firm age, sales, employment, intermediate costs, physical capital, and intangible capital. The empirical specification further incorporates fixed effects to account for unobserved heterogeneity at the 2-digit industry, regional, and year levels.

The inclusion of these firm-level controls is essential for mitigating a key source of endogeneity. Characteristics such as firm size, the pre-existence of other digital technologies, and capital structure are often linked both to a firm's propensity to adopt frontier technologies, such as 3D printing (Cho et al., 2022), and to its subsequent performance. Consequently, conditioning on these variables reduces potential self-selection biases.Furthermore, firm age is explicitly controlled for to account for heterogeneity in managerial practices and ICT capabilities that may simultaneously influence 3D printing utilization and overall performance. Given that younger firms tend to exhibit a greater likelihood of adopting emerging technologies, controlling for age serves two purposes: it helps reduce bias stemming from omitted variables while also isolating the independent effect of size from its potential interaction with 3D printing use.

4.2 Estimating the 3D printing-growth rate relationship

OLS results. Table 2 shows the results of the estimation of Equation 1. Across all specifications, the association between the use of 3D printing technologies the long-term growth rate of French manufacturing firms is positive and statistically significant, providing evidence in support of Hypothesis 1. This relationship holds after introducing fixed effects for industry, year, geography (Column 1), when controlling for time-varying firm characteristics (Column 2) and after introducing further control variables measuring the use of other ICTs and the presence of fast broadband (Column 3). Firms using 3D printers grew 7.1% more than non-users over the 5-years period considered. Comparable results are obtained when computing growth rates over three- and seven-year intervals. The annualized increase in growth rates from the fully controlled models, corresponding to Columns (3), (4), and (5), amount to 1.42%, 0.96%, and 1.22%, respectively.

Table 2: 3D Printing and Firm Growth

	(1)	(2)	(3)	(4)	(5)
3D Print (t)	0.0614***	0.0875***	0.0710***	0.0289**	0.0856***
	(0.0222)	(0.0204)	(0.0214)	(0.0131)	(0.0229)
Observations	3,758	3,758	3,758	3,731	3,511
Adj. R2	0.0341	0.132	0.150	0.0678	0.153
Firm Characteristics	No	Yes	Yes	Yes	Yes
ICT Controls	No	No	Yes	Yes	Yes
Industry, Year, Geog. FE	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of the OLS estimation of Equation 1. The dependent variable is the firm's sales growth rate between t and $t-5$ in Columns (1)-(3), $t-3$ in Column (4) and $t-7$ in Column (5). Other controls include the following firm-level controls (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots and availability of fast broadband, measured in t. All regressions include 2-digit industry, year and Île de France dummies. The specifications are estimated using survey weights. Standard errors are clustered at the survey strata level. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.

Threats to identification. It widely assumed that better-performing firms self-select into frontier digital technologies (Cathles et al., 2020; Acemoglu et al., 2023; Calvino and Fontanelli, 2025), making the relationship uncovered by Table 2 potentially endogenous. We complement baseline OLS results with a series of robustness checks to address the main threats to our identification and report them in Appendix A.1. First, we address them by exploring whether the use of 3D printing and growth were associated in a period wherein the use of 3D printing was highly unlikely given that 3D printers were very expensive. Second, we control for unobserved firm-level time-invariant heterogeneity in time-firm fixed effect specifications, which can be interpreted as event study specifications. Third, we balance the sample based on observable heterogeneity and estimate OLS on the balanced sample.

Our findings robustly support the interpretation that 3D printing use is positively associated with sales growth and that the relationship emerged after 2009.

5 Mechanisms

Production Substitution vs IMI. After assessing the link between 3D printing adoption (Hypothesis 1), we investigate whether such relationship is driven by the substitution of intermediate and final goods production (Production Substitution Hypothesis, HP2) or by an increased ability for firms to physically validate innovative ideas (Invention in the Method of Invention Hypothesis - IMI, HP3). Specifically, we extend the specification in Equation 1 to include separate coefficients for four distinct AM applications: (i) internal use of 3D printed prototypes, (ii) internal use of 3D printed goods, (iii) sales of prototypes, and (iv) sales of 3D printed goods. Table 3 presents the results from OLS specifications across different growth rate intervals (Columns 1–3). Notably, only the coefficient on the internal use of 3D printed prototypes is positive and statistically significant. In particular, the estimated annualized increase in growth rates from Table 3 is 1.44%, 1.54%, and 1.20%, closely matching the estimates from the model using the aggregate 3D printing coefficient (see Table 2). This indicates that almost the entire relationship between firm performance and AM adoption is driven by the internal use of 3D printed prototypes, highlighting the central role of rapid prototyping in fostering firm growth.

