Technische Universität München

TUM School of Management

The economics of additive manufacturing: From technology adoption to market disruption

Julian Schwierzy

Vollständiger Abdruck der von der TUM School of Management der Technischen Universität München zur Erlangung eines Doktors der Wirtschafts- und Sozialwissenschaften (Dr. rer. pol.) genehmigten Dissertation.

Vorsitz:	Prof. Dr. Sebastian Schwenen
Prüfende der Dissertation:	1. Prof. Dr. Hanna Hottenrott
	2. Prof. Dr. Claudia Doblinger

Die Dissertation wurde am 31.01.2025 bei der Technischen Universität München eingereicht und durch die TUM School of Management am 15.04.2025 angenommen.

Acknowledgements

Throughout my doctoral journey, I have been fortunate to receive incredible support from numerous individuals. First and foremost, I would like to express my deepest gratitude to my supervisor, Hanna Hottenrott, for her consistent guidance throughout this journey. Despite the physical distance between Mannheim and Munich, she always made herself available and provided invaluable support and insight. I am especially grateful for her patience and approachable, down-to-earth nature, which made every opinion feel valued and relevant. I want to thank Claudia Doblinger for agreeing to serve as my second examiner and Sebastian Schwenen for chairing my dissertation committee. Their time and effort are greatly appreciated.

My research would not have been possible without the contributions of my collaborators. Special thanks go to Robert Dehghan, Christoph Gschnaidtner, Ann-Christin Kreyer, Thomas Schaper, Sebastian Schmidt, Tobias Wenzel, and David Angenendt. Their collaboration and insights were instrumental in achieving the results of this research. I am also grateful to the research assistants who supported me throughout my doctorate. In particular, I want to thank Julian Greimel, Andreas Stömmer, and Kaan Uctum for handling tedious but essential tasks with dedication and efficiency.

This journey would have been much harder without my friends' support, who provided encouragement and much-needed balance. I want to thank Brendan Carr, Nicol Gloddek, Jolien Hacker, Felix Hagleitner, Jonathan Hanto, Maximilian Hegenbart, Richard Lindner, Markus Neumeyer, Markus Teschner, my brother Jan-Nils Schwierzy, and my parents, Thomas Schwierzy and Daniela Woydt. Their belief in me has meant the world. I am also grateful to my colleagues who have enriched this experience. In particular, I would like to thank Linda Bandelow, Annette Becker, and Pietro Fantini for their friendship and support.

This dissertation was funded by the German Research Foundation as part of the research group 'Multiple Competition in Higher Education' (FOR 5234). I am deeply grateful for the enriching exchange with the research group members. In particular, I would like to thank Maria Theißen for the regular formal and informal discussions, which provided clarity and inspiration.

Finally, I would like to thank my running shoes for helping me cope with this journey's constant pressure and serving as an unexpected but vital source of relief and balance.

Abstract

Europe faces major challenges in the 21st century, including climate change, social inequality, and demographic changes threatening economic growth and prosperity. Recent studies by the European Commission highlight the importance of investing in digital technologies to drive innovation and maintain competitiveness. Among these technologies, additive manufacturing (AM) provides the prospect of transforming traditional production, supply chains, and the transition from a linear to a circular economy. Despite its promise, many aspects of AM adoption remain insufficiently explored. Therefore, this dissertation investigates the drivers and implications of AM adoption and the effectiveness of policy instruments in Germany. The first study uses a game-theoretical model to examine how AM adoption affects competition and welfare in traditionally standardized product markets. The findings suggest that AM adoption reduces the number of firms and the prices of standardized products, increasing the total surplus. However, the impact on the consumer can be detrimental. The second study introduces a web-based indicator to map AM diffusion, highlighting the potential of this innovation indicator to track AM adoption and the role of technical universities and the manufacturing sector in promoting AM adoption. The third study evaluates the impact of Excellence Cluster funding on research output and industrial innovation, showing an increase in highly cited publications and industrial patents. The fourth study explores the role of fabrication laboratories (FabLabs) in promoting AM-based ventures. The analysis indicates that the establishment of a FabLab accelerates the creation of AM ventures, particularly for hardware and application-oriented ventures. Overall, the findings of this dissertation help policymakers to design effective mechanisms for AM adoption.

Table of Contents

List of Figures

List of Tables

1 | Introduction

The development of new technologies is a central component of the economic engine. As part of the innovation system, it affects firm performance, economic growth, and has contributed to improvements in the standard of living over the last decades (Aghion et al., 2021; Grossman and Helpman, 1993; Romer, 1990). The idea of innovation as the primary driver of growth and prosperity originates from Schumpeter's theory of economic development (Schumpeter, 1934), which emphasizes the importance of science and entrepreneurship for societies.

An essential concept of this theory is the idea of *creative destruction*. It refers to the process by which new products, services, or technologies replace outdated industries, making old technologies and business models obsolete (Schumpeter, 1942). While *creative destruction* boosts the economy by increasing productivity, efficiency, and ultimately creating new industries with new job opportunities, it can also cause negative disruptions such as job losses, environmental pollution, and the decline of traditional industries (Aghion et al., 2021).

An illustrative example of this double-edged sword is the automotive revolution of the early 20th century. The development and production of automobiles have changed the transportation sector and individual mobility by enabling faster movement between locations. Moreover, the automotive industry sparked technological advances such as the combustion engine and assembly line manufacturing, created thousands of jobs, and is now one of the largest contributors to the gross domestic product in some countries, including Germany. At the same time, however, access to automobiles led to the decline of horse-drawn carriages and the industries that supported them, such as blacksmiths and carriage builders, causing unemployment in the carriage industry. In addition, the widespread use of automobiles contributed to air pollution, as internal combustion engines emit pollutants, trapping the automotive sector in a path of 'dirty' mobility (Aghion et al., 2016). This pollution has led to ongoing environmental and health problems. More recently, electric engines are about to replace combustion engines – illustrating the forces of *creative destruction*.

In recent decades, we have witnessed how the evolution of modern computing and the rise of various digital technologies have disrupted traditional industries (Goldfarb and Tucker, 2019). Electronic commerce firms like Amazon have transformed the retail landscape, leading to the decline of brick-and-mortar stores and employment (Chava et al., 2024; Goldmanis et al., 2010). The rise of digital news platforms and social media has impacted the print newspaper industry, reducing advertising, circulation, and revenue for the print newspaper while improving consumer welfare (Nielsen and Fletcher, 2020; Gentzkow, 2007). Digital payment systems and mobile wallets such as PayPal, Apple Pay, and Google Wallet have made it easier for users to conduct financial transactions online and on mobile devices, reducing the need for cash and traditional banking methods (Humphrey, 2004).

For economists and policymakers, the categorization of emerging technologies is an important step in assessing their economic potential and choosing effective policy instruments. The literature discusses different technologies with the potential to change existing socioeconomic regimes by complementing or replacing current technologies (Geels, 2002). These include emerging technologies (Rotolo et al., 2015), general purpose technologies (Bresnahan and Trajtenberg, 1995), and key enabling technologies (KETs) (European Commisson, 2012), which differ in their characteristics and economic impacts. For European policymakers, KETs play a central role in the innovation strategy. These technologies are interdisciplinary and knowledge-intensive innovations that are expected to stimulate economic growth while addressing major societal and economic challenges (European Commisson, 2012).

1.1 Motivation and research topic

Given its political relevance, this dissertation aims to extend the knowledge of AM technology from an (innovation) economics perspective. In particular, this dissertation examines the drivers and implications of AM adoption and the effectiveness of policy instruments. The empirical studies of this dissertation focus on Germany due to the importance of its manufacturing sector for the European economy. Moreover, Germany represents an interesting case for studying innovation due to its history in manufacturing technologies and high level of absorptive capacity. As a result, this dissertation provides insights into AM technology that can help policymakers to design effective policy instruments for AM adoption.

1.2 Background on additive manufacturing

To better understand its importance as a KET, this section provides background information on AM. A brief overview of the characteristics of AM, how it differs from traditional manufacturing (TM) technologies, its economic impact, and its historical development provides insight into the economic potential of AM and its current state of development and diffusion.

