3D printing and the geography of production

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Abstract

This paper explores the impact of 3D printing (3DP), a technology popularly described as being able to "produce (almost) anything from anywhere", on the spatial organization of production. Although some scholars have theorized that 3DP may affect the location of manufacturing, empirical evidence on its implications for the spatial footprint of production activities remains limited. This study investigates how 3DP adoption, together with pre-existing local capabilities, is associated with the export performance of countries in terms of 3D-printable products. Using trade data and exploiting a recent change in the Harmonized System classification, we identify 3DP adopting countries and analyze the relationship between 3DP adoption, pre-existing specializations and export outcomes. Our findings suggest that countries not previously specialized in a product but that adopted 3DP technologies tend to catch up with, and in some cases overtake, previously specialized countries, a result compatible with the idea of a shifting geography of production. We further examine the heterogeneity across product types and levels of complexity. This paper contributes to the literature by conceptually framing the spatial implications of 3DP, leveraging a novel empirical approach to capture 3DP adoption, and providing new empirical insights on the relation between 3DP and export performance.

1. Introduction

Over the last decades, the rapid emergence of digital technologies has started to impact the ways in which firms organize their activities, structure their relationships and ultimately carry out their business (Corradini et al., 2021; De Propris & Bailey, 2020; Leigh & Kraft, 2018). While the effects of these technologies are widespread, they are also rather heterogeneous, as different digital technologies—robotics, AI, and additive manufacturing (AM)—affect firm processes and outcomes in rather specific ways. Against this background, additive manufacturing, also known as 3D printing (3DP)[1], is a particularly fascinating but still under-studied technology. Popularly imagined as the technology "to produce almost anything from anywhere" (Gershenfeld, 2012), 3DP allows the manufacture of goods and components through a process in which a machine joins raw material, usually layer by layer, on the basis of a digital model.

[1] Additive manufacturing and 3D printing are in this paper used as synonyms, even though they are not exactly the same. Additive manufacturing refers more explicitly to industrial processes, while 3D printing is a more general and popular terms which includes also hobbyist and home fabrication processes.

From an economic geography perspective, 3DP is particularly interesting because of its implications for the spatial organization of the economy. As highlighted by previous conceptual contributions (D'Aveni, 2018; Gress & Kalafsky, 2015; Rayna & Striukova, 2021), 3DP presents two path-breaking features: i) internal economies of scale matter less in additive manufacturing than in traditional processes (Baumers et al., 2016; D'Aveni, 2018; Laplume et al., 2016; Weller et al., 2015), and ii) the capabilities required for production differ between additive and traditional manufacturing (D'Aveni, 2018; Roscoe et al., 2023; Steenhuis, 2023). These features have led scholars to theorize a possible shift toward a diffuse system of production and lower reliance on global value chains (Gress & Kalafsky, 2015; Laplume et al., 2016; Rayna & Striukova, 2021; Rehnberg & Ponte, 2018). While we are still far from a system of diffuse manufacturing and AM has become common only in specific contexts (e.g., aerospace, machinery, medical) (Bonnín Roca et al., 2017; Steenhuis, 2023; The Economist, 2017), some empirical contributions suggest that the production of specific goods and their geography has undergone some changes (Choong et al., 2020; Freund et al., 2022; Kellner, 2017; Rylands et al., 2016).

These studies, however, overlooked two important aspects. On the one hand, pre-existing capabilities and localized knowledge may still be critical for production, even when 3DP is adopted. For example, 3D printing aerospace components may still require access to specific capabilities related to traditional methods of aerospace manufacturing and thus may be available in regions that have long been specialized in that industry (Hickie, 2006). Producing a prosthetic tooth instead requires many fewer capabilities, creating potential for localized production (Dawood et al., 2015; Revilla-León et al., 2023). On the other hand, the impact of the two geography-changing features of 3DP (lower importance of internal economies of scale; differences in capabilities) may be important for certain products (e.g., prosthetics) but not very relevant for others (e.g., food). This is likely to make the impact of 3DP rather heterogeneous, with stronger effects on the geography of production of certain goods rather than others (Steenhuis & Pretorius, 2017).

To better understand how 3DP may change the geography of production, this paper studies 3DP adoption and pre-existing capabilities as crucial factors affecting the export of 3D printable products. Using international trade data for the period of 2012-2023, we track the adoption of additive manufacturing technologies across countries and relate it to their export performance in 3D printable products. Specifically, our analysis investigates how the level of export activity changes across different groups of countries, depending on their pre-existing specializations and the adoption of 3DP. By studying four groups of countries[2], we uncover several interesting facts. Our regression analysis consistently shows that countries that have adopted 3DP technologies not only perform better than non-adopting non-specialized countries but also typically catch up and close the gap with countries that are already specialized (whether 3DP adopting or not). We further study these relationships, exploring their heterogeneity across different types of products and different levels of product complexity. While we stress that our findings should not be interpreted in a causal sense due to the limitations of our empirical settings, our results indicate that some changes in the geography of production are occurring and appear to be related to the adoption of 3DP technologies.

From this perspective, our paper offers three main contributions. First, it connects different strands of literature that have discussed the role of 3DP technologies and embeds the discussion in an (evolutionary) economic geography framework (Boschma & Frenken, 2010; Dam & Frenken, 2022; Hidalgo et al., 2007). We argue that taking an evolutionary perspective is particularly relevant for the study of 3DP because of the heterogeneous relationship this technology has with pre-existing local capabilities. Second, from an empirical point of view, we exploit recently available data on international trade in 3DP machineries to study their spatial distribution. While our contribution builds on previous studies in international economics (Abeliansky et al., 2020; Andrenelli & González, 2021; Freund et al., 2022), our empirical approach for capturing 3DP adoption is certainly novel and offers a new alternative to scholars in the field. Third, by exploiting this new approach, we are able to offer new and more general insights into the relationship between the use of additive manufacturing techniques, the presence of product-specific capabilities and the location of production. Our analysis identifies patterns suggestive of changes in the geography of production and confirms how the implications of 3DP adoption differ across types of 3D printable products (Steenhuis, 2023; Steenhuis & Pretorius, 2017).

We structure our contribution as follows. The second section provides an overview of 3DP technologies. The third section connects and embeds 3DP within the (evolutionary) economic geography literature, highlighting factors facilitating or limiting changes in the geography of production as a result of 3DP adoption. The fourth section presents the methodology and data

[2] Criss-crossing the dimensions of pre-existent specialization and 3DP adoption, four groups of countries can be easily identified: i) non-specialized and non-adopting countries, ii) specialized and non-adopting countries, iii) non-specialized and adopting countries and iv) adopting and specialized countries.

development efforts. The fifth section of the paper focuses on the results of our analysis and the robustness checks carried out. In the last section, we summarize the findings, draw some policy implications and conclude.

2. 3D printing technologies: an overview

Unlike traditional manufacturing methods, which typically entail the use of molds or the subtraction of material from a block, additive manufacturing relies on a machine combining material on the basis of a digital file. This defining characteristic is common across a number of different 3DP technologies, which nonetheless differ depending on the exact method through which the material is combined (e.g., sintering through a laser, material extrusion, powder bed fusion, etc.), the type of material that can be processed (plastic, metal, etc.) and the specific advantages and costs (Attaran, 2017; Steenhuis, 2023; Thomas-Seale et al., 2018).

Generalizing across different types of 3DP technologies highlights three main benefits associated with the adoption of 3DP (Attaran, 2017; Rylands et al., 2016; Steenhuis & Pretorius, 2017). First, 3DP allows for significant flexibility in manufacturing (e.g., using the same machine to make different products), which is crucial for customization and small-batch production (e.g., prosthetic implants) (Thomas, 2016). Second, additive manufacturing provides ample freedom in designing a good, as the technology allows the production of geometries that are not attainable using traditional manufacturing (Roscoe et al., 2023). Such design freedom can lead to innovative designs and higher-quality products, such as in the case of the General Electric LEAP fuel nozzle (Kennedy, 2019) or Adidas 4DFWD shoes (Adidas, 2021). Third, 3D printing has been linked to efficiency gains in terms of faster prototyping, shorter lead times, reduced inventory needs and distribution costs (Oettmeier & Hofmann, 2017; Thomas, 2016). Some of these improvements also relate to environmental sustainability, for instance, in terms of the reusability of materials and components (Niaki et al., 2019; Relativity Space, 2023).

Despite these advantages, the adoption of 3DP technologies still requires substantial investments (Yeh & Chen, 2018). With respect to machinery, an average industrial 3D printer able to produce metal parts is reported to cost approximately 250,000 USD (Steenhuis, 2023). The use of additive manufacturing technologies also presents other costs and risks for firms, particularly in relation to the re-organization of the production process, safety standards and output quality (Thomas-Seale et al., 2018). These limitations have played an important role in limiting the adoption of 3DP, which is typically confined to specific industries (e.g., aerospace, tooling or medical) and tasks (e.g., prototyping) (Steenhuis, 2023; Thomas-Seale et al., 2018). Nonetheless, we have recently witnessed an acceleration of patenting and innovations in 3DP (Cavallo et al., 2023; Ceulemans et al., 2020) and an increase in the materials and fields of industrial applications (D'Aveni, 2018). This has also spurred a scholarly debate on the impacts of 3DP across different fields, from economics (Abeliansky et al., 2020; Felice et al., 2022; Freund et al., 2022) and international business (Hahn & Massini, 2024; Hannibal & Knight, 2018; Laplume et al., 2016) to innovation studies (Marić et al., 2023; Pedota et al., 2021; Sandström, 2016) and geography (Butollo, 2021; Fuchs, 2020; Gress & Kalafsky, 2015). While different conceptual and theoretical contributions have been offered, large-scale empirical evidence on the changes in the geography of production has remained very limited.