These results lend support to the hypothesis that 3D printers are mainly used by firms to experiment in the innovation process that precedes manufacturing (Hypothesis 3) rather than in the process of manufacturing itself, via the substitution of production (Hypothesis 2).

In this section we investigate the relationship between 3D printing and its complements, leveraging data on R&D workforce and AI use.

Labor Complementarity. To test the labor complementarity hypothesis (HP4) – that 3D printing is positively associated with the demand for R&D technical workers, but not general technical ones, we further modify Equation 1 by replacing the dependent variable with i) the total wage expenditure or iii) the share of hours of technical workers in R&D or non-R&D activities, or iii) a dummy indicating their presence in the firm. When the dependent variable is total wage expenditure, we estimate a Heckman selection model; otherwise, we use OLS. Only approximately 37% of firms employ R&D technical workers (see Table 1). The exclusion restrictions in the Heckman selection model is the presence of R&D workers in the firm lagged five years.[17]

[17] Additional robustness checks include using the probability that similar firms employed R&D workers in

Table 3: 3D printing Applications and Firm Growth

	(1)	(2)	(3)
Internal Use of 3D Printed Prototypes (t)	0.0720**	0.0462*	0.0843**
	(0.0290)	(0.0251)	(0.0331)
Internal Use of 3D Printed Goods (t)	0.0268	-0.0173	0.00373
	(0.0458)	(0.0243)	(0.0377)
Sales of 3D Printed Prototypes (t)	0.00793	0.00668	0.0781
	(0.0379)	(0.0233)	(0.0494)
Sales of 3D Printed Goods (t)	0.0427	0.0162	-0.0362
	(0.0555)	(0.0433)	(0.0758)
Observations	3,758	3,731	3,511
Adj. R2	0.151	0.0683	0.155
Industry, Year, Geog. FE	Yes	Yes	Yes
Other Characteristics	Yes	Yes	Yes

Note: Columns (1)–(3) are estimated using OLS on the full sample of firms, measuring growth over different periods. The dependent variable is the firm's sales growth rate between t and $t-5$ in Column (1), $t-3$ in Column (2) and $t-7$ in Column (3). Other controls include the following firm-level variables (in logarithmic terms): sales, physical and intangible capital, firm age, employment, and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots, and availability of fast broadband, measured in t. All regressions include 2-digit industry, year, and Île-de-France dummies. Regressions are estimated using survey weights. Standard errors are clustered at the survey strata level. Estimated coefficients of firm-level controls are not reported but are available upon request. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: 3D printing functions and R&D workers

	R&D Technical Workers				**Non-R&D Technical Workers**			
	(1) Share	(2) LPM	(3) Wage	(4) Selection	(5) Share	(6) LPM	(7) Wage	(8) Selection
Internal Use of 3D Printed Prototypes (t)	0.0316***	0.0767***	0.446***	0.248***	0.0139	0.0144	0.0720	0.384
	(0.00893)	(0.0266)	(0.0827)	(0.0943)	(0.0149)	(0.0364)	(0.0790)	(0.375)
Internal Use of 3D Printed Goods (t)	-0.0126	-0.0397	-0.0714	-0.185	-0.0270*	-0.0425	-0.00968	-0.207
	(0.00867)	(0.0406)	(0.0912)	(0.176)	(0.0149)	(0.0570)	(0.104)	(0.391)
Sales of 3D Printed Prototypes (t)	-0.00570	-0.0309	-0.0962	-0.272	0.0425**	0.0224	0.115	0.0323
	(0.00638)	(0.0360)	(0.103)	(0.182)	(0.0166)	(0.0237)	(0.0773)	(0.238)
Sales of 3D Printed Goods (t)	0.0276***	0.134	0.282**	0.815**	0.0103	-0.0114	0.231**	-0.214
	(0.0103)	(0.0893)	(0.119)	(0.380)	(0.0224)	(0.0798)	(0.116)	(0.450)
Presence Techies (t-5)				1.530***				1.220***
				(0.0823)				(0.101)
Adj. R2	0.278	0.407			0.261	0.367		
ρ			-0.334	-0.334			-0.332	-0.332
P-value$_\rho$			0.0984	0.0984			0.198	0.198
Observations	3,758	3,758	3,758	3,758	3,758	3,758	3,758	3,758
Industry, Year, Geog. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Columns (1)–(4) report results for R&D technical workers, while Columns (5)–(8) refer to non-R&D technical workers. Columns (1), (2), (5), and (6) present OLS estimates. Columns (3), (4), (7), and (8) report Heckman selection model results, where Columns (3) and (7) correspond to the wage equations and Columns (4) and (8) correspond to the selection equations. Other controls include the following firm-level controls (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots and availability of fast broadband, measured in t. All regressions include 2-digit industry, year and Île de France dummies. The specifications are estimated using survey weights, respectively. Standard errors are clustered at the strata level. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.