1.2.1 What is additive manufacturing?

AM, often referred to as *3D printing*, is a digital technology that produces physical objects from digital data. The production process begins with a digital model, typically created using computer-aided design (CAD) software. This digital file contains all the necessary information about the object's shape, dimension, and other details. After the object is created, the digital model is converted into a format that the AM machine can process. The machine reads the digital file and executes the instructions to create the object, blending digital planning and physical execution.[1] Unlike TM technologies, the AM process combines materials layer by layer to create a physical object. AM encompasses a group of production processes that differ in several aspects, such as the layering method and the need for support structures.[2]

Considering the production process in a simplified way, each AM technology requires three fundamental input factors: an energy source, material, and a digital construction plan. First, the energy source serves as the driving force behind the operation of the machine. In some AM methods, energy also shapes and solidifies the material with sources such as lasers, electron beams, or lamps. Second, the material creates the physical shape of the object. Depending on the AM method, the physical state of the materials can range from liquid to solid powders and filaments. AM technology can use a wide range of materials, including polymers, resins, metals, ceramics, composites, biomaterials, food materials, etc. Each material is suitable for different applications and AM methods. Third, the digital construction plan coordinates the machine to add the material in the desired way.

[1] In addition to the digital process, AM often involves integration with other digital tools, such as simulation software to test the design before printing, or digital scanners for creating 3D models of existing objects.

[2] The ISO standard ASTM 52900 defines the main AM processes, such as binder jetting, powder bed fusion, fused filament fabrication, vat photopolymerization, sheet lamination, directed energy deposition, and material jetting.

1.2.2 Differences between AM and TM technologies

A key difference between the input factors of AM and TM technologies, such as subtractive manufacturing (e.g., milling) and formative manufacturing (e.g., molding), lies in the nature of the construction plan. In TM, the construction plan consists of physical tools or human labor. In contrast, AM relies on digital data containing information about the final object's geometry and the process of material deposition. From an economic perspective, a digital construction plan has fundamentally different properties than a physical input. For example, a CAD model incurs sunk costs because its development requires a one-time investment. In contrast, physical tools such as molds, cutting implements, and dies incur fixed costs, which amortize over time (Atzeni and Salmi, 2012). In addition, a CAD model can be duplicated and used simultaneously on multiple machines without degrading the original information, embodying a non-rival good's characteristics.

The digital nature of AM's construction plan affects the production function of AM technology by significantly reducing certain economic costs, including replication costs and transportation costs (for more information on these cost types, see Goldfarb and Tucker (2019)). Because of their relevance to this dissertation, I discuss changes in complexity costs, economies of scale, and economies of scope in more detail.

Complexity cost AM has a significant impact on complexity costs compared to TM. Unlike TM technologies, where complex geometries require additional tooling or machining time, AM can produce intricate shapes (Gibson et al., 2014). As part complexity increases, AM keeps costs relatively stable, while TM sees exponential cost growth (Kota et al., 2000). Thus, AM enables the production of complex geometries that would be difficult or impossible with TM technologies. This allows design optimization without incurring prohibitive costs. However, other aspects of the process are not as immune to complexity. Designing complex components, removing support materials, finishing surfaces, and performing quality inspections require more time, skills, and resources, leading to increased costs (Campbell et al., 2023; Pradel et al., 2017).

Economies of scale AM has relatively insignificant economies of scale. The role of economies of scale in AM technology has been the subject of an ongoing debate in the literature. Some researchers argue that AM lacks economies of scale due to the absence of significant fixed costs, such as tooling and molds (Weller et al., 2015; Berman, 2012). On the other hand, other researchers provide evidence for scale effects, e.g., through learning curve improvements (Baumers et al., 2016). In general, while the literature suggests the existence of economies of scale in AM, these effects are considerably weaker compared to those found in TM technologies (Baumers and Holweg, 2019).

Economies of scope AM facilitates economies of scope, improving cost efficiency in the production of a wide range of products (Weller et al., 2015). By eliminating the need for physical tooling, setup and changeover costs have minimal impact on a firm's production cost structure (Weller et al., 2015; Petrovic et al., 2011). Instead, AM machines only require a new digital model when producing a different product variant. The simple process of uploading a CAD file significantly reduces setup and changeover costs for firms. Moreover, firms can maximize efficiency by using unused space within the AM machine's build area to produce other types of products simultaneously (Baumers and Holweg, 2019).

1.2.3 Economic impact

By changing a firm's cost structure, the adoption of AM adds value in research & development (R&D), production, supply chain management, and sustainability compared to TM technologies. In the following, I discuss the advantages of these cost reductions for firms and the broader economy to outline the economic potential of AM.

Research & development AM presents an opportunity to reduce costs in the prototyping phase. Prototyping with TM methods often involves substantial upfront costs, including tooling and mold creation, which can be expensive for low-volume production or iterative design processes. In contrast, AM eliminates these initial investments, allowing for more cost-effective prototyping (Berman, 2012; Ben-Ner and Siemsen, 2017). AM's rapid iteration capability accelerates the product development cycle (Panda et al., 2023). This acceleration allows firms to bring new products to market faster and researchers to test parts more often, in a shorter time, and at less cost. In addition to rapid prototyping, firms are using AM for tooling to create custom tools, such as molds and fixtures (Gibson et al., 2014). Another advantage is that the same AM process and materials can be used for prototyping and production.

Production AM supports low-volume production and mass customization due to its weak economies of scale and strong economies of scope. TM faces challenges with customization because each variation often requires a new mold or fixture, adding significant cost. With AM, however, design modifications or customization do not require new tooling; firms simply need to adjust the digital model. As a result, small batches of products with different designs can be produced economically, allowing manufacturers to offer customized products without incurring substantial cost increases (Weller et al., 2015). Examples of customized products with AM range from bicycle helmets to robotic grippers.

The reduction in cost associated with part complexity expands the scope for designing and producing advanced products. With AM, developers can create biomimetic[3] design structures, often resulting in geometries that are both strong and lightweight (Du Plessis et al., 2019). Moreover, AM influences part consolidation. Integrating multiple parts into a single component makes it possible to simplify or even eliminate the need for assembly processes. Consolidated parts often outperform traditional parts due to optimized designs that incorporate features that improve functionality and efficiency (Petrovic et al., 2011). These product optimizations enable manufacturing parts that cannot be produced using TM technologies and can result in higher-quality products.

Supply Chain AM offers advantages for supply chains, particularly through decentralized production, which reduces the need for large, centralized factories and enables production closer to the point of demand. This flexibility reduces transportation costs and lead times because parts can be produced locally or in distributed locations as needed (Ben-Ner and Siemsen, 2017). AM also minimizes the number of part variations and simplifies inventory management by enabling on-demand manufacturing (Choong et al., 2020), which reduces the need for extensive physical inventory. In general, AM enables more agile, responsive, and cost-effective supply chains.

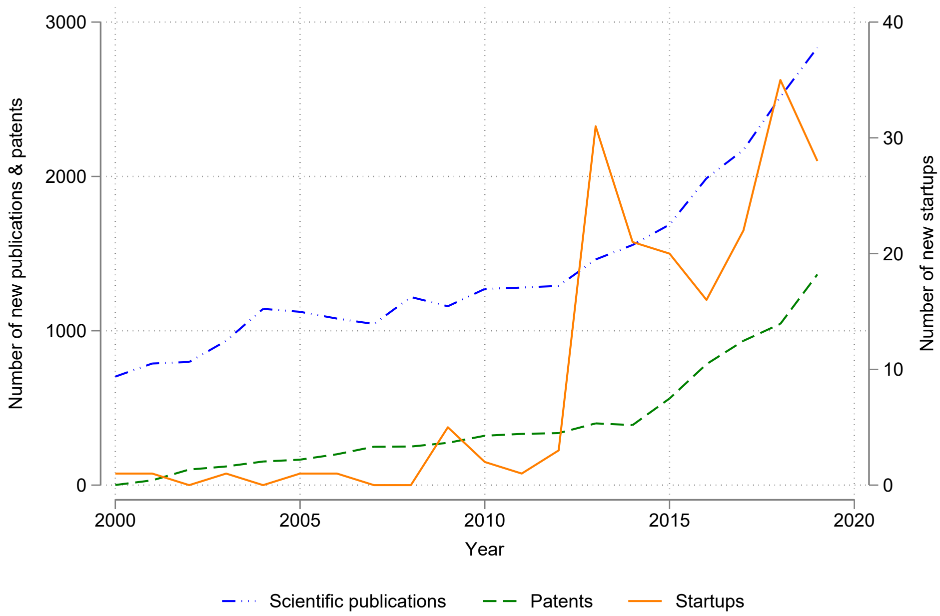
Sustainability AM promotes sustainability, particularly through waste reduction and decentralized production. In contrast to TM, which often removes material from a larger block, AM builds objects layer by layer, using only the material needed. This method minimizes material waste, leading to more efficient use of resources. Furthermore, AM allows for decentralized production, reducing the need for large transportation networks (Ben-Ner and Siemsen, 2017). This localized production model reduces transportation-related emissions. These features can, among other things, improve the environmental sustainability of firms and contribute to a circular economy (Sauerwein et al., 2019; Despeisse et al., 2017).