3. Review of the literature

From a theoretical perspective, two are the fundamental characteristics of 3DP, which give this technology the potential to affect the global geography of production. The first characteristic is that additive manufacturing allows the production of goods at constant cost per unit (Steenhuis & Pretorius, 2017), which reduces the burden of internal economies of scale (Baumers et al., 2016; Thomas, 2016; Weller et al., 2015). Lower internal economies of scale imply that "indivisibilities" related to production processes matter less, and production activities can be more easily split and scattered across space (Barba Navaretti & Venables, 2004; Baumers et al., 2016). The flatter average cost of 3DP also reinforce its use for highly customized products, which in turn typically requires more frequent interactions and close proximity to customers (Rylands et al., 2016). This characteristic of 3DP is the core reason why this technology has been associated with a more geographically diffused manufacturing system (Attaran, 2017; Bonnín Roca et al., 2019).

The second important characteristic of 3DP is the different and new capabilities required to use this technology (Steenhuis & Pretorius, 2017). The capabilities for additive manufacturing differ from those used in traditional manufacturing in three main respects. First, to take full advantage of the freedom provided by digital design and 3DP, firms are required to change the way their goods are designed, with a greater role played by creativity and “out of the box” thinking and a lower reliance on “off-the-shelf” solutions (Steenhuis, 2023; Thomas-Seale et al., 2018). Second but also related to the previous point, additive manufacturing allows the printing of multiple components at the same time, even parts with built-in joints and attachments. This makes some components or certain steps in the production chain redundant (Roscoe et al., 2023) and leads to a shift toward vertical integration and in-house production (Choong et al., 2020; D’Aveni, 2018). Finally, some capabilities crucial in traditional manufacturing, such as those of shop floor technicians, lose much of their importance. In this respect, Thomas (2016) indicates that interactions between engineers and technicians, which are important in traditional manufacturing for assessing the feasibility of a manufacturing process, are typically no longer required in additive processes.

While these characteristics of 3DP offer some arguments for a more decentralized system of production, two interconnected elements, external economies of scale and the uneven spatial distribution of capabilities, are likely to limit the tendency toward spatial diffusion (Gress & Kalafsky, 2015; Thomas-Seale et al., 2018). External scale economies refer to the advantages attainable by firms, for instance, in terms of productivity or innovation, related to external factors and, in particular, to location (Jacobs, 1969; Marshall, 1890). These location-related economies of scale, or agglomeration economies, represent one of the main factors behind firms’ location choices. If capturing new insights and knowledge spillovers from competitors, frequent interactions with customers or access to specific infrastructure (Combes & Gobillon, 2015; Duranton & Puga, 2003) remain important in additive manufacturing, the greater location freedom given by 3DP may, in practice, play a rather limited role. The same applies if the capabilities required for production through additive manufacturing are spatially concentrated, which would reduce to a few places the viable options for firms to locate their facilities (Freund et al., 2022; Rayna & Striukova, 2021). Importantly, while these two factors are conceptually distinct (e.g., capabilities may be available locally, but agglomeration economies may be limited), empirically, they are likely to strongly overlap, with locations providing access to agglomeration economies also making available the necessary skills for 3DP (Balland et al., 2020).

The unique characteristics of 3DP discussed above are at the core of the theoretical arguments suggesting a change (or lack thereof) in the geography of production as a result of 3DP adoption. From an empirical point of view, however, the results are less clear. The analysis of hearing aid devices by Freund et al. (2022) revealed a change in the location of production of these devices, with new countries having entered and gained shares in the global hearing aid market (Mexico and Vietnam, among others). This suggests that, at least in some cases, the capabilities required for the production of hearing aids are spatially diffuse, making decentralized production feasible (Rayna & Striukova, 2021). At the same time, the authors also study how, for a sample of 35 products, different levels of complexity (Hidalgo & Hausmann, 2009) moderate the relation of 3DP on exports. The argument put forward is that complex goods, by requiring greater skills (spatially concentrated capabilities) and immobile complementary inputs (e.g., universities), can be produced only in specific locations. The authors indeed find in their analysis that these complex products have to be traded internationally rather than produced close to consumers. While Freund et al. (2022) do not explicitly model the role of pre-existing capabilities, Schwierzy et al. (2022) offer interesting results in these respects. Studying the adoption of 3DP technologies in Germany, the authors find that companies that use 3DP either for production or for offering it as a service frequently but not exclusively locate in urban areas. In addition, the authors highlight a relationship between different uses of 3DP technologies and the characteristics of the location. Specifically, 3DP adopters located in areas traditionally specialized in manufacturing engage more in production, whereas those in proximity to technical universities focus more on 3DP services (Schwierzy et al., 2022). This descriptive finding suggests that a relationship exists between the adoption of 3DP for a specific use and the pre-existing capabilities locally available.

3.1 Local factors, 3D printing and the global geography of production

The role of pre-existing capabilities and external economies of scale has long been recognized in the literature in explaining not only spatial differences in economic and innovation performance (Carlino & Kerr, 2015; Combes & Gobillon, 2015) but also the structural evolution of local economies (Cortinovis et al., 2017; Dam & Frenken, 2022; Hidalgo et al., 2007). Specifically, the literature on evolutionary economic geography (EEG) provides important insights concerning the geographical factors that explain the emergence of new industries and technologies (Content et al., 2022; Cortinovis et al., 2017; Hidalgo et al., 2007; Laffi & Boschma, 2022). In the EEG context, capabilities are conceptually defined as the broad set of inputs required to manufacture a product and thus encompass a range of production factors, from machinery and raw materials to specific know-how, necessary for production to take place (Dam & Frenken, 2022; Hidalgo et al., 2007). In relation to our discussion above, the general term of capabilities thus can include both specific know-how and competences (which we refer to as pre-existing capabilities) but also factors connected to external economies of scale relevant to the specific product or industry (Corradini et al., 2021; De Propris & Bailey, 2020).

In the context of 3DP, capabilities as location factors are likely to play a rather heterogeneous role because of the variety of industries and products affected by the technology. In this respect, Steenhuis and Pretorius (2017, p. 137) highlight that "AM technology has widespread applicability and while it may represent incremental innovation in one industry, it can lead to radical changes in other industries". Taking these considerations into account suggests a heterogeneous relationship between AM and local capabilities. In other words, whether the production of a specific 3D printable product picks up in "new" locations or concentrates in traditional manufacturing hubs is likely to depend on both the specific characteristics of the product (e.g., specific knowledge or frequent interactions with customers required) and the location itself (e.g., availability of human capital, clustering of customers in the area).

From an economic geography perspective, local capabilities are especially interesting, as they play a critical role in the emergence of new products and industries, as well as in the structural composition of the economy (Dam & Frenken, 2022; Hidalgo et al., 2007). In the context of additive manufacturing, however, the capabilities required for production may differ from those used in traditional manufacturing. If producing a good under AM does not require the capabilities necessary in traditional processes (e.g., because some production steps have become superfluous), the adoption of 3DP technology may allow new locations to start producing that good. In this way, 3DP generates opportunities for changes in the geography of production (e.g., Poland entering and currently leading the hearing aid market). In contrast, if the requirement for traditional capabilities remains high, the production of a good will realistically take place in countries already engaged in the manufacturing of that specific good (e.g., Vietnam and Indonesia maintaining the lead in sport shoe manufacturing), leaving the spatial footprint of manufacturing unchanged. Finally, products for which 3DP provides valuable opportunities (e.g., in terms of changing the design of products) but nonetheless requiring capabilities to a significant extent similar to those in traditional manufacturing (e.g., specialized suppliers) are likely to see only a limited change in the geography of production, with traditional hubs having adopted 3DP to keep the lead (e.g., the US maintaining the lead in the production of aircraft components). In this last case, however, some changes in where production takes place may occur depending on the relative importance of the advantages related to 3DP as opposed to the role of traditional capabilities.

In our empirical analysis, we focus on the export performance of countries as a proxy of the country's ability to competitively manufacture a product. Specifically, we explore how the adoption of 3DP technologies and the presence of pre-existing production capabilities shape, both directly and in interaction, the export performance of countries. Following the extant literature (Freund et al., 2022), we also consider how the relationships between local capabilities, 3DP adoption and export performance may change across products of different types and different levels of complexity.

4. Methodology and data

The objective of our empirical analysis is to obtain some *prima facie* evidence on the relation between 3DP and the geography of production, depending on the local availability of traditional capabilities. To study whether 3DP adoption is changing the patterns of production, we use a rather simple approach. As a proxy for production, we follow the international trade literature (Andrenelli & González, 2021; Freund et al., 2022) and take the value of exports for 178 3D products printable by country in 2022. This will be our dependent variable. The list of 3D printable products (based on the Harmonized Standard (HS) product classification[3]) was identified through qualitative research involving interviews with experts from the 3D printing industry and from the exposed sectors (Andrenelli & González, 2021; Freund et al., 2022). To identify countries that have adopted the technology, we exploit a recent change in the HS classification, particularly the addition of HS code 8485 "Machines for Additive Manufacturing". In this sense, our approach is comparable to the one extensively used in the economic literature, in which trade data are leveraged to capture automation (Acemoglu et al., 2020, 2023; Acemoglu & Restrepo, 2020). Importantly, however, the HS code 8485 was introduced only in 2022. On the one hand, this makes it impossible to assess changes in production that occurred afterwards given the short time span available. In addition, this approach only enables the identification of adoption ex post, without providing precise information on the timing of adoption. On the other hand, as adoption is likely to have already occurred in a number of countries, using trade data from

[3] On a global scale, exports and imports of products are tracked (for tax reasons) and reported according to different classifications, among which the Harmonized Standard Classification developed and updated by the World Customs Organization.

2022 still allows us to capture the use of 3DP technology. Overall, while using trade data to capture 3DP adoption has several limitations (e.g., we cannot observe how extensively across industries the technology is used), we believe it represents an important step forward compared with alternatives such as patents (Felice et al., 2022). Finally, to measure the presence of pre-existing capabilities related to a specific good, we use the Balassa Index, also called revealed comparative advantage, measured in 2012 (Balland, 2017; Hidalgo et al., 2007). We employ this index computed using data from 2012, as we are interested in the capabilities available in the period preceding the widespread adoption of 3D printing technology. This allows us to capture patterns in capabilities prior to any technological impact while remaining sufficiently close to the actual adoption period to minimize bias from other factors influencing changes in production. In this way, we are able to capture the profile of countries in terms of manufacturing capabilities when the AM was still in its infancy[4].