We report the results in Table 4. The internal use of 3D printed prototypes is positively and significantly associated with the share (Column 1), presence (Column 2), and wage expenditure (Column 3) of R&D technical workers, whereas no association is found between 3D printing applications and the share, presence, or wages of non-R&D technical workers. Similarly, the sales of 3D printed goods are positively and significantly linked to both the share and wage expenditure of R&D technical workers.[18] Taken together, these results suggest that 3D printing activities are predominantly tied to R&D-related functions within firms, underscoring the technology's role in supporting innovation-oriented labor – producing ideas, or "bits" – rather than broader categories of technical employment. This evidence is in line with the predictions made in hypothesis 4 on labour complementarities, and with the view of 3D printing as an Innovation in the Method of Inventions.

Innovation Outcomes. Does the increased possibility to validate ideas fostered by 3D printing adoption translate in an increase in innovation outcomes for adopting firms? We test this question underlying hypothesis 5 (Innovation Outcomes) by replacing the dependent variable in Equation 1 with a set of variables capturing various innovation outcomes obtained by matching our main dataset to the French Community Innovation Surveys. These include the introduction of product or process innovations by firms, and a breakdown of both categories into goods, services, new to the market, or similar to market (product innovation); or whether it occurs in logistics, marketing, accounting and administration, production, or decision making/HR (process innovation). As in the previous two subsections, the key explanatory variables are dummies reflecting different 3D printing applications.

Results are reported in Table 5, and offer further evidence that the use of 3D printing acts as a catalyst for innovation.[19] Columns 1-4 report on product innovation, while Columns 5-11 focus on process innovation. The internal use of 3D printers for prototyping is positively associated with the introduction of product innovations (Column 1), but not of new services (Column 2), and that the novelty is relatively high in terms of being new to the market (Column 3), as opposed to being similar to what exists in the market (Column 4). In terms of process innovation, the significant association between the internal use of 3D-printed prototypes and process innovations related to internal procedures and external relations

the past, captured by the share of firms with R&D workers within given bins (results unreported, confirming the baseline). We also considered 4-digit industry and employment bins, either lagged five or ten years, and including or excluding firms located in the same department, to account for potential local labor market dynamics. These results are available upon request.

[18]Unreported results indicate that this association weakens or becomes statistically insignificant once the machinery sector (NAF 28) is excluded from the sample, suggesting a sector-specific pattern. Indeed, the machinery sector ranks third in terms of the share of firms using 3D printing for the sales of goods, but does not appear among the top five sectors for any other 3D printing uses.

[19]Unreported evidence – available upon request – shows that results remain robust when including other firms smaller than 250 employees and randomly matched.

may reflect organizational changes accompanying the integration of 3D printing into firms' innovation processes.

Conversely, the internal use of 3D-printed goods is negatively related to innovation in both goods (column 1) and services (column 2), as well as to process innovations concerning internal procedures and external relations (column 5)—though the significance on the latter is marginal. This possibly indicates that these firms focus more on optimizing internal processes rather than developing new products.

The sale of 3D-printed goods is very positively associated with process innovations in production (column 10), suggesting that such use is complementary to changes in manufacturing methods. Finally, the sale of 3D-printed prototypes is negatively related to process innovations in marketing and work organization, perhaps reflecting that these firms operate in niche markets where complex organizational structures and extensive marketing activities are less relevant.