[3]Biomimetics is „the practice of designing materials, processes, or products that are inspired by living organisms or the relationships and systems formed by living organisms“ (Petrescu et al., 2023).

1.2.4 Historical development

Like other technologies, AM follows a clear evolutionary path from idea to R&D to diffusion. The concept of AM has already appeared in science fiction. Short stories such as *Things Pass By* (Leinster, 1945) and *Tools of the Trade* (Jones, 1950) describe technologies that use a layering process to create objects from scanned drawings. In the late 1960s, scientific interest in AM grew, with increasing research resources. At the Battelle Memorial Institute, scientists explored the production of solid objects using photopolymers and laser technology (Campbell et al., 2023). These broader research efforts during the 1970s and 1980s contributed to several AM-related inventions, such as Gottwald (1971) and Kodama (1981). However, these early inventors were unable to commercialize their inventions. The first successful commercialization of AM came with Chuck Hull's US patent Hull (1884), which introduced the stereolithography process, forming the foundation of 3D Systems Corporation. Over the next two decades, the AM industry experienced rapid growth, driven by the development of new methods such as FDM and SLS and the establishment of firms such as Stratasys Ltd. and Electro Optical Systems GmbH (EOS).

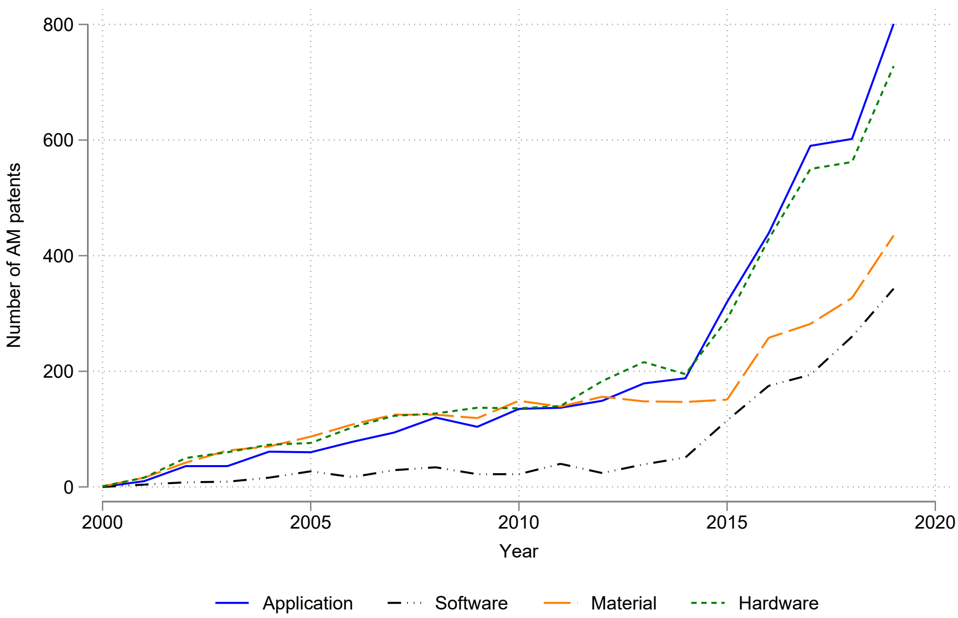
Figure 1.1: Technological advancements in AM technology



This figure shows the growth of AM-related scientific publications, patents, and startups in Germany from 2000 to 2019. Scientific publications were obtained from the Elsevier SCOPUS database using a keyword-based semantic search of abstracts with German affiliations (for the keyword list, see Table A.2.1). Patents were retrieved from the EPO database (Cavallo et al., 2023) based on the inventor's location. Startups were identified by the venture capital firm AM Ventures Management GmbH.

In the first decade of the 21st century, several initiatives were implemented to expand the manufacturing capabilities of AM. In 2001, Professor Neil Gershenfeld from the Massachusetts Institute of Technology (MIT) started the fabrication laboratory (FabLab) initiative, a global network of local laboratories that provide access to digital fabrication tools.(Gershenfeld, 2005). The core mission is to enable invention by providing widespread access to modern means of digital fabrication. Furthermore, FabLabs aim to empower people to create smart devices customized to local or personal needs. In 2005, Adrian Bowyer of the University of Bath in England initiated the Replicating Rapid Prototyper (RepRap) project. The project's primary goal was to create a low-cost AM machine capable of printing most of its components, essentially allowing the machine to replicate itself (Jones et al., 2011). By making AM technology accessible and affordable, Fab Labs and RepRap aim to empower people and small communities around the world to become creators and innovators. The maker movement has emerged during this time, inspiring people to share knowledge and collaboratively create diverse objects (Browder et al., 2019; Dougherty, 2012).

Figure 1.2: Development of AM patents



This figure illustrates the development of AM-related patents in Germany (2000–2019) based on inventor location, categorized as application, software, material, and hardware. Hardware includes equipment and techniques for transforming digital designs into physical objects. Material refers to input substances in various forms (solid, powder, wire, sheet, liquid). Software covers the digital process from CAD design to process control. Application encompasses end uses, from prototyping to production. Data is retrieved from the EPO database (Cavallo et al., 2023).

In the 2010s, the growing open source community, falling prices, and the expiration of key patents in the field of FDM and SLS technology facilitated the creation of numerous AM ventures such as Formlabs and Ultimaker (West and Kuk, 2016). In Germany, the number of AM-related startups has increased sharply since 2013 (see Figure 1.1). This growth has been accompanied by a rise in scientific output. Although the number of new scientific publications in Germany has increased significantly since 2013, a similar pattern can be observed in patent applications, albeit with a two-year lag. A more detailed analysis of patent trends shows a more pronounced increase in patents related to applications, compared to those in the categories of hardware, software, and materials (see Figure 1.2). This development indicates the growing importance of AM for series production applications, in line with the emergence of new startups in recent years (Campbell et al., 2023). According to a survey by Diegel et al. (2024), 31.7% of AM machine users produce final parts. However, the main use case is prototyping (32.8%). Other relevant applications are tooling (17%) and education & research (11.6%). The main users of AM technologies are firms in the automotive, consumer goods, dental, and aerospace industries (Diegel et al., 2024). The global market for AM products and services has grown steadily over the past three decades at a compound annual growth rate of approximately 25%. The size of the market increased from $1.3 billion USD in 2010 to $12.8 billion USD in 2020, reaching a total value of $20.04 billion USD in 2023 (Diegel et al., 2024).

1.3 Contribution of this thesis

In this dissertation, I investigate the drivers and implications of AM adoption. In particular, I address three relevant questions for economists, policymakers, and practitioners seeking to design effective policy instruments for the adoption of AM technology. First, how does AM affect competition and welfare? Second, what is the current state of AM diffusion and how can it be measured? Third, what policy instruments are appropriate to promote the adoption of AM technology? Using these questions as a framework, my dissertation contributes to recent literature in various fields such as industrial organization, science funding, and innovation policy.

1.3.1 Impact of AM adoption on competition and welfare

The impact of new technologies on competition and welfare remains a central issue in economic debates (Zhang et al., 2022; Smuha, 2021; Adner and Zemsky, 2005). Given that

AM is still in its early stages as a technology for end products, the economic literature on its broader effects is relatively sparse. However, some studies have examined the impact of AM on supply chains (Song and Zhang, 2020), sustainability (Despeisse et al., 2017), and market structure (Kleer and Piller, 2019).

In chapter 2, I examine the scenario in which firms adopt AM technology specifically for product customization. In this context, I investigate how AM adoption affects market competition focusing on changes in market structure, including pricing, the number of firms, and the resulting welfare implications. Building on the frameworks of Kleer and Piller (2019), Balasubramanian (1998), and Salop (1979), I construct a spatial game-theoretical model to analyze competition between firms using TM technologies for standardized products and those using AM for customized products.