Combining the information on adoption and pre-existing capabilities, our study compares the level of export of different 3D printable products in 2022 among four groups of countries: 1) countries that have not adopted 3DP by 2022 and were not specialized in a given product in 2012; 2) countries which have not adopted 3DP by 2022 and were specialized in a given product in 2012; 3) countries which have adopted 3DP by 2022 and were not specialized in a given product in 2012; and 4) countries that have adopted 3DP by 2022 and were already specialized in a given product in 2012. Comparing these different groups of countries allows us to assess whether the levels of exports in specific 3D printable products in 2022 are more strongly related to pre-existing capabilities (group 2), to the adoption of 3DP technologies (group 3) or their interaction (group 4).

In formal terms, the equation that we estimate is the following:

$$logX\_2023_{p,c} = \alpha * logX\_2012_{p,c} + \beta * 3DP_c + \gamma * RCA\_2012_{c,p} + \delta * 3DP_c * RCA\_2012_{c,p} + \theta * CV_{p,c} + \varphi_p + \varepsilon_c$$

where $logX\_2023_{p,c}$ represents the log of exports for product p by country c in 2023, $RCA\_2012_{c,p}$ measures whether country c is specialized in product p in 2012 and where $3DP_c$ is the 3DP adoption dummy (measured in 2022). Intuitively, including the two variables of interest and their interaction term allows us to study how the level of exports in 2023 differs across different groups. The regression model also includes different control variables

[4] In the robustness check we use the Balassa Index computed for 2002 obtaining comparable results.

($CV_{p,c}$) and product-specific fixed effects (φ_p)[5] and clusters the error term at the country level (ε_c), since that is the level at which 3DP adoption is measured[6] (Abadie et al., 2023; Cameron & Miller, 2015).

While the use of country fixed effects would be preferable in this setting, the time-invariant nature of our measure of 3DP adoption does not allow for that[7]. We therefore rely on control variables covering different factors potentially affecting the export performance of countries or confounding the relationship with 3DP adoption. First, we introduce controls aimed at capturing the effect of economic fundamentals. To this end, we include three variables: GDP per capita in 2012, total population in 2012 and R&D investment as a share of GDP in 2012. We also include a control for local institutions and policy (*Policy Index*), which we calculate as the average score for the period 2010-2014, across four indicators from the World Bank Governance database: control of corruption, regulatory quality, rule of law and government effectiveness. We choose to focus on these four and to exclude two more "political" ("voice and accountability", "political stability") as the most relevant for technological adoption and innovation[8]. In particular, Zhu et al. (2024) show that "voice and accountability" and "political stability" are more weakly correlated with the global index of innovation published by the WIPO. Second, in addition to accounting for the past level of production and specialization of the focal product (*log_X_2012, RCA_2012*), we control for the overall 3DP-related industrial base of a country building a proxy for the domestic production of industries where 3DP may be used. To this end, we leverage the information on 3DP-related online job postings by industries in the US (Bloom et al., 2020) and select industry codes with at least 50 job postings mentioning 3DP over the whole period 2007-2019[9]. We then use these 70

[5] Our database is essentially a country-product cross-sectional database. Because our measure of adoption, as discussed below, varies only across countries we cannot include country-specific fixed effects. This is an important limitation of our study, as unobserved country-level specific factors (infrastructure, policy, etc.) are likely to play a role in the relation between 3DP and exports.

[6] The choice of clustering at the country level is justified by the fact the 3DP adoption is assigned at the country level. Besides, products within the same country are subject to the common macroeconomic and policy shocks and therefore should not be considered as independent observations.

[7] In the robustness checks, we exploit the richness of our data to include also country-level FE. We do so by estimating the model using all type of products (non only 3D printable ones) and interact the regressors with a dummy for 3DP printable products. The results are in line with our baseline.

[8] Including all six indicators of governance does not affect the results, as shown in the robustness checks in the appendix. Similarly, we use data for the period 2010-2014 since it allows to keep the institutions pre-determined relative to the adoption to avoid biasing estimates (e.g. information mixing pre- and post-adoption years, especially if policy follows or is affected by adoption). We use data for the whole period 2010-2022 in a robustness check in the appendix.

[9] The underlying assumption is that the adoption of 3DP technologies by industry in the US is somewhat representative of what industries may be using 3DP elsewhere in the world. The choice of excluding industries with very few job postings is necessary to avoid inflating the amount of domestic production. For instance, over the whole period a relatively large industries like "Rubber product manufacturing" and "Pulp, paper and

industry codes to compute the total domestic production pertaining to 3DP-related industries for the period 2013-2022 using the 2025 ITPD-E database (Larch et al., 2025), which provides estimates of domestic production and bilateral trade by industry (rather than products like the BACI database). Third, while the R&D variable helps control for innovation dynamics, we control for robot adoption in 2019 to reduce concerns that our 3DP variable may absorb the impact of other adopted technologies. Given the variety of tasks that robots can perform, we focus on robots that are potentially substitutes for 3DP[10]. Finally, we include a variable for "relatedness density" to better control for the structure of the country's economy (Hidalgo et al., 2018). With this variable, we aim at effectively controlling for the presence in the country of capabilities related (Farinha et al., 2019; Hidalgo et al., 2007) to those needed for focal product *p*. It is important to notice that our empirical approach allows to capture only associations, rather than causal relations. The next section discusses more in detail how the variables are constructed.

The main data source is the BACI database[11], developed and made available by CEPII (Gaulier & Zignago, 2010), which provides data on export values and quantity by country, 6-digit HS product code and year. This information is used to construct the dependent variable, the main variables of interest and one control variable (relatedness density). We also use the CEPII Gravity database (GDP, population), the World Bank database (R&D investments as a percentage of GDP), the Worldwide Governance Indicators of the World Bank, the above cited ITPD-E database (Larch et al., 2025) and data from the International Federation of Robotics (robot installations) for our control variables.

4.1 Variable construction

Keeping in mind the focus of our analysis on the comparison between different types of countries, we opted for a dummy variable to capture 3DP adoption. In this respect, our

paperboard" have 2 3DP related job postings. As use of 3DP in these industries is limited, but the industries themselves are relatively large, including them would make the control variable more noisy and less relevant.

[10] Specifically, we include robots whose applications are related to processing (e.g. laser cutting), welding and soldering, and handling operations (e.g. metal casting or plastic molding). The choice of these robot applications reflect the possible substitute to additive manufacturing. If that is the case, the estimates for adoption may be driven by the adoption of robots rather than 3D printing technology. Robot adoption is measured in 2019, the closest year to 2022, when we measure 3DP adoption.

[11] The BACI database, commonly used in the trade and international economic literature, contains bilateral trade flows for more than 200 countries and more than 5000 products. The exports and imports of products are reported according to the Harmonized System classification, developed and updated by the World Customs Organization.

preferred measure is a variable ($3DP_c$) that takes a value 1 if the total AM imports and exports of a country are above 10 million USD and 0 otherwise[12]. We choose the threshold for 3DP adoption considering that, on average, industrial 3DP machinery costs approximately 250,000 USD (Steenhuis, 2023), so the level of 10 million USD ensures a substantial use of 3DP machinery. In formal terms, if $AMX_{c,2022}$ and $AMM_{c,2022}$ represent the amount of AM machinery exported and imported by country *c* in 2022, and T represents the 10 million USD threshold:

$$3DP_c = \begin{cases} 1\ if\ (AMX_{c,2022} + AMM_{c,2022}) \geq T \\ 0, otherwise \end{cases}$$

To measure specialization, we resort to a dummy capturing the revealed comparative advantage for each country in each product in 2012 ($RCA\_2012_{c,p}$). In formal terms,

$$RCA\_2012_{p,c} = \begin{cases} 1\ if\ \dfrac{\left(X_{c,p}/\sum_p X_{c,p}\right)}{\left(\sum_c X_{c,p}/\sum_{c,p} X_{c,p}\right)} > 1 \\ 0, otherwise \end{cases}$$

where $X_{c,p}$ represents the 2012 amount of exports in product *p* by country *c*. $RCA\_2012_{c,p}$ therefore takes value 1 when the share of exports of product *p* by country *c* is larger than the global share and 0 otherwise.

With respect to our control variables, we build a measure of robot adoption to replicate the 3DP adoption dummy as closely as possible. Given the scope of tasks a robot can perform, we focus on robot applications performing similar tasks to those of a 3D printer (see footnote 5). Since it is difficult to establish a clear threshold for robot installations, we consider a country as having adopted a specific robotic application (e.g., welding) if the country is in the top 16th percentile of the distribution of robot installations for that specific application. The 16th percentile has been chosen as a threshold based on the distribution of 3DP adopting countries (as shown in the descriptive below, 16% of the countries are considered 3DP adopters when we take 10 million USD as a threshold for 3DP adoption). To aggregate the data on robot adoption across different applications, the control variable in our model takes value 1 if a country is in the top 16th percentile of installation for at least one type (processing, welding and soldering, handling) of robot applications, and 0 otherwise.

[12] In the robustness checks we test our findings using different proxy for adoption, in particular looking at different thresholds and using a dummy variable based on trade in additive manufacturing per capita.