Table 5: 3D Printing Applications and Innovation Outcomes

	Innovation Performance										
	Product Innovation				Process Innovation						
	(1) Good	(2) Service	(3) New to Market	(4) Similar to Market	(5) Proced. & Ext. Relations	(6) ICT	(7) Logistics	(8) Marketing	(9) Accoun. & Admin.	(10) Production	(11) Work, Decision, HR
Internal Use of 3D Printed Prototypes (2017)	0.165***	0.0282	0.186***	0.0768	0.138**	-0.00158	-0.00946	0.00627	-0.0889	0.106	0.0787
	(0.0579)	(0.0616)	(0.0688)	(0.0700)	(0.0625)	(0.0703)	(0.0609)	(0.0652)	(0.0575)	(0.0709)	(0.0690)
Internal Use of 3D Printed Goods (2017)	-0.150**	-0.167**	-0.122	-0.136	-0.124*	0.0474	-0.00639	-0.0422	-0.0387	-0.0657	0.0144
	(0.0712)	(0.0655)	(0.0829)	(0.0889)	(0.0709)	(0.0810)	(0.0696)	(0.0730)	(0.0707)	(0.0846)	(0.0817)
Sales of 3D Printed Prototypes (2017)	0.0709	-0.0126	0.00184	-0.0168	0.0280	0.0640	-0.00363	-0.146*	0.126	-0.0149	-0.193**
	(0.0718)	(0.0793)	(0.0982)	(0.0965)	(0.0874)	(0.0955)	(0.0822)	(0.0825)	(0.0787)	(0.0997)	(0.0862)
Sales of 3D Printed Goods (2017)	0.0539	0.00373	-0.0560	0.144	0.131	0.0341	0.0303	0.0826	0.120	0.225**	0.127
	(0.0649)	(0.157)	(0.145)	(0.115)	(0.158)	(0.178)	(0.159)	(0.164)	(0.127)	(0.107)	(0.155)
Observations	536	536	536	536	536	536	536	536	536	536	536
Industry, Geog. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.0784	0.203	0.0920	0.0661	0.0994	0.0567	0.0439	0.0713	0.0537	0.0764	0.0685

Note: Columns (1)–(4) report results for product innovation outcomes, while Columns (5)–(11) refer to process innovation ones. All regressions are estimated by OLS. Other controls include the following firm-level controls (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots and availability of fast broadband, measured in t. All regressions include 2-digit industry, year and Île de France dummies. The specifications are estimated using survey weights, respectively. Standard errors are clustered at the strata level. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.

AI Complementarity. Finally, we provide empirical results to a test of our last hypothesis – that firms using 3D printing are more likely to use AI systems, particularly when 3D printing is used for prototyping (and vice versa). We match the ICT surveys in 2018 and 2019, reporting information on the use of 3D printing and AI respectively. AI use records refer to 2018, so the respective variable is shifted by one year forward or backward with respect to the variable measuring 3D printing use, which is measured in 2017 and 2019. The resulting sample is representative for large firms (500+).

Table 6: Rates of 3D Printing Use (2017 and 2019) by AI Use (2018)

	2017		2019	
	AI = 0	AI = 1	AI = 0	AI = 1
3D Printing (%)	29.59	53.33	36.24	54.72
Significance of Difference	***		***	
Internal Use of 3D Printed Prototypes (%)	27.41	50.83	33.03	47.80
Significance of Difference	***		***	
Internal Use of 3D Printed Goods (%)	10.84	25.00	17.43	25.16
Significance of Difference	***		*	
Sales of 3D Printed Prototypes (%)	7.53	15.00	9.63	18.87
Significance of Difference	**		***	
Sales of 3D Printed Goods (%)	1.51	8.33	2.29	8.81
Significance of Difference	***		***	

Notes: The table reports the share of firms using 3D printing technologies by AI adoption status (AI = 0: non-users, AI = 1: users) in 2017 and 2019. Significance of differences between AI users and non-users is indicated as *** p<0.01, ** p<0.05, * p<0.1. 3D printing measured in 2017 and 2019; AI measured in 2018.

We compare the rates of 3D printing adoption by AI users and non-users in Table 6. The results indicate that firms employing 3D printing are also more likely to use AI technologies (and vice versa), suggesting a positive association between the two digital technologies. Use rates are particularly high for the internal use of 3D printed prototypes, reaching around 50% in both waves of the sample. This pattern provides "correlation test" (Brynjolfsson and Milgrom, 2013) of complementarity, where AI is primarily used to generate ideas and design concepts, while 3D printing facilitates the rapid translation of these ideas into tangible prototypes and products. Together, these technologies are likely to enable firms to accelerate innovation cycles and experiment with new product designs more efficiently.