The analysis shows that the adoption of AM technology reduces prices for standardized products compared to markets without AM, while prices for newly introduced customized products are higher. The model demonstrates an inverse relationship between AM's competitive advantage and the number of TM firms, with increasing AM competitiveness leading to a reduction in TM firms in the market. Consumer surplus initially benefits from the adoption of AM when the number of TM firms remains constant. However, this effect may diminish with endogenous firm entry as consumer surplus is closely related to the presence of TM firms. A threshold level of AM's competitive advantage is identified, beyond which further gains in AM's market position become detrimental to consumers, even as the total market surplus increases. Furthermore, intensified competition among AM firms may benefit consumers by lowering prices for customized products, but it may also reduce the probability of AM entry.

1.3.2 Measuring AM adoption & diffusion

To measure technology adoption and diffusion, researchers generally draw on data from intellectual property applications, surveys, and business reports of firms. In the context of AM, data sources include the KOF Swiss Innovation and Digitalization Survey (Arvanitis et al., 2017)[4], the patent classes identified by the European Patent Office (Cavallo et al., 2023), and the annual Wohlers Report (Campbell et al., 2023). However, traditional measures are prone to various biases, which can overlook important trends in the diffusion process of

[4] To the best of my knowledge, there is no survey that specifically asks about the use of AM among German firms.

interdisciplinary and fast-evolving digital technologies (Hall, 2022; Hall, 2006).

In chapter 3, I present an alternative measure based on web text mining to track AM adoption and diffusion. Building upon the approaches outlined by Kinne and Lenz (2021) and Gök et al. (2015), I apply web scraping and deep learning techniques to analyze textual data from corporate websites in Germany. The results of this analysis allow me to map the overall adoption of AM technology and compare its diffusion across firm characteristics, geographic regions, and sectors. Furthermore, I identify different actors and analyze their role in the diffusion process.

The results demonstrate that the web text mining approach provides a valuable tool for technology mapping, complementing traditional measures based on patents or survey data. The analysis reveals adoption patterns consistent with those observed in patent data. However, the approach also identifies significant adoption hotspots not captured by patent data alone. In particular, several regions exhibit high levels of AM adoption intensity, which appear to be closely linked to two primary factors: proximity to technical universities and established manufacturing industries. Moreover, when I examine the adoption intensity in relation to firm characteristics, I find that young and smaller firms contribute substantially to AM adoption rates. In terms of environmental sustainability, the identified firms show a higher level of engagement compared to the broader firm population.

1.3.3 Policy instruments for promoting AM adoption

Governments use a variety of policy instruments to promote the development and adoption of new technologies. These instruments can aim to support R&D activities, education and skills development, infrastructure and ecosystem, intellectual property protection, international collaboration, and open innovation, and funds for commercialization (Hottenrott, 2022; Hottenrott et al., 2017; Hottenrott and Lopes-Bento, 2014; Hottenrott and Richstein, 2020). In recent years, the United States and Europe have launched large-scale initiatives to promote AM adoption. In the United States, the *AM Forward* initiative provides access to capital and technical assistance to small and medium-sized manufacturers, invests in specialized workforce, and establishes industry standards to support AM adoption (The White House, 2022). In Europe, the *Horizon Europe* program advances AM technology development by supporting R&D efforts across universities and industries (European Commisson, 2024a).

In chapter 4, I analyze the impact of targeted university research funding on scientific output and its spillover to the local industry. In particular, I focus on the Cluster of Excellence program within the German Excellence Initiative, examining funding initiatives in the field of AM. To assess the effects of the program, I compare the funded regions with university locations that received support from another major program, the Collaborative Research Centers, using a synthetic difference-in-differences estimation (Arkhangelsky et al., 2021). The analysis covers the first funding period of the Cluster of Excellence program from 2006 to 2011.

The analysis shows that Cluster of Excellence funding led to an increase in scientific publications related to AM. Interestingly, top publications—those in the top percentile of most cited papers—increased significantly. This growth is driven primarily by academic institutions rather than industry authors or collaborations. The increase in high-quality research was associated with a rise in highly cited AM patents by local firms, although overall patenting activity did not increase.

In chapter 5, I explore the relationship between community workshops and entrepreneurship, focusing on the impact of fabrication laboratory (FabLab) establishments on the emergence of new startups in the field of AM. The FabLab is an interesting type of community workshop due to its unique institutional structure. In the analysis, I use a staggered difference-in-differences method (Callaway and Sant'Anna, 2021) considering Germany during the period 2000 to 2019.

The findings indicate that the establishment of a FabLab increases the probability of AM startups by 16 percentage points, a significantly larger effect compared to other community workshops such as makerspaces and hackerspaces. This effect is particularly pronounced for hardware- and application-focused startups, while no significant effects are observed for software- or material-based ventures. In contrast, the analysis of AM-specific patents as an alternative measure of innovation reveals no observable influence of the presence of FabLabs.

2 | Mass customization with additive manufacturing: Blessing or curse for society?

Summary

AM enables mass customization and has thereby the potential to revolutionize traditional manufacturing. In this chapter, I examine how the adoption of AM affects competition and social welfare in traditionally standardized product markets. Analyzing a game-theoretical model of spatial product differentiation, I find a decline in standardized product prices. In contrast, the price of customized products will exceed the price level of the initial market. These price changes are accompanied by a reduction in traditional manufacturers. In terms of social welfare, AM adoption increases the total surplus. However, it can be detrimental to consumer surplus if the competitive advantage of AM technology is excessively large. Based on these findings, I discuss policy implications for the manufacturing industry. I suggest complementary measures of ensuring a competitive environment for firms with AM technology and subsidizing their fixed cost in order to realize benefits for both consumers and producers.

This chapter is based on joint research with Tobias Wenzel.

2.1 Introduction

The adoption of new technology serves as a catalyst for economic growth and paradigm shifts within and across industries (Romer, 1990; Aghion et al., 2021). In recent decades, digital technologies have disrupted traditional market landscapes and unlocked new avenues for innovation and competition (Goldfarb and Tucker, 2019). This digital revolution requires attention from economists, industry managers, and policymakers in order to exploit its full potential for societal advancement.

Within the domain of technological innovations, Additive Manufacturing (AM), commonly known as 3D printing, is a key driver in propelling the digitalization of the manufacturing sector. AM has drawn significant attention in recent literature, with discussions centered around its implications for production efficiency, supply chain dynamics, and reshaping market structures (Weller et al., 2015; Baumers et al., 2016; Song and Zhang, 2020). While its usage has mainly comprised rapid prototyping, AM is evolving in its applications to produce final products (Campbell et al., 2023). Besides the advantages of manufacturing sustainable and complex products, AM unlocks the potential for product customization at a large scale (Gibson et al., 2014; Sethuraman et al., 2023). Manufacturers in several industries have already adopted this digital technology to meet diverse consumer needs by offering customized products. For example, medical professionals utilize 3D-printed implants, prosthetics, and splints that conform precisely to a patient's body, providing better support for rehabilitation.

In recent years, AM has been diffusing into traditionally standardized product markets. A prime example is the market for bike and football helmets. There, consumers can choose between helmets with standardized sizes or customized-sized helmets from firms using AM, such as HEXR and Vicis. A well-fitted helmet can significantly enhance the user experience and minimize injury risks. It is therefore not surprising to see many professional football players opting for customized 3D-printed helmets.[2,3] AM's diffusion and the increasing availability of customized products could dramatically transform the competitive landscape, changing how products are differentiated and priced. Despite these possible developments,

[2]For anecdotal evidence, see the following article. https://www.forbes.com/sites/carolynschwaar/2023/10/01/nfls-safest-helmets-absorb-impact-with-3d-printing-instead-of-foam/?sh=7e3d6fe678e7 accessed on 08/01/2025.

[3]Another example represents the customization of robot grippers in the automotive industry. https://www.press.bmwgroup.com/global/article/detail/T0442351EN/bmw-group-expands-use-of-3d-printed-customised-robot-grippers?language=en accessed on 08/01/2025.

the broader implications of AM adoption remain largely unexplored, especially in terms of welfare and the need for policy interventions.

This chapter aims to investigate the influence of adopting industrial AM for product customization on market structure and welfare. By analyzing market structure, I focus on the number of firms in the market and their pricing strategies, depending on the competitive advantage and competitive environment of the AM technology. Drawing on established game-theoretical models of product differentiation (among others Salop, 1979), I examine a spatial model.