The last control variable to discuss is relatedness density, a common measure in the EEG literature used to capture the availability of capabilities related to product p in country c (Hidalgo et al., 2007, 2018). By studying the systematic co-occurrence of specializations ($RCA\_2012_{c,p}$) in the same country, it is possible to estimate the relatedness of each pair of products to each other (Balland, 2017)[13]. In the equation below,

$$\rho_{p,s} = \frac{c_{p,s}}{\left[\left(\frac{S_p}{T}\right) * \left(\frac{S_s}{T - S_p}\right) + \left(\frac{S_s}{T}\right) * \left(\frac{S_p}{T - S_s}\right)\right] * \left(\frac{T}{2}\right)}$$

where $c_{p,s}$ is the co-occurrence count of $RCA\_2012_{c,p}$ for products p and s in 2012; S_p and S_s are the total number of occurrences of each of the two industries, respectively; and T is the total number of occurrences of any sector. Essentially, $\rho_{p,s}$ is the ratio between the number of cases in which the specializations in p and s simultaneously occur in a random benchmark (van Eck & Waltman, 2009). To compute the relatedness density, we use the following equation:

$$Rel.Density_{p,c} = \frac{\sum_{s \neq p} \rho_{p,s} * RCA\_2012_{s,c}}{\sum_{s \neq p} \rho_{p,s}}$$

The indicator of relatedness density is essentially the share between how related a product p is to any other product s in which country c is currently specialized and the maximum possible proximity, in which country c is specialized every related product related to p.

5. Econometric analysis

5.1 Descriptive statistics

The figures below show the distribution of AM adoption across different thresholds[14] and help characterizing the adopting countries. According to the map shown in Figure 1, (high) 3DP adopting countries tend to be countries in the Global North but with different exceptions both in Asia (India, China, Vietnam, Malaysia, Thailand) and South America (Brazil).

[13] For instance, if specializations in "tanning of hides" and "production of leather bags" often occur together in a number of countries, this empirical regularity suggests the two products are related (Hidalgo et al., 2018).

[14] The four categories that we include in the descriptives are: No 3DP: less than 1 million USD in total trade of AM; Low: more than 1 but less than 5 million USD in total trade of AM; Medium: more than 5 but less than 10 million USD in total trade of AM; High: at least 10 million USD in total trade of AM.

FIGURE 1 and 2 HERE

As shown in Figure 2 (Panel A), about 16% of the countries meet the threshold for high adoption, and approximately one in three countries meets at least the lowest threshold for adoption. In terms of exports (Panel B), adopting countries tend to export a broader set of products: countries with at least low adoption of 3DP export, on average around 4,000 products, whereas those which have not adopted 3DP yet export, on average, fewer than 1,000 products. The two panels at the bottom of Figure 2 also show positive relationships between the level of adoption expressed as total trade in additive manufacturing per capita (vertical axis) and GDP per capita (Panel C) and R&D as a percentage of GDP (Panel D). In these two panels, the light blue triangles represent countries in the "High Adoption" group.

Table 1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Export (2023)	26,996	39,818,142.000	687,123,563.000	0.000	56,223,923,392.000
Export (2012)	26,996	29,005,562.000	466,748,784.000	0.000	34,982,578,889.000
Rel. Density	26,726	11.536	10.428	0.000	80.090
GDP pc	22,229	22,744.610	22,184.600	717.455	144,578.100
Population	22,229	51,309.250	169,434.500	5.031	1,375,199.000
R&D/GDP	26,996	0.618	0.888	0.000	4.036
Robot (dummy)	26,996	0.447	0.497	0	1
Dom. prod.	26,996	536,802.900	2,665,360.000	0.000	26,501,589.000
Policy index	22,725	0.162	0.972	-2.125	2.048
RCA (dummy)	26,996	0.127	0.333	0	1
3DP (dummy)	26,996	0.237	0.425	0	1

Table 2: Correlation table

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Export (2023) (log)	(1)	1	.	.	.	.	.	.	.	.	.	.
Export (2012) (log)	(2)	.78	1	.	.	.	.	.	.	.	.	.
Rel. Density	(3)	.69	.68	1	.	.	.	.	.	.	.	.
GDP pc (log)	(4)	.39	.42	.38	1	.	.	.	.	.	.	.
Population (log)	(5)	.37	.35	.40	-.23	1	.	.	.	.	.	.
R&D/GDP	(6)	.52	.52	.62	.53	.18	1	.	.	.	.	.

Table 2: Correlation table												
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Robot (dummy)	(7)	.52	.54	.55	.48	.37	.55	1	.	.	.	.
Dom. prod. (log)	(8)	.55	.52	.57	.42	.51	.62	.68	1	.	.	.
Policy index	(9)	.42	.45	.48	.76	-.23	.71	.40	.41	1	.	.
RCA (dummy)	(10)	.41	.42	.47	.15	.09	.23	.17	.17	.19	1	.
3DP (dummy)	(11)	.61	.57	.69	.45	.38	.71	.56	.58	.55	.24	1

The tables above also provide an overview of the distribution and correlation of the variables we include in our models. Our database includes information at the country level for 178 6-digit HS code products, which the literature has identified as 3D printable (Andrenelli & González, 2021). Based on Table 1, approximately 23.7% of the observations belong to countries that, by 2022, have adopted 3DP. Interestingly, the level of installations of robots performing tasks similar to those of a 3D printer is higher, with 49.7% of observations falling in this group. Table 2 also confirms some of the features of 3DP-adopting countries that we already highlighted. The 3DP adoption dummy is strongly and positively related to R&D investments, robot adoption and the policy index. Observations pertaining to products in 3DP adopting countries are also characterized by high relatedness density.

5.2 Regression analysis

Table 3 below reports the results of our baseline regression estimations, which are based on the model discussed in the previous section. In Table 3, we progressively augment the model to study the relationship between 3DP adoption (*3DP (dummy))* and pre-existent specialization (*RCA (dummy)*) independently (Columns 1 and 2) and jointly (Column 3) before interacting them (Column 4). *3DP (dummy) x RCA (dummy)*). As the two three columns of Table 3 show, adopting and previously specialized countries tend to outperform the reference group. As this group includes countries that have neither adopted 3DP nor specialized in the focal product in 2012, this finding is interesting but not too surprising, also considering the structural weakness of countries in this group. A more interesting result emerges from the third column of Table 3, which shows a positive correlation indicating that, on average, the level of exports for non-specialized 3DP-adopting countries is larger ($\beta = 0.613$) than those of both the reference group and group ofspecialized non-adopters ($\gamma =$

0.495). However, moving to the fourth column of the table, our analysis suggests that non-specialized adopting countries and specialized non-adopting countries perform quite similarly (respectively, $\beta = 0.676$ and $\gamma = 0.706$), while countries that are specialized and have adopted 3DP perform even better ($\delta = 0.676 + 0.706 - 0.371$), despite the negative and marginally significant interaction term. This result suggests that while countries that combine both 3DP adoption and previous capabilities perform best in terms of exports, 3DP and previous capabilities do not mutually reinforce each other. In this sense, keeping in mind its marginal significance, the negative sign of the interaction term may be an indication of the challenges and changes that integrating 3DP into existing production processes poses (Roscoe et al., 2023; Rylands et al., 2016). Overall, these findings indicate that non-specialized countries that adopt 3DP perform on a par, in terms of exports of 3D-printable products, with previously specialized countries that do not adopt 3DP. We interpret these associations as being consistent with changes in the spatial organization of production for 3D-printable goods. The estimated coefficients on the control variables are generally consistent with expectations (with the exception of *R&D/GDP*). It is interesting to note that the two proxies for the industrial base (*Exp. 2012 (log)* and *Dom. Prod. (log)*), as well as the *Policy index* and *Robot (dummy),* are all positive and significant.

Table 3: Baseline regressions

Dependent Variable: Export of 3D printable products in 2023 (log)

	Baseline	Baseline	Baseline	Baseline
3DP (dummy)	0.573**		0.613**	0.676**
	(0.210)		(0.215)	(0.207)
RCA (dummy)		0.447***	0.495***	0.706***
		(0.084)	(0.089)	(0.120)
3DP (dummy) x RCA (dummy)				-0.371*
				(0.158)
Exp. 2012 (log)	0.464***	0.445***	0.435***	0.428***
	(0.020)	(0.022)	(0.021)	(0.020)
Rel. Density	0.066***	0.065***	0.060***	0.062***
	(0.007)	(0.007)	(0.008)	(0.008)
GDP pc PPP (log)	0.177	0.251*	0.198	0.207+
	(0.125)	(0.126)	(0.124)	(0.125)
Pop. (log)	0.215***	0.315***	0.248***	0.255***
	(0.054)	(0.059)	(0.056)	(0.056)
R&D/GDP	-0.223*	-0.144	-0.229*	-0.231*
	(0.095)	(0.089)	(0.097)	(0.095)
Dom. Prod. (log)	0.058**	0.052*	0.058**	0.059**
	(0.021)	(0.022)	(0.021)	(0.021)
Policy index	0.331*	0.439**	0.374*	0.377*

Table 3: Baseline regressions				
Dependent Variable: Export of 3D printable products in 2023 (log)				
	Baseline	Baseline	Baseline	Baseline
	(0.149)	(0.164)	(0.152)	(0.151)
Robot (dummy)	0.435*	0.472*	0.478*	0.474*
	(0.201)	(0.204)	(0.205)	(0.204)
Num.Obs.	16722	16722	16722	16722
R2 Adj.	0.747	0.746	0.748	0.749
R2 Within Adj.	0.722	0.722	0.724	0.724
HS FE	Yes	Yes	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter

Clustered standard errors in parenthesis

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

We further explore this finding by estimating the same model for different subsamples of our database. First, in Table 4, we investigate whether heterogeneity exists across different types of products. Andrenelli and González (2021) compiled a list of 3D printable products and grouped them by type, loosely associated with industries. As we discussed in our review of the literature, it can be expected that 3DP technology affects different products differently. For example, the advantages of reduced internal economies of scale may be important for machinery components, which can then be produced locally and on demand. In contrast, in industries that strongly rely on external economies of scale (e.g., aerospace), 3DP may not lead to significant changes in the geography of production. To explore these differences across industries, we re-estimate our model for each of the five types of 3D-printable products identified by Andrenelli & González (2021). Second, in Table 5, we follow the literature (Freund et al., 2022) and investigate whether the relationship changes for products in different quartiles of product complexity (Hidalgo & Hausmann, 2009). On the one hand, greater complexity may be associated with less "mobile" production, as complex goods may rely on external economies of scale. On the other hand, the greater design freedom in additive manufacturing and the ability to create shapes and geometries otherwise impossible to produce may reduce the need to rely (and locate nearby) on specialized human capital pools or firms (Steenhuis, 2023). In Tables 4 and 5, we do not report the estimated coefficients of control variables for the sake of brevity, since the coefficients are in line with those of the baseline estimations.