6 Conclusion

This paper approaches AM as a method-of-invention technology whose central economic effects are likely to operate through reduced costs of physical validation, with outcomes that depend on industry-level design complexity, experimentation intensity, and complementary high-skill R&D capabilities. This framing accommodates production-side possibilities while emphasizing an upstream innovation channel that has been comparatively under-theorized in economics and strategy, and that connects directly to current work on digital technologies, complements, and uneven diffusion.

Across multiple empirical specifications, we find that the use of 3D printing is robustly associated with higher long-term sales growth. Importantly, this relationship is not uniform across applications as it is specifically driven by firms employing 3D printing for internal prototyping rather than for the production or sale of printed goods. These results suggest that the performance benefits of 3D printing arise from the way the technology allows to turn ideas into physically validated prototypes, consequently increasing firms' innovative activities. In support of this interpretation, we show that the use of 3D printing for prototyping is positively associated with the employment of R&D workers and with the introduction of products that are new to the market. Moreover, we find a correlation between the adoption of Artificial Intelligence – which is typically associated to idea generation and concept generation – and 3D printing. This further supports the argument that 3D printing technologies are being used by firms to turn idea generation into tangible innovative outputs.

Such evidence aligns with the hypothesis that 3D printing strengthens firms' innovation capabilities rather than merely substituting production of intermediate and final goods. In this sense, 3D printing operates as a complementary asset within the innovation pipeline: it reduces frictions in early-stage product development, facilitates iterative experimentation in response to design and customer feedback, and enhances the feasibility of producing highly specialized or customized goods. These mechanisms are consistent with an innovation-driven explanation for the growth premium observed among using firms.

Taken together, these findings highlight the strategic importance of 3D printing for firms seeking to enhance their innovation capacity and sustain long-term growth. Rather than primarily serving as a substitute for external suppliers or a tool for cost reduction, 3D printing functions as a tool for the physical validation of new ideas. This suggests that policies aiming to foster the diffusion of additive manufacturing should focus not only on technology acquisition, but also on the organizational and human capital conditions that allow firms to integrate 3D printing into their innovation workflows. Future research could explore how these dynamics unfold over longer time horizons and in different institutional environments, as well as how 3D printing interacts with other digital technologies in shaping firms' innovation strategies.

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A Additional Tables and Figures

A.1 Threats to identification

Pre- vs post-2009. The recent history of 3D printing is characterized by a sequence of key technological events. In 2004, the original stereolithography (SLA) patent, filed by 3D Systems founder Chuck Hull, expired.[20] Furthermore, in 2009, the foundational fused deposition modelling (FDM) patent, held by Stratasys founder Scott Crump, expired, which enabled the emergence of low-cost desktop 3D printers such as RepRap and MakerBot.[21] Subsequently, between 2013 and 2015, many other crucial SLA and selective laser sintering (SLS) patents held by major industry players – including 3D Systems, DTM Corporation, and Stratasys – also expired. During this period, legal disputes highlighted the commercial potential of the technology: for instance, in 2012, 3D Systems sued the MIT spin-off Formlabs over U.S. Patent 5,597,520, which expired in 2014.[22] These events collectively lowered technological barriers and fostered wider accessibility of 3D printing (Andrenelli and González, 2021).[23]

We exploit these discontinuities in intellectual property protection to construct long-difference and event study specifications. The underlying mechanism is that the expiry of the 3D printing patents mentioned above reduced 3D printers' prices by intensifying competition in the 3D printer manufacturing industry, thereby facilitating broader diffusion of the technology. Consequently, we infer that the use of 3D printing technologies by French firms was negligible prior to 2009, enabling a clear identification of adoption dynamics in the subsequent years.