Following the approaches of Balasubramanian (1998) and Kleer and Piller (2019), my model describes the competition between firms with traditional manufacturing (TM) technologies offering standardized products and firms with AM providing customized products, a scenario likely to unfold in the future. Wohlers (2023) suggests that AM acts as a complementary technology to TM, particularly in the production of final products. AM is not expected to replace TM for low-volume and simple geometric parts due to cost implications for large-scale production. In my base model, only one firm adopts AM due to the risk of Bertrand competition and marginal cost pricing for potential competitors utilizing the same technology.

The resulting market equilibrium indicates lower prices for standardized products compared to a market without AM technology. Yet, the price of the newly introduced customized products exceeds the level of markets with only standardized products. Furthermore, the model results show a negative correlation between the competitiveness of AM technology and the number of TM firms. In other words, more firms utilizing TM technology leave the market as the AM technology improves over time (e.g. through a decline in production costs). This effect is mainly attributed to an increased market power of the firm with AM technology.

In the welfare analysis, I show that the adoption of AM benefits consumers when the number of TM firms remains constant. However, this finding may not hold when considering the endogenization of firms' market entry. Consumer surplus depends on the number of TM firms and, therefore, declines with an increasing competitive advantage of AM technology. I identify a critical level of competitive advantage beyond which AM adoption becomes detrimental for consumers. However, AM adoption raises the total surplus by increasing competition. This analysis implies harmful effects for consumers if governments implement policies that foster AM's competitive advantage even though it boosts total surplus. Nevertheless, I show that subsidizing fixed costs can raise both consumer and total surplus if it induces AM adoption.

In my base model, the increased market power of the AM firm plays a critical role in the welfare outcomes. Therefore, I extend my model to include competition with potential rivals for the AM firm. Intensified competition for the AM firm leads to two main implications. On the one hand, competitive pressure drives down effective prices for customized products, benefiting consumers. On the other hand, AM entry becomes less likely. Therefore, promoting AM competition may require subsidies to incentivize the adoption of AM technology and ensure the highest level of consumer surplus.

The analysis and findings of this chapter are important for at least three reasons: First, AM plays an increasingly important role in a firm's serial production. Revenues of the global AM market for products and services have grown at a compound annual growth rate of roughly 25% between 2010 and 2020. While the market size encompassed $1.3 billion USD in 2010, the size grew to $12.8 billion USD in 2020 and resulted in an overall value of $18 billion USD in 2022 (Campbell et al., 2023). This development is in line with the growth of international patent families (IPFs) for AM. According to Cavallo et al. (2023), IPFs increased from 1,576 in 2013 to 8,090 in 2020. In addition, the number of startups using AM for the production of goods has increased in absolute and relative terms compared to startups developing hardware, software, or material solutions (Campbell et al., 2023). These developments demonstrate the relevance of AM for the manufacturing sector suggesting that my discussed changes in competition will occur more frequently and become more prevalent.

Second, governments actively promote digitalization by providing funding programs. These programs typically support research & development or technology acquisition, reducing marginal cost and fixed costs. There are various AM-tailored programs to foster its adoption. In Europe, the European Commission provides R&D funding for AM within the framework of the Horizon program, helping to achieve the UN's Sustainable Development Goals and boosting the EU's competitiveness and growth. In the United States, the government provides access to capital for small & mid-size enterprises in order to sustain high-paying jobs and improve supply chain resilience (The White House, 2022). With my analysis, I shed light on the effectiveness of these programs and provide implications for an efficient design.

Third, the results of my model can be applied to other technologies and applications, e.g. the rise of smart factories and supply chain flexibility. Several digital technologies reduce transportation costs and enable a decentralized production (Goldfarb and Tucker, 2019). In other words, the production occurs close to the consumer's location instead of in central manufacturing hubs. My model allows to reframe the spatial dimension's interpretation and consider a geographical perspective. Therefore, I can also draw conclusions for the competition between centralized and decentralized factories, among other examples.

2.2 Literature review

This chapter builds on research in the domain of industrial organization and draws from literature in digital economics, spatial product differentiation, flexible manufacturing, and additive manufacturing. A brief discussion of insights from these research fields provides an overview of the relevant literature as well as illustrates the research gap and my contribution.

Research in digital economics examines how digital technologies affect economic activities (Goldfarb and Tucker, 2019). Among others, studies in this field are interested in the competition between offline versus online marketplaces (Forman et al., 2009), physical versus digital products (Pattabhiramaiah et al., 2022) and its impact on consumer surplus (Brynjolfsson et al., 2003). A common approach to model this kind of competition is spatial models (Balasubramanian, 1998; Bouckaert, 2000). Most spatial models based on the groundwork of a linear street (Hotelling, 1929) or circular city (Salop, 1979) and were constantly improved over the last years, e.g. Bar-Isaac et al. (2023). With my study, I contribute to this stream of literature by investigating the competition between firms with TM technology and firms with AM technology, a digital manufacturing technology, and the resulting consequences for welfare.

Until the late twentieth century, manufacturing facilities were specialized to produce standardized products in large quantities to realize economies of scale. The rise of information technology has opened up new opportunities for the manufacturing industry with respect to its flexibility. Firms have been provided with the opportunity to adopt flexible manufacturing (FM) technologies and thereby increase their product variety (Milgrom and Roberts, 1990). Due to the capability of AM technology to flexible manufacture products, it can be categorized as a FM technology (Eyers et al., 2018). AM encompasses a group of production technologies combining material, energy, and digital data of the product design to create a physical product in a layer-upon-layer process (Gebhardt and Hötter, 2016). Conversely to TM technology, e.g. injection molding, AM technology utilizes CAD models and does not require any product-specific tools, molds, or preparations for the production of goods (Gibson et al., 2014). Hence, it reduces the cost penalty for flexibility and provides the opportunity to extend product variety without significantly compromising cost efficiency. Furthermore, the reduction of flexibility costs allows firms to realize economies of scope (Baumers and Holweg, 2019).

Economic literature discusses the consequences of the adoption of FM for market structure and welfare (Ungern-Sternberg, 1988; Eaton and Schmitt, 1994; Alexandrov, 2008), especially in terms of mass customization (Dewan et al., 2003; Bernhardt et al., 2007). Some studies discuss firms' incentives to adopt FM technology. Röller and Tombak (1990) show how the choice of technology differs under varying market structures and conclude that firms are more likely to adopt FM in larger markets, in markets with a high degree of product differentiation, and few competitors. Chang (1993) argues that its adoption aims to hedge markets with demand uncertainty and deter potential market entries. Based on an entry game, he shows that an incumbent threatened by a potential entry is more likely to adopt FM technology if the variability in consumer preferences is high. In line with this result, I find a higher likelihood of AM adoption if consumers strongly prefer differentiated products. Moreover, I show the importance of AM's cost structure, competitive environment, and consumers' customization involvement cost for the technology adoption decision.

The adoption of FM technology has tremendous implications for the competition intensity in markets with differentiated products. The capability of FM to flexibly manufacture various product variants lowers the unique positioning of products and, therefore, the firm's market power. Hence, the adoption of FM technology leads to a tougher price regime and a higher level of market concentration (Eaton and Schmitt, 1994; Norman and Thisse, 1999). Norman and Thisse (1999) show that the production flexibility of FM technology allows a change in the price of one product variant without changing others because of the capability to manufacture products that perfectly match consumers' preferences. Therefore, firms with FM are not committed to a set of prices and can more easily change their pricing strategy to deter potential entrants. In line with these findings, my results indicate increased competition by a decline in the number of firms with TM technology and a reduction of standardized product prices. Furthermore, only one firm adopts AM technology, which deters competitors from adopting the same technology. Surprisingly, the AM firm exhibits the capability to charge a premium price for its customized products.

More ambiguous are the consequences for welfare especially for consumer surplus. According to Röller and Tombak (1990), consumers always benefit from the adoption of FM technology. In contrast, the model of Eaton and Schmitt (1994) indicates the risk of negative implications for consumers due to higher market concentration. The effect on consumer surplus depends on the elasticity of individual demand. I extend these insights by investigating the influence of AM's competitive advantage and competitive environment on welfare and identifying the thresholds where consumers benefit from AM adoption.