Table 4: Regressions by different types of products					
Dependent Variable: Export of 3D printable products in 2023 (log)					
	Lowtech	Machinery	Aerospace	Medical	Orthopedic

Table 4: Regressions by different types of products					
Dependent Variable: Export of 3D printable products in 2023 (log)					
	Lowtech	Machinery	Aerospace	Medical	Orthopedic
3DP (dummy)	0.695**	0.731***	0.745**	0.137	0.836**
	(0.225)	(0.215)	(0.277)	(0.301)	(0.298)
RCA (dummy)	0.715***	0.633***	-0.270	0.639*	1.002**
	(0.150)	(0.174)	(0.558)	(0.295)	(0.384)
3DP (dummy) x RCA (dummy)	-0.368*	-0.423*	0.677	-0.828*	-0.263
	(0.183)	(0.205)	(0.581)	(0.337)	(0.414)
Num.Obs.	10998	2363	745	1079	1537
R2 Adj.	0.742	0.768	0.753	0.723	0.744
R2 Within Adj.	0.722	0.760	0.745	0.661	0.739
Control variables included	Yes	Yes	Yes	Yes	Yes
HS FE	Yes	Yes	Yes	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter	Exporter

Clustered standard errors in parenthesis

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

The coefficients in Table 4 confirm the positive relationship between the adoption of 3DP technologies and the level of exports in 2023, with the exception of medical products. Overall, the results confirm our previous findings, with the coefficient of *3DP (dummy)* being consistently significant and larger than that of *RCA (dummy)*. As in Table 3, the interaction terms between our two variables of interest suggest that countries that are both specialized and adopters are the group for which the level of exports is highest. One particularly interesting case is that of machinery (Column 2, Table 4). On the basis of the estimated coefficients, the adoption of 3DP in countries that were not previously specialized in machinery products leads to a greater increase in current exports ($\beta = 0.731$) than in countries that were previously specialized ($\gamma = 0.633$). On the other hand, previously specialized countries that adopted the technology (the sum of the three coefficients, $\delta = 0.941$) still outperform both groups. While pinpointing the mechanism at play is not possible in our empirical settings, this result is in line with the intuition presented above: machinery products are less strongly affected by external economies of scale, making pre-existing capabilities less important. Different anecdotes support this idea, for instance, the use of 3D printers aboard container ships to manufacture, quite literally anywhere, tools and components on demand (Molitch-Hou, 2025; Schwaar, 2023). Similarly, Ford extensively uses additive manufacturing to design and print tools on demand across different locations, reporting that printing on demand and on location without relying on suppliers produces massive savings in terms of time and resources (Ford, 2023; Yahoo Finance, 2024). Another case of interest emerging from Table 4 pertains to aerospace products (Column 3). The point estimates of our model show that the coefficient *3DP (dummy)* is the largest and significant, the interaction term is also positive, although not significant, and *RCA (dummy)* is negative and not significant. Further testing suggests that the difference between countries specialized and adopting 3DP (the sum of the three coefficients, $\delta = 1.151$) is marginally indistinguishable from the adoption effect alone (*p-value*$= 0.15$). This statistical ambiguity likely reflects both the relatively small sample size for aerospace (n=745) and the transitional nature of the industry. Qualitative evidence from industry sources illustrates this complexity: aerospace firms emphasize both new 3DP capabilities and access to traditional aerospace infrastructure when explaining location choices. For instance, Beehive Industry, an American company specializing in aerial defense, stresses the combination of using pioneering manufacturing technology and the locational characteristics of Clermont County (with "experienced aerospace engineering talent pool, proximity to Wright-Patterson Air Force Base, and collaboration with local academic institutions such as University of Cincinnati") as a key factor (Beehive Industries, 2025). Similar insights are provided by the European aerospace consortium Ariane Group extensively using 3DP and indicating that their locations in Vernon (France) and Ottobrun (Germany) are strongly connected to the presence of specialized companies (ArianeGroup, 2020).

Table 5: Regressions by level of product complexity (by quartile)

Dependent Variable: Export of 3D printable products in 2023 (log)

	Low ECI	Medium-low ECI	Medium-high ECI	High ECI
3DP (dummy)	0.610*	0.499*	0.664**	0.897***
	(0.269)	(0.214)	(0.229)	(0.239)
RCA (dummy)	0.998***	0.685***	0.393*	0.714***
	(0.233)	(0.165)	(0.187)	(0.191)
3DP (dummy) x RCA (dummy)	-0.358	-0.416*	-0.066	-0.488*
	(0.337)	(0.187)	(0.227)	(0.247)
Num.Obs.	2076	4785	4562	5299
R2 Adj.	0.696	0.746	0.744	0.776
R2 Within Adj.	0.665	0.707	0.729	0.759
Control variables included	Yes	Yes	Yes	Yes
HS FE	Yes	Yes	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter

Clustered standard errors in parenthesis

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The findings of our baseline also find confirmation when the sample is split on the basis of the complexity of the product (Table 5). Interestingly, while the importance of 3DP adoption is greater for more complex products, the coefficients of *RCA (dummy)* are larger for low complexity and high complexity products than for medium-level complexity products. As in the previous cases, while the interaction effect is typically negative and occasionally significantly different from 0, the total effects implied by the estimated coefficients suggest that “specialized 3DP adopters” are the top performers. We summarize the findings graphically in Figure 3 below, where we compute the predicted level of exports for different categories, based on the results in Tables 3 and 4 (skipping Table 5 for the sake of brevity).

FIGURE 3 HERE

The graphs in Figure 3 provide a summary of our findings. The vertical axis reports the predicted value of exports (in log) based on our models for different groups of countries. The lines on the left-hand side (where on the horizontal axis, the value for specialization is 0) represent the predicted values for countries that were not specialized in a certain product in 2012, whereas the lines on the right-hand side (right above value 1 on the horizontal axis) represent the predicted values of exports for specialized countries. The cases of countries that have adopted 3DP are marked by a triangle, while non-adopters are marked by a circle. In summarizing our findings, we focus on comparing the predicted value of exports for countries having adopted 3DP but not previously specialized in the focal product (triangle on the left-hand side of each graph) with those of the other groups of countries. The numbers reported close to the square brackets are the *p-values* of the differences between the predicted values of the “non-specialized 3DP adopting” group *vis-à-vis* all the other groups. The main point emerging from Figure 3 is that the focal group (triangle on the left-hand side) tends to catch-up in terms of export levels with previously specialized countries (dot and triangle on the right-hand side of each graph). The fact that the difference in the point estimates between adopters of 3DP is usually not statistically significant is also rather telling: 3DP adopters effectively managed to increase their exports and catch-up with global leaders (both “previously specialized non adopting” countries and “previously specialized and 3DP adopting” countries). We take these findings as compatible with the idea of a changing geography of the production of 3D printable products.

6. Robustness checks

To ensure that our findings are not dependent on specific methodological choices or measures, we test their robustness in several ways. First, we check whether changing the measure of 3DP adoption leads to different results. In the first two columns of Table 6, we change the definition of adopters. In the first column, we account for differences across countries related to differences in income and investment capabilities using the variable *3DP alt. (dummy)*. This alternative measure of 3DP adoption is computed by dividing the total trade in AM of each country by its gross per capita national income (*GNI pc*). Countries with higher trade in AM relative to their per capita income can therefore be considered adopters even if they do not reach the USD 10 million threshold. To make our measure binary (to assign countries to different groups), we select countries in the top 15% of the distribution of AM trade divided by the GNI per capita[15]. We consider 15% as a threshold, as it allows the inclusion of smaller and less prosperous countries while maintaining a relatively high threshold for adoption (thus avoiding the import of one 3DP machinery being enough to be considered an adopter). With this alternative measure, the 3DP adopting country with the lowest level of trade in AM machinery is Cambodia, with approximately USD 1.9 million in AM trade. In the second column of Table 6, we identify adopter countries for which the amount of AM traded is at least USD 1000 per capita (*3DP 1kpc*). This allows us to account for differences in size, as larger countries may more easily reach the USD 10 million threshold in AM trade, possibly biasing the measure of adoption toward smaller countries[16]. When using *3DP alt. (dummy)* as a measure for adoption, the estimated coefficient for 3DP is lower than that for *RCA (dummy)*. Importantly, however, the two coefficients are not significantly different from each other, suggesting that even in this case, 3DP would have a comparable effect to pre-existing capabilities. Besides this, the main difference between the first two columns of Table 6 and the results in Table 3 is the loss of significance of the interaction term, which occurs in multiple cases in Tables 4 and 5. In addition, in the third,

[15] As intended, some countries which we previously considered as 3DP adopters (Arab Emirates, Switzerland, Finland and Portugal) are no longer listed as such, while other countries (Costa Rica, Nigeria, Cambodia and Philippines) are now considered as having adopted 3DP. The core of the list however has not significantly changed.

[16] Using this alternative measure of adoption, we identify seven more countries as adopters (Costa Rica, Estonia, Ireland, Latvia, Malta, Slovenia and Slovakia), while sixteen countries are no longer considered as adopters (Brazil, Canada, China, Spain, France, India, Italy, Japan, South Korea, Mexico, Portugal, Romania, Russia, Thailand, Turkey and Vietnam). Whereas some of these changes are reasonable (e.g. Costa Rica has a substantial presence of high-tech industries), others are difficult to motivate (e.g. South Korea, Japan, Spain and Italy as non-adopters).

fourth and fifth columns of Table 6, we check whether using data from different periods for capturing pre-existing capabilities changes our results. The regression in the third column (RCA 2002) aims at controlling for the fact that, if 3DP had been adopted before 2012, some countries may have gained a specialization because of their adoption of AM. Calculating the measure of specialization in 2002, when 3DP was very much in early development, largely confirms previous findings. We further test our findings to make the measure for pre-existing capabilities more flexible, considering a country specialized in a certain product if it had an RCA higher than 1 in 2007, 2010 or 2012 (fourth column, RCA 07-12) or in 2010, 2012 or 2014 (fifth column, RCA 10-14). These checks largely confirm our previous findings. Interestingly, when we change the definition for RCA, the interaction terms in our models remain negative but become larger and more strongly significant than those in our baseline. Our last check (sixth column, Robot int.) focuses on the role of robot technologies, as we augment our model by adding the interaction term not only for *3DP (dummy)* and *RCA (dummy)* but also for robot adoption and RCA. Additionally, in this case, the results effectively remain the same, with the interaction term *Robot (dummy) x RCA (dummy)* being positive but statistically insignificant.