First, we estimate the following long-difference models, capturing the relationship between firm growth and 3D printing use before (A.1) and after (A.2) the key year 2009:

$$\begin{aligned}\text{Growth Rate}_{i,2009-2004} = \alpha + \beta_1 \text{3D Printing}_{i,t} + \beta_{x,t}\textbf{ICT Controls}_{i,t} \\ + \beta_{x,2004}\textbf{Controls}_{i,2004} + \textbf{FE}_s + \text{FE}_{Ile} + \epsilon_i.\end{aligned} \tag{A.1}$$

$$\begin{aligned}\text{Growth Rate}_{i,t-2009} = \alpha + \beta_1 \text{3D Printing}_{i,t} + \beta_{x,t}\textbf{ICT Controls}_{i,t} \\ + \beta_{x,2009}\textbf{Controls}_{i,2009} + \textbf{FE}_s + \text{FE}_{Ile} + \epsilon_i;\end{aligned} \tag{A.2}$$

We report the results on Table A.1, which report the estimated coefficient of 3D printing separately for the 2020 and 2018 ICT surveys (see "3D Printer Year" at the bottom of the table) and the two regressions (see "Growth Period" at the bottom of the table). The findings indicate that the relationship between 3D printing use and firm growth is statistically significant only after 2009, but not before. This pattern provides evidence mitigating the concern that self-selection of firms into the use of 3D printers is driving our results. Specifically, the pre-trend test shows that firms classified as 3D printing users in 2017 and 2019 did not exhibit faster growth prior to the key year 2009, before which use was unlikely. This confirms that the self-selection of fast-growing firms into 3D printing technologies is unlikely to drive our results.

Next, we build two-period datasets in which the 3D printer dummy is set to 0 in 2009 and to its observed value in the year in which we observe the use (2017 or 2019). Using these datasets, we are able to estimate the following firm-level fixed effects model separately on the 2020 and 2018 waves of the ICT survey:

$$\text{Growth Rate}_{i,t,t-5} = \alpha + \beta_1 \text{3D Printing}_{i,t} + \beta_x \textbf{Controls}_{i,t-5} + \textbf{FE}_i + \textbf{FE}_t + \epsilon_{i,t}, \tag{A.3}$$

[20] See the patent at this link: https://patents.google.com/patent/US4575330/en.

[21] See the patent at this link: https://patents.google.com/patent/US5121329A/en.

[22] See the patent at this link: https://patents.google.com/patent/US5597520A/en.

[23] As reported by the IT-specialized magazine *Computerworld* in 2011: "Commercial models – capable of cranking out industrial manufacturing prototypes – that once cost $100,000 now start at about $15,000." 3D printing expert Pete Basiliere noted that "it used to be a six- or seven-figure cost". The article is available at: https://www.computerworld.com/article/1542443/3d-printers-almost-mainstream.html. Similarly, specialized reports estimate the average price of industrial 3D printing machines at approximately $73,220 in 2011 (of Standards and Technology, 2013).

Table A.1: Long difference regressions

	Post-2009		Pre-2009	
	(1)	(2)	(3)	(4)
3D Print (t)	0.164***	0.124**	0.0307	0.0637
	(0.0242)	(0.0472)	(0.0307)	(0.0402)
Observations	1,479	1,865	1,113	1,408
Adj. R2	0.166	0.129	0.161	0.179
3D Printing Year	t=2019	t=2017	t=2019	t=2017
Growth Period	2019-2009	2017-2009	2009-2004	2009-2004
Industry, Geog. FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: The table reports the results of the OLS estimation of Equation (A.2) and (A.1). The dependent variable is the firm's sales growth rate between t and 2009 in Columns (1)-(2) and 2009 and 2004 in Columns (3)-(4). Columns (1) and (3) refers to the 2019 sample. Columns (2) and (4) refers to the 2017 sample. Controls include the following firm-level variables: (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots and availability of fast broadband, measured in t. All regressions include 2-digit industry, year and Île de France dummies. The specifications are estimated using survey weights. Standard errors are clustered at the survey strata level. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.

where $\mathbf{FE}_i$ and $\mathbf{FE}_t$ are firm and year fixed effects, and errors are clustered at the firm level. Dummies related to other digital technologies and services ($\mathbf{ICT\ Controls}_{i,t}$) are excluded from this specification, because they do not vary over time and would be absorbed by individual fixed effects. Given that 3D printing use was highly unlikely prior to 2009, this specification can be interpreted as an event-study design.

Again, we estimate the model separately for the two waves of the survey and we report the results on Table A.2. In both cases, the coefficient on 3D printing is positive and statistically significant, suggesting that the use of 3D printers is associated with higher sales growth in French firms over the observed period.