A substantial part of the existing literature on AM are studies in the field of engineering (Weller et al., 2015), although many of these studies investigate an economic perspective such as the impact of AM on supply chains (Delic and Eyers, 2020), sustainability (Ghobadian et al., 2020), self-replicating innovative goods (Hu and Sun, 2022), and production costs (Baumers and Holweg, 2019). However, literature on AM in industrial organization is scarce and limited to just a few studies, see e.g. Hartl and Kort (2017) or Sun et al. (2020). Weller et al. (2015) analyze the effects of AM technology at the firm level and apply their findings to several economic models to examine changes in market structure. Among other things, Weller et al. (2015) extend the FM model of Eaton and Schmitt (1994) to design the cost structure of AM technology. Typically, digital technologies reduce some costs considerably, which may approach zero and open up new economic actions (Goldfarb and Tucker, 2019). For the case of AM, they assume zero cost for modifying a basic product to any other product variant due to the elimination of assembly steps, fewer manual interventions, and the absence of molds or tools. This change in the cost structure allows a firm to cover the whole market space and produce any variant for the same marginal costs. They simulate the entry of a firm adopting AM technology into Hotelling's linear city with three firms using FM technology. Based on their analysis, the authors conclude a decline in product prices as the entrant with AM lowers the upper-price barrier for the three incumbents.

More recent work by Kleer and Piller (2019) investigates the impact of competition between producers with AM technology and firms with TM technology. Their spatial model builds upon the approach of Salop (1979), considering an exogenously given number of firms that are equally distanced from each other on the circumference of a circle. Furthermore, they assume that producers with AM can manufacture any good within the attribute space in an AM facility, while firms manufacture standardized products in a centralized production factory. Their analysis provides insights into changes in consumer surplus, market structure, and competitive dynamics due to the adoption of AM. Kleer and Piller (2019) show a decline in firms' product prices. In addition, lower prices and consumers' opportunity to purchase customized products increase consumer surplus.

While this chapter provides important insights about competitors' reactions to AM entry, it remains unexplored how AM adoption changes market structure as such. In particular, how the number of incumbents reacts to the increased competition and the corresponding decline in product prices, which in turn affects competition. In order to understand the effect of the market dynamic on prices and welfare, the market adjustments on the supply side need to be taken into account by endogenizing the number of firms. Furthermore, extending the model of Kleer and Piller (2019) seems valuable to examine the welfare implications in detail and derive welfare maximizing policy measures. The aim of this chapter is to fill these research gaps. In order to consider the market dynamics and the corresponding welfare implications of industrial AM, my model assumes that firms enter and leave the market until each producing firm with TM technology obtains zero profits. Moreover, my model examines the role of AM's competitive environment and cost advantage compared to TM technology on market structure and welfare.

2.3 Theoretical model

In the following four sections, I discuss the analysis of my game-theoretical model. In section 2.3, I start to lay out the market framework of my game and then describe the outcome of a market where firms only adopt TM technology. This market serves as a benchmark to determine AM adoption's effects. In section 2.4, I derive the market equilibrium where TM firms compete with AM firms and compare the results with the outcome of my benchmark market. In section 2.5, I examine the consequences for welfare, including consumer surplus and total surplus.

2.3.1 Model set-up

I consider a market with consumers and firms trading horizontally differentiated products. A unit-circumference of a circle defines the product space as in Salop (1979).

Technology In this market, there are two distinct technologies for manufacturing products. First, TM technology manufactures one specific product variant (henceforth standardized product), corresponding to a single location on the circle. Second, additive manufacturing (AM) allows to produce any product variant (henceforth customized product) and perfectly tailor products to consumers' needs.

I define two types of market structures in terms of technology adoption. In the first market structure (henceforth market structure I), all firms use the TM technology for production. In the second market structure (henceforth market structure II), both TM and AM technologies are in use, assuming an exclusive adoption.

Consumer Consumers are uniformly distributed around the circle and its number is normalized to one. The location corresponds to the consumer‘s most preferred product variant. Moreover, I assume a covered market. In other words, each consumer purchases one unit of either a standardized or customized product.

When consumers decide to buy a standardized product, they incur a linear transportation cost t per unit of distance if the product's characteristics deviate from their most preferred product variant. In this case, a consumer with location x receives the following utility:

$$U_T^i = v - t|x^i - x| - p_T^i, \tag{2.3.1}$$

where v is the base utility, $|x^i - x|$ the distance between the firm's product and the consumer, and p_T^i is the price charged by firm i.

Instead, when purchasing the customized product, the consumer's utility is

$$U_A = v - \theta s - p_A. \tag{2.3.2}$$

As the product is customized, the consumer does not face any transportation costs. However, customization involves a cost, denoted as θs, which represents the time and effort costs associated with digital customization environments or the provision of potentially sensitive data. Here, $\theta > 0$ serves as a preference parameter of the consumer reflecting factors such as patience, communication skills in expressing product preferences, and the desire for data privacy. Similarly, $s > 0$ is a parameter related to the digital customization environment, indicating the difficulty for consumers to convey their preferences to the firm. Firms have the ability to influence this parameter by providing tools, such as user-friendly software for product design or scanners to facilitate the measurement of individual-specific geometries. Importantly, I assume the same costs for all consumers. The customized product price is denoted by p_A.

Firm If a firm enters the market, it can either adopt TM or AM technology. I define the group of firms with TM technology as TM sector and the group of firms with AM technology as AM sector. In the TM sector, there are N firms. I assume that TM firms are uniformly distributed around the circumference of a circle, with each firm equidistant from its neighboring competitor with TM technology at a distance of $\frac{1}{N}$. TM firms incur constant marginal costs of production of c_T and fixed entry costs of F_T.

In my base model, only one firm has the incentive to adopt AM technology. Since a customized product cannot be differentiated by definition, it represents a homogeneous product. In light of Bertrand competition, the entry of an additional firm with AM technology would lead to marginal cost pricing and, hence, in the presence of entry costs to losses for all AM firms. In an extension, I later consider the implications of additional competition in this sector. Firms incur constant marginal production costs of c_A. In order to enter the market with AM, a firm must pay a fixed cost of F_A.

While costs are identical within each sector, I allow costs to differ across technologies. In my later analysis, it will be useful to define a measure for the competitive advantage of AM, denoted by ω. Let

$$\omega = c_T - c_A - \theta s \gtreqless 0,$$

such that higher values of ω represent a higher competitive advantage of the AM technology. Note that this measure comprises elements from the production side (c_A and c_T) as well as elements from the consumption side (θs). One main objective of my analysis is to investigate the impact on market outcomes as the competitive advantage of AM technology increases.

Timing I consider the following sequence of events. In the first stage, the firm with AM technology decides whether to enter the market. In the second stage, firms using TM technology make their market entry decision. In the third stage, all firms simultaneously determine their pricing strategies. My analysis focuses on solving for subgame perfect Nash equilibria.

2.3.2 Benchmark market with TM firms

In this subsection, I consider market structure I. This market structure serves as a benchmark case and corresponds to the standard Salop setting (Salop, 1979). In this market, all firms adopt TM technology. For convenience and for later comparisons, I briefly reproduce the main results (Tirole, 1988).

Given the consumer utility in (2.3.1), I can derive the marginal consumer who is indifferent between any two neighboring standardized products. Consider the standardized product from firm i whose demand is given by

$$q_T^i = \frac{1}{N} + \frac{p - p_T^i}{t},$$

where p_T^i is the price charged by firm i and p is the price charged by all other firms. Given demand q_T^i, each firm i maximizes its profits given by

$$\Pi_T^i = (p_T^i - c_T)q_T^i - F_T.$$

For a given number of TM firms N, symmetric equilibrium prices and profits are represented by

$$p = \frac{t}{N} + c_T,$$

and

$$\pi = \frac{t}{N^2} - F_T,$$

while consumers receive a surplus of

$$CS^I(N) = v - \frac{5}{4}\frac{t}{N} - c_T.$$

TM firms have an incentive to enter the market as long as non-negative profits are expected. Hence, I determine the number of TM firms via a zero-profit condition, yielding an equilibrium number of firms of

$$N^I = \sqrt{\frac{t}{F_T}}.$$

Given N^I, the resulting equilibrium price is

$$p^I = \sqrt{F_T t} + c_T,$$

and consumer surplus is

$$CS^I = v - \frac{5}{4}\sqrt{tF_T} - c_T, \tag{2.3.3}$$

when the number of TM firms is endogenously determined. I note that consumer surplus is reduced when production, entry, and transportation costs are high.