Table 6: Robustness checks

Dependent Variable: Export of 3D printable products in 2023 (log)

	3DP alt.	3DP 1kpc	RCA 2002	RCA 07-12	RCA 10-14	Robot int.
3DP alt. (dummy)	0.372*					
	(0.172)					
3DP 1kpc (dummy)		0.497**				
		(0.172)				
3DP (dummy)			0.885**	0.692***	0.714***	0.678**
			(0.296)	(0.206)	(0.206)	(0.209)
RCA (dummy)	0.631***	0.544***				0.677***
	(0.121)	(0.105)				(0.161)
RCA 2002 (dummy)			0.939***			
			(0.169)			
RCA07|10|12 (dummy)				0.723***		
				(0.106)		
RCA10|12|14 (dummy)					0.874***	
					(0.103)	
3DP alt. (dummy) x RCA (dummy)	-0.314+					
	(0.164)					
3DP 1kpc (dummy) x RCA (dummy)		-0.181				
		(0.160)				
3DP (dummy) x RCA 2002			-0.752***			

Table 6: Robustness checks						
Dependent Variable: Export of 3D printable products in 2023 (log)						
	3DP alt.	3DP 1kpc	RCA 2002	RCA 07-12	RCA 10-14	Robot int.
(dummy)						
			(0.206)			
3DP (dummy) x RCA07|10|12 (dummy)				-0.344*		
				(0.147)		
3DP (dummy) x RCA10|12|14 (dummy)					-0.406**	
					(0.144)	
3DP (dummy) x RCA (dummy)						-0.393*
						(0.186)
Robot (dummy) x RCA (dummy)						0.053
						(0.241)
Robot (dummy)	0.470*	0.427*	0.595*	0.478*	0.493*	0.466*
	(0.204)	(0.206)	(0.255)	(0.206)	(0.206)	(0.207)
Num.Obs.	16722	16722	11504	16722	16722	16722
R2 Adj.	0.747	0.748	0.716	0.750	0.751	0.749
R2 Within Adj.	0.723	0.723	0.692	0.725	0.727	0.724
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
HS FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter

Clustered standard errors in parenthesis
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These robustness checks focus on the definition of 3DP adoption and pre-existing specialization and are further complemented by a battery of placebo tests, in which the adoption variable is randomized using different stratifications. The placebo tests provide further confirmation of our empirical approach and are reported in the Appendix.

While we emphasize that our findings should not be interpreted in a causal sense, we explore more extensively possible issues with respect to endogeneity to better establish the robustness of our analysis. A first test we perform is using propensity score matching to create more balanced subsamples between 3DP adopters and non-adopters. To this end, we use information on the years before 2012 and match countries based on observable characteristics. Some difficulties in applying a propensity score matching approach in our empirical settings exist, given the relatively few "treated" units that may be structurally heterogeneous from the rest. To build the samples, we used two algorithms, one based on nearest neighbor matching and the other on optimal full matching (Ho et al., 2011), in combination with a caliper (0.1). The variables used for the matching, which we consider critical factors in shaping the probability of future adoption, are three: GDP per capita (average for the period 2008-2010), R&D as share of GDP (average for the period 2008-2010) and the (log) count of specializations in 3D printable products in 2007. Overall, both matching strategies help us make the sample significantly more balanced (see figure 4 below). However, the number of available observations becomes much smaller. The nearest neighbor sample includes 15 adopters matched to 9 control units. In the full optimal sample, we have 49 controls for 15 adopters. The first four columns of Table 7 report the results of these robustness checks. It should be noted that, while for NN matching (first two columns), we simply select the relevant matched observations in our data, for full matching (third and fourth column), we estimate weighted regressions where each observation is weighted by its full-matching propensity score weight. Regardless of the matching algorithm used, the results are well in line with our previous findings, with the estimated coefficient being larger for *3DP (dummy)* than for *RCA (dummy)*, while their interaction does not produce a significant coefficient.

FIGURE 4 HERE

Table 7: Propensity score matching and fixed effect regressions

Dependent Variable: Export of 3D printable products in 2023 (log)

	PSM - NN	PSM - NN	PSM - Full	PSM - Full	FE model	FE model
3DP (dummy)	0.427*	0.423*	0.647*	0.663*		
	(0.159)	(0.157)	(0.302)	(0.301)		
RCA (dummy)	0.155	0.138	0.335***	0.372***		
	(0.116)	(0.110)	(0.071)	(0.072)		
3DP (dummy) x RCA (dummy)		0.024		-0.137		
		(0.100)		(0.128)		
3DP (dummy) x 3D printable (dummy)					0.255***	0.294***
					(0.042)	(0.045)
RCA (dummy) x 3D printable (dummy)					-0.028	0.081
					(0.051)	(0.100)
3DP (dummy) x RCA (dummy) x 3D printable (dummy)						-0.204+
						(0.122)
Num.Obs.	4043	4043	6764	6764	422093	422093
R2 Adj.	0.814	0.814	0.815	0.815	0.719	0.719

Table 7: Propensity score matching and fixed effect regressions						
Dependent Variable: Export of 3D printable products in 2023 (log)						
	PSM - NN	PSM - NN	PSM - Full	PSM - Full	FE model	FE model
R2 Within Adj.	0.739	0.739	0.670	0.670	0.351	0.351
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
HS FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter

Clustered standard errors in parenthesis
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

An additional way in which we test the validity of our results against possible endogeneity issues is to estimate the same model as in our baseline on the whole spectrum of products and to interact the key variable of interest (*RCA (dummy)* and *3DP (dummy)*) with a binary variable for products that are 3D printable (*3D printable (dummy)*). This allows us to include country-level FE, thus effectively controlling for possible omitted variables related to the specific country characteristics (e.g. specific policy measures). We report the results in the fifth and sixth columns of Table 7. While the interpretation of the estimated coefficients is somewhat more complicated (since the country-level FE absorbs the direct effects of the variables of interest), it is still possible to compare the size and significance of the coefficients "holding constant" the 3D printable nature of the product. When considering 3D printable products, countries that we classify as adopters outperform previously specialized and even previously specialized countries that have adopted the technology (both differences are significant at the 5% level). This result is rather interesting and, based on our baseline estimations, somewhat unexpected since, throughout our analysis, the group of countries having adopted 3DP and having been previously specialized in the focal products were usually those performing best. While future research should further investigate this specific finding, the positive and significant coefficient for *3DP (dummy) x 3D printable (dummy)* is reassuring and well in line with our previous results.

We further test for unobservable selection and coefficient stability using the procedure developed by Oster (Oster, 2019) and calculate two statistics, $\delta^*$and β^*, with the first one indicating how strong selection on unobservables must be to eliminate the estimated relation and the second denoting the lower bound of the estimated coefficient after a correction for selection on unobservables. Both statistics do not signal problems with our models, as discussed in the appendix. In the appendix, we also replicate our baseline using different sets of control variables and different definitions of the *Policy index* (using all 6 indicators in the World Bank Governance database; using data up to 2022). We report these robustness checks in the appendix, as they overall provide strong support for our empirical analysis. Overall, the robustness checks we performed confirm the solidity of our findings. At the same time, we acknowledge and further discuss in the conclusions the empirical limitations that prevent causal interpretation of our findings.

7. Conclusions

The advent of 3D printing technologies has received only limited attention from economic geographers, despite the possible implications these new manufacturing methods have for the spatial footprint of production. In this paper, we provide some preliminary evidence on the relation that the adoption of 3DP technologies, pre-existing capabilities, and their interaction have on the export performance of countries. To evaluate how the level of export activity changes across different groups of countries (non-adopting and non-specialized countries, non-adopting and specialized countries, adopting and non-specialized countries, and adopting and specialized countries), we uncover some interesting facts. Specifically, countries that have adopted 3DP technologies seem not only to perform much better than "non-adopting non-specialized" countries but also to close the gap with countries that are already specialized. This may suggest that, at least in general terms, the adoption of 3DP may facilitate the emergence and growth of some specific productions, as in the case of hearing aid devices (Freund et al., 2022)[17]. We further study these relationships, exploring their heterogeneity across different types of products and products at different levels of complexity. Our findings indicate that moving from non-adopting to 3DP-adopting status is associated with higher levels of export across the board (the only exception being for medical and possibly orthopedic products), while previous specializations are associated with higher levels of exports only in a few cases (e.g., low-complexity goods). Overall, while our analysis cannot be considered as capturing causal relations, we interpret our findings as highlighting broad changes in the geography of production, with AM playing a role in shaping the export performance of countries for 3D printable products.

[17] In this specific industry, for instance, countries like Poland and Mexico have become, after the widespread adoption of 3DP in the industry, the leading exporters of hearing aids device, outperforming established producers like Denmark and Switzerland.