Refining identification: OLS estimates after CEM balancing. The characteristics of users may drive the relationship between 3D printing and growth. To mitigate these concerns, we estimate Equation 1 on samples of users and non-users balanced based on their observable characteristics by applying Coarsened Exact Matching (CEM) (Iacus et al., 2012). This method that reduces imbalance and model dependence by grouping covariates into discrete strata and performing exact matches within these strata, and ensures that treated and control firms are directly comparable before analyzing the relationship between 3D printing and firm growth. By accounting for systematic differences between users and non-users, this approach strengthens the credibility of our comparisons and helps isolate the effect of 3D printing use on growth outcomes.

Implementing CEM estimators involves a two-step process. First, continuous and categorical covariates are coarsened into discrete bins or intervals, creating strata that group observations with similar characteristics. Within each stratum, treated and control units are directly comparable on the coarsened covariates. The choice of coarsening granularity is critical: overly coarse bins may fail to achieve adequate balance between groups, while overly fine bins can excessively prune observations, reducing the effective sample size and statistical power.

Specifically, we match firms within bins defined by the industry classes used for stratifying the reference population of the ICT survey, ICT controls (robots, cloud, e-commerce, big data analysis, and fast broadband), survey year, and the location of the main office in the Île-de-France region.[24] Other variables are

[24]The survey strata are based on size-industry bins. Industry classes follow the 3-digit NAF classification:

Table A.2: Event study regressions

	(1) t=(2017, 2009)	(2) t=(2019, 2009)
3D Print (t)	0.0672*	0.0953*
	(0.0368)	(0.0503)
Observations	2,816	2,226
Adj. R2	0.444	0.358
Firm, Year, Geog. FE	Yes	Yes
Controls	Yes	Yes

Note: The table reports the results of the OLS estimation of Equation (A.3). The dependent variable is the firm's sales growth rate between t and $t-5$. Column (1) refers to the 2019 sample. Column (2) refers to the 2017 sample. All the time-varying firm-level control variables are measured at $t-5$. Firm-level controls include (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure. All regressions include 2-digit industry, year and Île de France dummies. Standard errors are clustered at the firm level. The specifications are estimated using survey weights. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.

divided into bins based on two parameterizations:

1. **Loose Binning**: Employment (20, 50, 100, 250, 500); Age (5, 10); Log Physical Capital, Intangible Capital, Sales, and Intermediate Costs using 2 cutpoints.
2. **Strict Binning**: Employment (20, 50, 100, 250, 500, 1000); Age (5, 10, 20); Log Physical Capital, Intangible Capital, Sales, and Intermediate Costs using 4 cutpoints.

In the second step, we compare 3D printing users and non-users in the matched sample. 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 3D printing adoption are omitted from the stratification.

Table A.3 reports the average values of covariates for users and non-users in the matched samples.[25] Using the loose binning approach, the sample achieves balance across nearly all characteristics between 3D printing users and non-users, with only a small and weakly significant difference in employment size. This approach leads to the exclusion of approximately 2,500 firms relative to the full sample. In contrast, strict binning ensures perfect balance across all covariates, but its stricter requirements reduce the sample size to around 500 firms.

We then estimate model 1 on both matched samples, with results reported in Table A.4. Columns (1) and (2), corresponding to the loose and strict binning approaches, respectively, show results that are fully consistent with the baseline estimates using the full sample (Table 2). The annualized growth rates are approximately 1.16% and 1.24%, only slightly lower than the 1.42% observed in the full sample.

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, and 951. Size classes are based on the following employment cutpoints: 20, 50, 100, 250 and 500.

[25] Variables with perfect matching are omitted, as their final average difference is zero. These include robots, cloud, e-commerce, big data analysis, fast broadband, survey year, and the location of the main office in the Île-de-France region.

Table A.3: Average characteristics after CEM

	Loose Binning		Strict Binning	
	Non-User	User	Non-User	User
Log Employment	5,16	5,22*	4,72	4,74
Log Age	3,34	3,38	3,47	3,43
Log Physical Capital	8,74	8,92	8,37	8,46
Log Intangible Capital	4,59	4,71	4,21	4,21
Log Sales	10,60	10,66	10,10	10,11
Log Intermediate Costs	10,16	10,20	9,62	9,62
Firms' Count	802	399	323	179

Note: Estimated p-values based on CEM weights. *** p<0.01, ** p<0.05, * p<0.1.