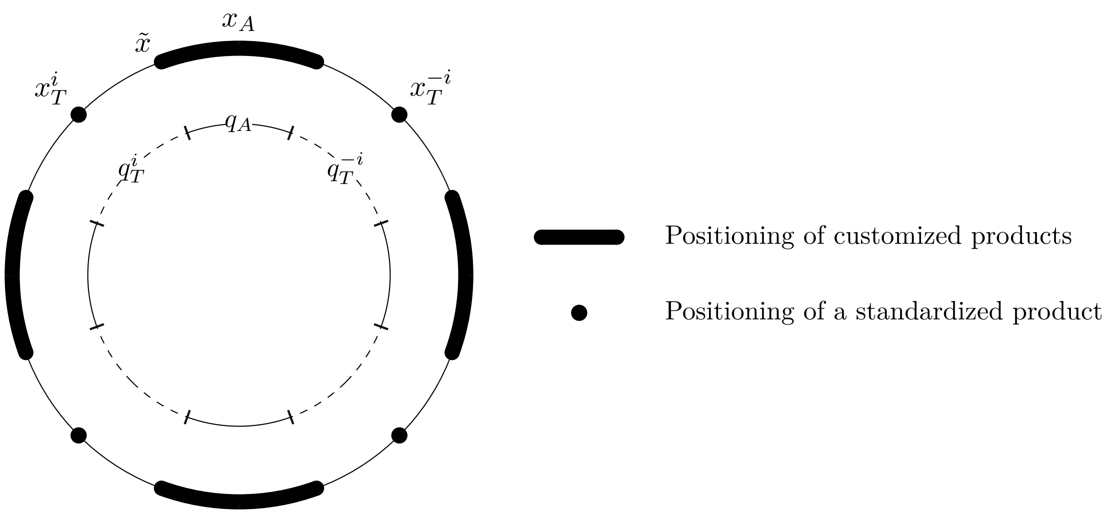
2.4 Competition between AM & TM firms

In market II, both technologies coexist, leading to competition between TM firms and an AM firm. The analysis starts with the derivation of the market shares for both the TM sector and AM sector, followed by the determination of equilibrium prices and the resulting equilibrium market structure.

Market share of the TM and AM sector In market II, a consumer has the option to choose between a standardized product offered by one of the TM firms or a customized product from the AM firm. Notably, the customized product ensures a constant utility for consumers, while the utility of TM firms' products depends on the consumers' locations. As illustrated in Figure 2.1, the customized products are strategically positioned between the locations of any two standardized products. This positioning avoids direct competition between TM firms (Balasubramanian, 1998; Weller et al., 2015). In this scenario, the AM firm competes directly with all TM firms, while TM firms only engage in indirect competition among themselves. Figure 2.1 provides a visual representation for the case involving four TM firms and one firm utilizing AM technology. The bold lines denote the locations of customized products, and the dots indicate the positions of standardized products. Additionally, the arcs of the bold lines represent the locations where consumers are drawn to customized products, while the arcs around standardized products signify the consumers served by a TM firm.

In order to derive the demand functions, I identify the marginal consumer located at $\tilde{x}$. In this market, the marginal consumer is defined as the consumer who is indifferent between

Figure 2.1: Firm positioning and demand in market structure II



the consumption of a standardized product and a customized product:

$$\tilde{x} = \frac{p_A - p_T^i + \theta s}{t}.$$

All consumers located between x_T^i and $\tilde{x}$ opt for a standardized product. Due to symmetry in the market, firm i captures the demand of twice this distance. Consequently, the demand for firm i is expressed as

$$q_T^i = 2\frac{p_A - p_T^i + \theta s}{t},$$

such that the total demand by the TM sector is

$$Q_T = 2N\frac{p_A - p_T + \theta s}{t},$$

imposing that all TM firms charge the same price p_T in equilibrium. Hence, the AM sector faces demand of

$$q_A = 1 - 2N\frac{p_A - p_T + \theta s}{t}.$$

The demand functions show that an increase in the transportation cost decreases the market share of the TM sector (Q_T) while, ceteris paribus, an increase in the number of TM firms and the price difference between standardized and customized products increases the market share. In contrast, the impact of these variables on the market share of the AM sector (q_A) has the opposite effect.

Equilibrium prices with an exogenous number of TM firms I start my equilibrium analysis by assuming an exogenous number of TM firms. Subsequently, I will investigate how the number of TM firms changes following the entry of a firm with AM technology.

In the following analysis with an exogenous number of TM firms, I make the following parameter assumptions.

Assumption 1:

$$t > \max[2N\omega, -N\omega]$$

This assumption ensures that, in equilibrium, both types of firms remain active, each serving a positive mass of consumers.

Given the market shares, the representative TM firm i aims to maximize

$$\pi_T^i = 2\left(\frac{p_A - p_T^i + \theta s}{t}\right)(p_T^i - c_T) - F_T,$$

and the AM firm maximizes

$$\pi_A = \left(1 - 2N\frac{p_A - p_T + \theta s}{t}\right)(p_A - c_A) - F_A,$$

which already takes symmetric TM prices into account. Consequently, the resulting equilibrium prices are

$$p_T = \frac{1}{3}\left(\frac{t}{2N} - \omega\right) + c_T,$$
$$p_A = \frac{1}{3}\left(\frac{t}{N} + \omega\right) + c_A.$$

As in standard models, I observe that prices are increasing in transportation costs t. This effect is more pronounced for the price of firm A. As t increases, the AM firm raises its price to a greater extent. This strategic decision is due to the fact that higher transportation costs increase the attractiveness of the customized product relative to the products of TM competitors. Additionally, my findings indicate a decline in prices with the number of TM firms. Interestingly, the AM firm is more responsive to changes in the number of rivals with TM technology leading to a stronger reaction in its pricing strategy.

Given prices, the equilibrium market share of the AM firm is

$$q_A = \frac{2}{3}\left(1 + \frac{N\omega}{t}\right),$$

and its profits are

$$\pi_A = \frac{2}{9}\frac{(t + N\omega)^2}{Nt} - F_A.$$

Differentiation of the market share and profits with respect to N yields the following result:

Lemma 1: *(i) A larger number of TM firms increases the market share of the AM firm if its competitive advantage is sufficiently strong ($\omega > 0$) and reduces it otherwise ($\omega < 0$). (ii) A larger number of TM firms reduces TM profits.*

Contrary to standard intuition, the first part of the lemma suggests an incline in the market share of the AM sector if the number of TM firms increases. This effect occurs when the AM firm faces relatively weak TM firms and offers a superior product ($\omega > 0$). However, the market share of the AM sector decreases with the number of TM firms if the production technology is inferior ($\omega < 0$).

Part (ii) of the lemma asserts that a firm with TM can never benefit in terms of higher profits from a larger number of TM firms. The negative effect of lower prices dominates the potentially positive effect of a larger market share.

Number of TM firms and prices with endogenous entry In the following, I examine the effects of AM entry when the market structure changes due to AM adoption. Therefore, I consider the scenario of free market entry for TM firms.

With free market entry, TM firms enter the market until each TM firm profits, π_T, equals fixed costs, F_T. By using this condition and solving for N, I can determine the equilibrium number of TM firms active in the market:

$$N^{II} = \frac{t}{3\sqrt{2F_T t} + 2\omega}.$$

The number of firms with TM technology depends on transportation costs and the characteristics of both technologies. An increase in transportation cost or a decrease in the competitive advantage of TM firms (ω) increases, ceteris paribus, the number of firms with TM technology. In contrast, an increase in the TM fixed cost decreases, ceteris paribus, the number of TM firms.

For later reference, I compare the entry-level in this setting with the standard Salop setting. The comparison yields:

Proposition 1: *Market structure II contains a smaller number of firms using TM technology than market structure I ($N^{II} < N^{I}$).*

The proposition shows that the number of standardized products is smaller in the presence of a firm offering a customized product. The intuition for this findings is straightforward. The entry of an AM firm increases the intensity of competition, reducing the profits of TM firms. In turn, this forces some TM firms out of the market such that the overall number of firms is reduced.