From this perspective, our findings suggest some further avenues for research to address some of the limitations of our analysis. With respect to aspects that deserve further attention, a first important question, especially for scholars in EEG, concerns whether 3DP adoption leads to the acquisition of new specializations locally and what role related capabilities play in these dynamics (Boschma & Capone, 2015). Capturing these diversification dynamics was hardly possible in our analysis, given the short time dimension and the country-level perspective of our empirical exercise. Using more fine-grained data may therefore be crucial for better understanding the mechanisms at play. A second aspect for future research to consider is whether similar implications can be found for other digital technologies. While 3DP has some very interesting and specific features, as discussed in the first sections of this paper, other technologies, particularly robotics and artificial intelligence, may also contribute to reshaping the current economic geography landscape. In this respect, the finding that robot adoption was also correlated with a higher level of exports is rather interesting. While the motivation to control for robot installations was to reduce the risk of bias in estimates for 3DP adoption, robots may also work as precursors for additive manufacturing. Studying how the adoption of one technology may facilitate, hinder or, more generally, interact with the use of another technology is an interesting and highly relevant question for further research. Similarly, the relationship between 3DP adoption and pre-existing capabilities should be explored further, for example, to understand whether previous specializations facilitate adoption of the technology and which other factors (e.g., artificial intelligence, robots) may help compensate for the lack of such capabilities. A third venue for further research should address the role of policy more clearly than what we have been able to do. Different countries have introduced policy measures to spur the adoption of new technologies like 3DP and have taken markedly different approaches. For instance, the Chinese government designated 3DP as a strategic industry and provided significant resources (Wübbeke et al., 2016), while the Biden Administration in the US leveraged public-private partnerships (The White House, 2022). Understanding whether and how different types of policy may support the adoption of new technologies and possibly facilitate industrial development is a highly relevant question. To effectively pursue this line of research, compiling and curating a database on 3DP-specific policy initiatives would be crucial. Last, our paper can only report associations because of the limitations of the empirical settings. For instance, in spite of our numerous robustness checks, endogeneity may affect our findings if countries with stronger industrial capabilities or better export prospects may be more likely to adopt 3DP technologies. Similarly, capturing 3DP adoption using HS code 8485 poses some issues, since this code only became available in

2022. This limits our ability to observe both earlier adoption as well as its dynamics and effects. Future research should therefore focus on causally investigating the impacts of 3DP and leveraging more robust techniques (e.g., traditional country-level fixed effects models once a long time dimension in the data becomes available). Establishing causal relationships is indeed important to offer clearer insights into the mechanisms at play.

To shed light on the effects of 3DP technologies and provide clear policy implications for governments, future research should address the challenges mentioned above, make an effort to theoretically pin down and empirically identify the mechanisms linking 3DP to changes in the geography of production. We hope our paper offers a first step in this direction and, more generally, toward a better understanding of the spatial implications of 3D printing.

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Appendix

Different measures of adoption

The table below reports the ISO codes of countries that are considered to have adopted 3D printing according to different measures of adoption.

Table 1.A: Countries having adopted 3DP

3DP (dummy) At least USD 10 million of trade in AM	**3DP alt. (dummy)** Top 15% in (AM trade/GNI pc)	**3DP 1kpc (dummy)** At least USD 1,000 per capita of trade in AM
AE	AT	AE
AT	AU	AT
AU	BE	AU
BE	BR	BE
BR	CA	CH
CA	CN	CR
CH	CR	CZ
CN	CZ	DE
CZ	DE	DK
DE	DK	EE
DK	ES	FI
ES	FR	GB
FI	GB	HK
FR	HK	HU
GB	HU	IE
HK	IL	IL
HU	IN	LT
IL	IT	LU
IN	JP	MT
IT	KH	MY
JP	KR	NL
KR	LU	PL
LU	MX	SE
MX	MY	SG
MY	NG	SI
NL	NL	SK
PL	PH	US
PT	PL	
RO	RO	
RU	RU	
SE	SE	
SG	SG	
TH	TH	
TR	TR	
US	US	
VN	VN	

Additional robustness checks

Table 2.A below reports the main coefficients of interest for our placebo tests. In these tests, we selected different countries as having adopted 3D printing in different ways. In the first two columns of Table 2.A we simply randomly draw 36 countries (the number of adopters in our baseline). In the remaining columns, to make the checks more credible, we first divide our sample into two groups (e.g., countries with high and low R&D shares) and check how many of the adopters we identify fall into each group (e.g., 0 in the low R&D group and 36 in the high R&D group). We then randomly draw the same number of placebos as true adopters from the two groups. We stratify our placebo using four different variables: R&D as a share of GDP (third and fourth columns), GDP per capita (fifth and sixth) and the share of specializations (seventh and eight). For each placebo test, we also calculate how many true adopters are in the sample ("Share true" row in Table 2.A; the countries considered true adopters are in bold in the placebo lists). None of the placebo tests invalidated our results. Interestingly, even when nearly 40% of the placebos are true adopters, the regression does not produce a significant coefficient. We take this as further convincing evidence of the validity of our approach.

Table 2.A: Placebo checks

Dependent Variable: Export of 3D printable products in 2023 (log)

	Unconditional	Unconditional	R&D Strata	R&D Strata	GDP Strata	GDP Strata	RCA Strata	RCA Strata
Placebo	-0.101	-0.072	-0.057	-0.069	0.082	0.123	0.047	0.062
	(0.151)	(0.145)	(0.123)	(0.131)	(0.149)	(0.161)	(0.126)	(0.127)
RCA (dummy)	0.447***	0.473***	0.445***	0.423***	0.447***	0.507***	0.452***	0.473***
	(0.084)	(0.091)	(0.085)	(0.102)	(0.084)	(0.101)	(0.087)	(0.099)
Placebo x RCA (dummy)		-0.146		0.069		-0.219		-0.073
		(0.195)		(0.179)		(0.210)		(0.160)
Num.Obs.	16722	16722	16722	16722	16722	16722	16722	16722
R2 Adj.	0.746	0.746	0.746	0.746	0.746	0.746	0.746	0.746
R2 Within Adj.	0.722	0.722	0.722	0.722	0.722	0.722	0.722	0.722
Share True	0.14	0.14	0.33	0.33	0.39	0.39	0.25	0.25
HS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter

Clustered standard errors in parenthesis

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Placebos lists:

Unconditional: AI, AZ, BO,CI, CR, EG, ET, **FR**, GW, GQ, HT, **IN**, IS, JM, **JP**, KW, LC, MO, MA, MV, MM, ME, MR, NE, **NL**, NO, PS, QA, **SG**, SS, TD, TV, UY, VE, VU, YE

Table 2.A: Placebo checks

Dependent Variable: Export of 3D printable products in 2023 (log)

	Unconditional	Unconditional	R&D Strata	R&D Strata	GDP Strata	GDP Strata	RCA Strata	RCA Strata

R&D: AR, AM, **AT**, **BE**, BO, BW, CL, **CN**, **CZ**, EE, GA, GH, GR, **HK**, **IN**, **IL**, **KR**, LV, MG, **MX**, MK, MT, NP, NZ, OM, PK, PS, **RU**, **SG**, SV, RS, SK, TJ, TZ, UY, **US**

GDP: AW, AI, AM, **AU**, AZ, **BE**, BW, **CH**, KM, CR, KY, **CZ**, **DE**, **FR**, GQ, **HK**, **IL**, KZ, KW, LU, LV, MO, MV, ME, **MY**, SA, **SG**, SK, SC, TC, **TH**, TJ, TT, **TR**, **US**, VE

RCA: AI, **AT**, **BE**, **BR**, CM, CK, CV, **CZ**, **ES**, FJ, **FR**, GR, GT, **HU**, ID, JO, LB, LV, MD, MV, MM, MP, MS, YT, NE, PH, SV, PM, RS, **SE**, TK, TO, TN, **TR**, UA, UY

Table 3.A below further complements our robustness checks investigating the stability of the estimated coefficient for *3DP (dummy)* and how inclusion (or lack of relevant controls, as requested by one of the referees) may affect our findings. In the first column of Table 3.A, we follow Oster (2019) and evaluate the possible unobservable selection bias. Since the procedure proposed by Oster (2019) and implemented in R through the robomit package (Schaub, 2025) requires one variable of interest to be tested, we focus on possible omitted variables in the model with both *3DP (dummy)* and *RCA (dummy)* but without an interaction term. We set our maximum R-squared to 0.901, which is 20% higher than what our baseline obtained (Oster, 2019) and more than 10 points higher than that of a model including both product and country fixed effects (0.785). We then calculate the Oster delta and lower bound of our coefficient of interest via a bootstrapping procedure (Schaub, 2025). The results confirm the validity of our approach, with the selection of unobservable variables being lower than that of observable variables (delta>1) and the coefficient of interest remaining relatively large.

Table 3.A: Additional robustness checks

Dependent Variable: Export of 3D printable products in 2023 (log)

	Oster	No CV	No GDP	No Rob	Policy all	Policy up to 2022	Public R&D	AM Patents
3DP (dummy)	0.613**	5.148***	0.727***	0.672**	0.699**	0.579**	0.657**	0.721***
	(0.215)	(0.284)	(0.207)	(0.221)	(0.212)	(0.202)	(0.206)	(0.215)
RCA (dummy)	0.495***	3.472***	0.656***	0.659***	0.708***	0.729***	0.701***	0.698***
	(0.089)	(0.216)	(0.121)	(0.126)	(0.119)	(0.123)	(0.120)	(0.121)
3DP (dummy) x RCA (dummy)		-0.929***	-0.330*	-0.390*	-0.371*	-0.370*	-0.374*	-0.369*
		(0.270)	(0.157)	(0.151)	(0.157)	(0.164)	(0.157)	(0.158)
Policy index (6 dimensions)					0.364*			
					(0.149)			
Policy index 2022						0.519**		

Table 3.A: Additional robustness checks								
Dependent Variable: Export of 3D printable products in 2023 (log)								
	Oster	No CV	No GDP	No Rob	Policy all	Policy up to 2022	Public R&D	AM Patents
						(0.164)		
Gov. R&D							-0.006+	
							(0.003)	
AM Pat (log+1)								-0.043
								(0.065)
Num.Obs.	16722	20556	16722	16722	16722	16722	16722	16722
R2 Adj.	0.748	0.502	0.748	0.747	0.748	0.747	0.749	0.749
R2 Within Adj.	0.724	0.467	0.723	0.722	0.724	0.723	0.725	0.724
Max R-Sq.	.901							
Oster Delta (boot.)	1.362							
Lower bound (boot.)	0.227							
HS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables included	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Clustering SE	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter	Exporter