A.2 Sectoral results

We estimate Equation 1 on sectoral samples, with results reported in Table A.5.[26] The results reveal that the coefficient of 3D printer use on growth is heterogeneous across sectors. Positive effects are observed in industries with high innovation intensity and complex design requirements, including rubber and plastics (NAF 22), electrical equipment (NAF 27), motor vehicles (NAF 29), and other transport equipment (NAF 30).[27] Similarly, a positive association is found for firms active in food and beverage (NAF 10-11) and pharmaceuticals (NAF 21), where 3D printing may be employed to produce customized molds, packaging prototypes, or laboratory equipment.[28]

By contrast, in traditional scale-intensive sectors (NAF 13–20 and 24–25), the effect is not statistically significant, suggesting that 3D printing had not yet reached its potential for high-scale production. The effect is negative for firms in non-metallic mineral products (NAF 23), likely reflecting that 3D printing is used in niche applications where growth is limited by demand.

Finally, the absence of a significant effect in electronics and machinery suggests that 3D printing is not yet a major driver of performance in these sectors.

[26]Due to the low number of firms and users in certain sectors, some were grouped. For example, the beverage sector (NAF 11) has an unweighted count of 76 firms, of which only 10 are users.

[27]See the reconsideration of the Pavitt taxonomy in Chapter 3 of Dosi (2023).

[28]Notably, the positive effect in the food sector is driven by bakery and pasta products (NAF 107) and other food items (NAF 108), including chocolate manufacturing.

Table A.4: 3D Printing and growth rate after CEM

	(1)	(2)
3D Print (t)	0.0580**	0.0622*
	(0.0232)	(0.0329)
Observations	1,201	502
Adj R2	0.142	0.202
Industry, Year, Geog. FE	Yes	Yes
Other Characteristics	Yes	Yes
Number of Strata	2083	2991
Number of Matched Strata	278	157
Binning	Loose	Strict
Clustered SE	CEM bin	CEM bin

Note: The table reports the results of the OLS estimation of Equation 1 after CEM balancing. The dependent variable is the firm's sales growth rate between t and $t-5$. Other controls include the following firm-level controls (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots and availability of fast broadband, measured in t. All regressions include 2-digit industry, year and Île de France dummies. Column (1) uses the loose binning and Column (2) the strict binning. The specifications are estimated using CEM weights. Standard errors are clustered at the CEM bin level. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: 3D Printing and sectoral growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Food & Bev. NAF 10-11	Textile NAF 13-15	Wood & Paper NAF 16-18	Chemical NAF 20	Pharmaceuticals NAF 21	Rubber & Plastics Prod. NAF 22	Non-Met. Mineral Prod. NAF 23
3D Print (t)	0.149**	-0.0626	-0.0657	0.0786	0.208*	0.160***	-0.151**
	(0.0759)	(0.107)	(0.0859)	(0.0848)	(0.111)	(0.0582)	(0.0758)
Observations	813	203	261	188	84	195	135
Adj. R2	0.163	0.130	0.114	0.195	0.351	0.241	0.176
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Metal (Basic & Prod.) NAF 24-25	Electronics NAF 26	Electrical Equip. NAF 27	Machinery NAF 28	Motor Vehicles NAF 29	Other Transport Equip. NAF 30	Other Manuf. NAF 31-33
3D Print (t)	0.0883	0.0464	0.219**	0.0759	0.228**	0.405***	-0.0242
	(0.0594)	(0.0499)	(0.0938)	(0.0692)	(0.105)	(0.152)	(0.0539)
Observations	551	302	117	259	195	80	375
Adj. R2	0.134	0.106	0.242	0.351	0.109	0.321	0.188
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports the results of the OLS estimation of Equation 1 on sectoral samples. The dependent variable is the firm's sales growth rate between t and $t-5$. Other controls include the following firm-level controls (in logarithmic terms) sales, physical and intangible capital, firm age, employment and intermediate goods expenditure, measured in $t-5$, and dummies for engagement in e-commerce activities, purchase of cloud services (mail excluded), use of Big Data analytics, presence of robots and availability of fast broadband, measured in t. All regressions include 2-digit industry, year and Île de France dummies. Column (1) uses the loose binning and Column (2) the strict binning. The specifications are estimated using survey weights. Standard errors are clustered at the survey strata level. Estimated coefficients of firm-level controls are not reported, but available upon request. *** p<0.01, ** p<0.05, * p<0.1.