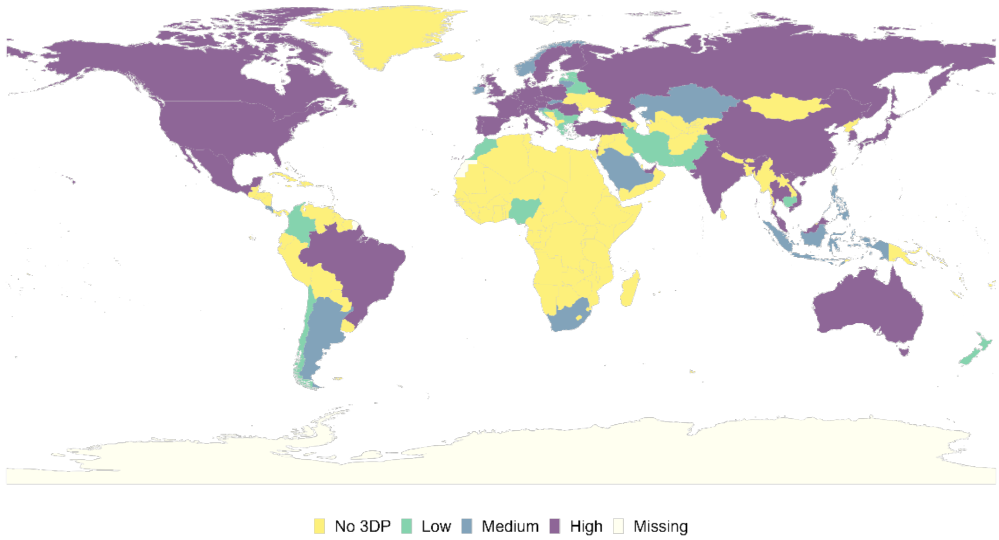
Clustered standard errors in parenthesis

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

The remaining columns of Table 3. A shows the change in the coefficient when no control variable is included (second column), with some changes in the variables considered (removing GDP per capita in column 3, removing the robot adoption measure in column 4). In column 5, we use a different version of the Policy index, including all 6 indicators (see footnote 7), and in column 6, we consider the four most relevant indicators up to 2022. We also include additional variables, specifically a measure of public R&D (column 7) and the number of 3DP patents registered to inventors residing in the country by 2019 (column 8). None of the changes affected our main findings.

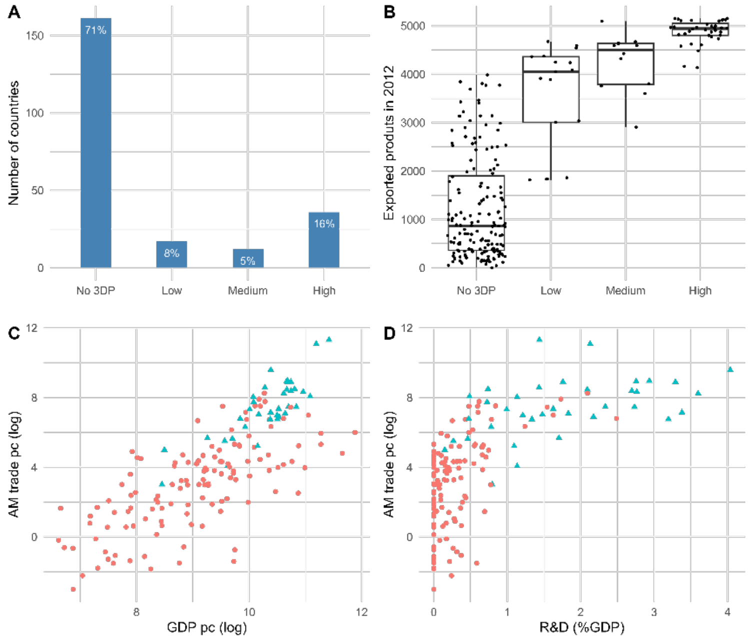
Figures

Figure 1: Levels of adoption of 3DP across countries



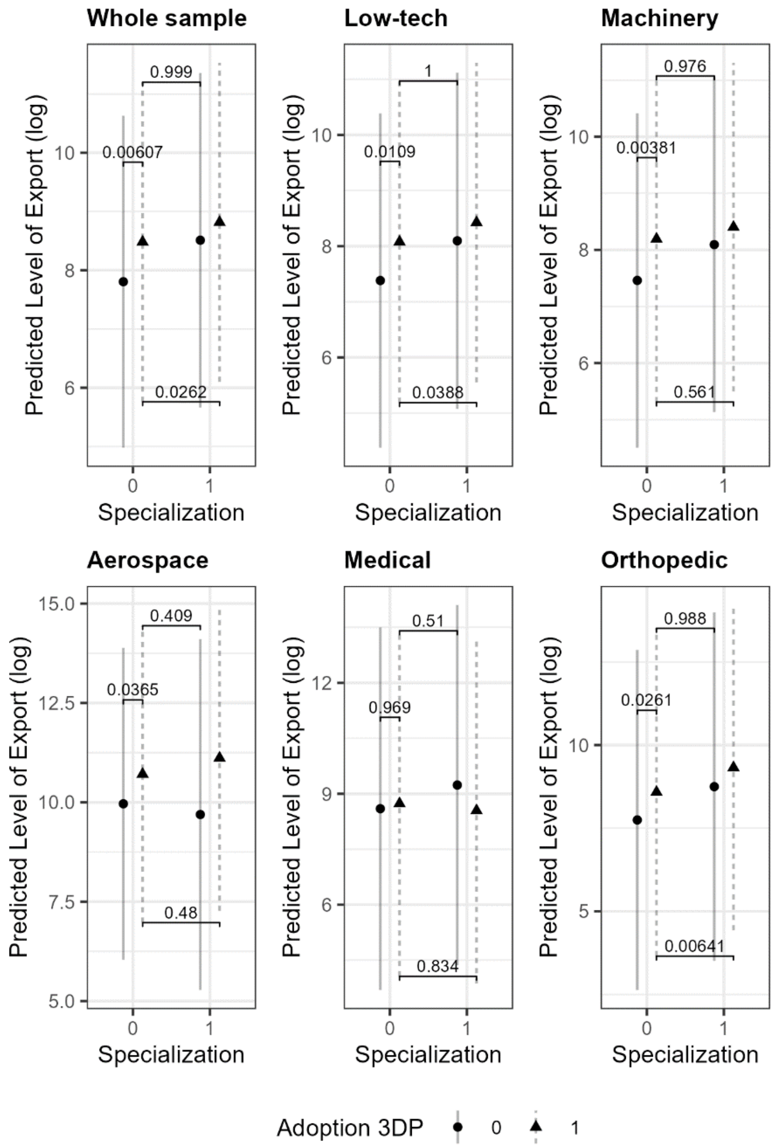
The map reports the spatial distribution of different levels of 3D printing adoption (low = 1 million USD, medium = 5 million USD, high = 10 million USD) across countries.

Figure 2: Distribution and characteristics of countries across levels of 3DP adoption



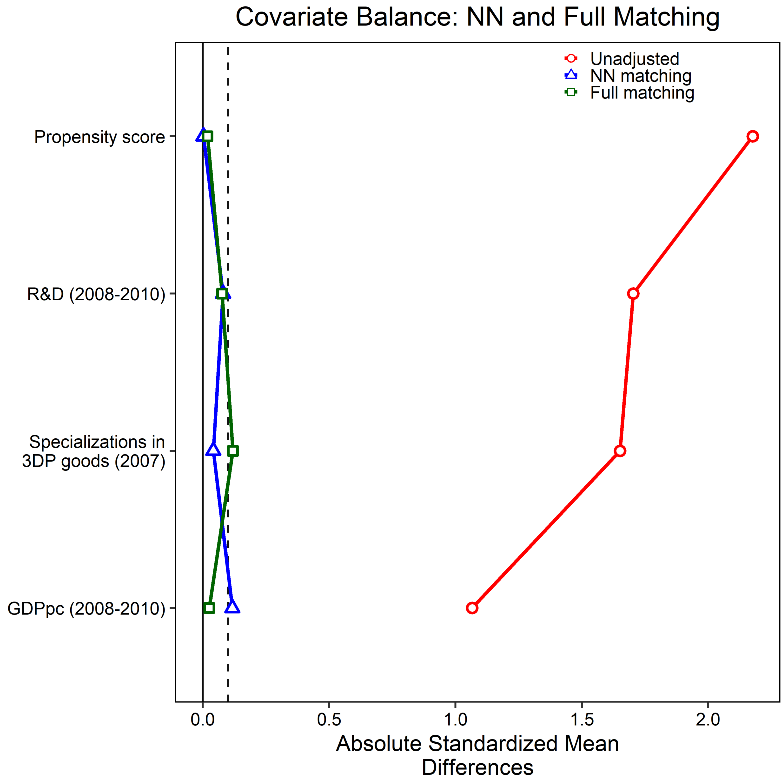
The figure describes the distribution and characteristics of 3DP adopting countries. Panel A shows the share of 3DP adopting countries using different threshold for adoption (low = 1 million USD, medium = 5 million USD, high = 10 million USD). Panel B shows the distribution of exported products by level of adoption. Panel C and D depict the correlation between GDP per capita and R&D and the amount of trade per capita in 3DP.

Figure 3: Predicted levels of exports across groups of countries for the whole sample and product type subsamples



Predicted levels of export for the whole sample and by type of product. Overall, non-specialized but 3DP-adopting countries tend to catch-up in terms of export levels with previously specialized countries (dot and triangle on the right-hand side of each graph), through with some heterogeneity across types of products.

Figure 4: Covariate Balance Before and After Matching



The love plot above reports absolute standardized mean differences before matching and after nearest-neighbor and full matching. Prior to matching, treated and control units differ substantially across all covariates and in the estimated propensity score. Both matching procedures markedly improve covariate balance, reducing all standardized differences well below the conventional 0.1 threshold for most covariates. Overall, the figure indicates satisfactory common support and effective balancing of observed characteristics.