I now determine prices taking into account the effects of endogenous market entry. Inserting the number of TM firms into the prices yields the following prices:

$$p_T^{II} = \sqrt{\frac{F_T t}{2}} + c_T,$$

$$p_A^{II} = \sqrt{2F_T t} + c_T - \theta s.$$

In the equilibrium with free TM entry, the prices of both technologies depend on the transportation cost, fixed cost, and marginal cost of firm T, like in market II. An increase in one of these costs leads, ceteris paribus, to higher product prices. Moreover, the AM firm charges a higher price than firms with TM technology.

For my later welfare analysis, it is useful to compare the price levels across the two market structures. I observe that the prices of standardized products are always lower when the AM technology is adopted, specifically $p_T^{II} < p^I$. This aligns with intuition as TM firms face intense competition from the AM firm, leading to fewer TM firms and lower prices. In contrast, the price of the AM firm may be either higher or lower than prices in the market with only TM firms ($p_A^{II} \lesseqgtr p^I$). More specifically, I find that consumers may face higher prices due to AM entry when $\theta s < (\sqrt{2} - 1)\sqrt{F_T t}$. In other words, consumers may have to pay a higher price if the customization costs are low. For low values of θs, the AM firm offers a superior product compared to TM firms, enabling it to charge high prices. In summary, these price comparisons reveal that a priori, it is ambiguous whether consumers can benefit from the entry of the AM technology in terms of prices.

Equilibrium market structure Thus far, my analysis has assumed entry and production of firms with both technology types in the market. In the following, I am deriving conditions that ensure both AM and TM firms indeed have the incentive to enter the market.

Thereby, I will also determine the equilibrium market structure, which is contingent on the characteristics of the production technologies.

For the existence of market structure II, two conditions must be satisfied. First, the AM firm needs to make a non-negative profit. Second, at least one TM firm must find it profitable to enter. In turn, I consider both requirements.

The firm with AM technology realizes non-negative profits, $\pi_A(N^{II}) \geq 0$, when

$$\omega \geq \frac{F_A}{2} - \sqrt{2F_T t} + \frac{1}{2}\sqrt{2F_A\sqrt{2F_T t} + F_A^2} = \omega_L$$

In words, the firm with AM technology finds it worthwhile to enter the market only if its competitive advantage, ω, is larger than the critical threshold level ω_L.

The second requirement is that TM firms find it profitable to enter the market, $N^{II} \geq 1$. At least one firm uses TM technology if

$$\omega \leq \frac{t}{2} - \frac{3}{\sqrt{2}}\sqrt{F_T t} = \omega_H.$$

That is, for TM firms to enter the market the competitive advantage of the AM technology must not be too large.

Taken together, the market structure II results only if both conditions are satisfied simultaneously. In other words, market structure II occurs for $\omega_L \leq \omega \leq \omega_H$. Therefore, a necessary condition for existence of market structure II is $\omega_H > \omega_L$:

$$t \geq F_A + \sqrt{2F_A\sqrt{2F_T t} + F_A^2} + \sqrt{2F_T t}, \tag{2.4.1}$$

which I will assume in the following. Consequently, a market with both technologies can only exist when the transport cost parameter t is sufficiently large. In other words, the preference for a specific product must be sufficiently high. Summarizing the preceding discussion, the next proposition presents the equilibrium market structure.

Proposition 2: *Suppose condition* (2.4.1) *holds. Then:*

(i) If $\omega > \omega_H$: The AM firm holds a monopoly.

(ii) If $\omega_H \geq \omega \geq \omega_L$: Mixed market with AM and TM firms.

(iii) If $\omega < \omega_L$: Only TM firms are active.

The proposition outlines the equilibrium market structure, emphasizing its dependence on the technological characteristics of both technologies. When ω takes on large values, the dominance of AM technology allows the adopting firm to monopolize the market. Conversely, for small values of ω, the inferiority of AM technology hinders its competitiveness against TM firms. In such cases, there is no AM entry, and the market is characterized by firms only offering standardized products. Finally, for intermediate values of ω, both technologies coexist in equilibrium.

2.5 Welfare analysis

This section presents the welfare implications encompassing both consumer and total surplus. The analysis unfolds in two steps. In the first step, I calculate consumer surplus and total surplus for market structure II and provide comparative statics. In the second step, I investigate the impact of AM entry by comparing welfare under this scenario with my benchmark market (market structure I).

2.5.1 Welfare in market structure II

I begin my analysis by calculating consumer surplus in market structure II. Given equilibrium entry and prices, the expression for consumer surplus is as follows:

$$CS^{II} = 2N^{II} \int_0^{\frac{1}{2}q_T(N^{II})} (v - p_T - tx)dx + Q_A(N^{II})[v - p_A - \theta s].$$

In this expression, the two terms represent the surplus from the two market sectors. The first term is the surplus from the traditional sector providing standardized products. A consumer at x earns a surplus of $v - p_T - tx$, which is integrated over all consumers buying this product type. The second term provides the surplus from the consumption of the AM product. Each consumer receives a surplus of $v - p_A - \theta s$, which is multiplied by the AM equilibrium market share.

I can rewrite consumer surplus as

$$CS^{II} = v - p_A^{II} - \theta s + \frac{N^{II} F_T}{2}. \tag{2.5.1}$$

For my later analysis, the following finding is useful.

Lemma 2: *A larger number of TM competitors increases consumer surplus.*

An increasing number of TM firms contributes to a rise in consumer surplus for two reasons. First, consumers benefit from elevated competition, resulting in lower prices for standardized products. Second, consumers also experience advantages from the reduction in total transportation costs, facilitated by a larger number of standardized products, which better aligns with their preferences.

The total surplus in market structure II is calculated as follows.

$$TS^{II} = 2N^{II} \int_0^{\frac{1}{2}q_T(N^{II})} (v - c_T - tx)dx + q_A(N^{II})[v - c_A - \theta s] - N^{II}F_T - F_A.$$

Analogously to consumer surplus, the first two terms denote total surplus generated in the two market sectors. The last two terms account for fixed costs associated with market entry. It is noteworthy that prices are mere transfers between consumers and firms and, therefore, do not directly impact total surplus.

From the calculations of the consumer surplus and total surplus, I can derive the following proposition about the comparative static effects of AM's competitive advantage on welfare.

Proposition 3: *Suppose $\omega_H \geq \omega \geq \omega_L$ and endogenous entry of TM firms. Then, a larger competitive advantage of the AM technology (ω)*

(i) reduces consumer surplus.

(ii) increases total surplus.

The proposition states detrimental effects on consumers if factors, either by reducing the marginal cost of AM technology or by lowering the customization cost, strengthen the competitiveness of AM. This counterintuitive finding challenges standard assumptions as technology improvement typically enhances consumer surplus. Three effects emerge when AM becomes more competitive. There is a direct positive effect, resulting in lower costs or improved services that benefit consumers through reduced prices of standardized products or customized products, eliminating transportation costs. Concurrently, there are two effects working in the opposite direction. An increase in ω improves the competitive standing of the AM firm regarding the TM firms allowing to raise the price of customized products. Furthermore, the expansion of AM firm's market power compels some TM firms to exit the market, resulting in higher transportation costs for some consumers due to a decline in the variety of standardized products. In this framework, the combined negative impact of increased average market prices and higher transportation costs dominates, leading to detrimental consequences for consumers.

In contrast to consumer surplus, the proposition also claims a rise in total surplus if the competitive advantage of the AM technology increases. Since total surplus is unaffected by prices, only two effects need consideration. First, there is the direct effect of lower costs and an enhanced product fit. Second, it is widely acknowledged that the standard model, without AM firms, exhibits excessive market entry (Salop, 1979). Therefore, a decline in TM firms contributes to a growth in total surplus. Combining these effects leads to the unambiguous conclusion that total surplus rises with improvements in AM technology. The next finding follows directly from Proposition 3.

Corollary 1: *Suppose $\omega_H \geq \omega \geq \omega_L$. Then, consumer surplus is maximal when $\omega = \omega_L$ and total surplus is maximal when $\omega = \omega_H$.*

Proposition 3 and Corollary 1 yield policy implications, visually represented in Figure 2.2. In an equilibrium where both technologies are adopted, a divergence emerges between consumer surplus and total surplus. Total surplus is maximized when the competitive advantage of AM technology is at its peak, while consumer surplus reaches its zenith when the competitive advantage of AM technology is minimized. This holds true as long as both technologies maintain positive market shares in equilibrium.

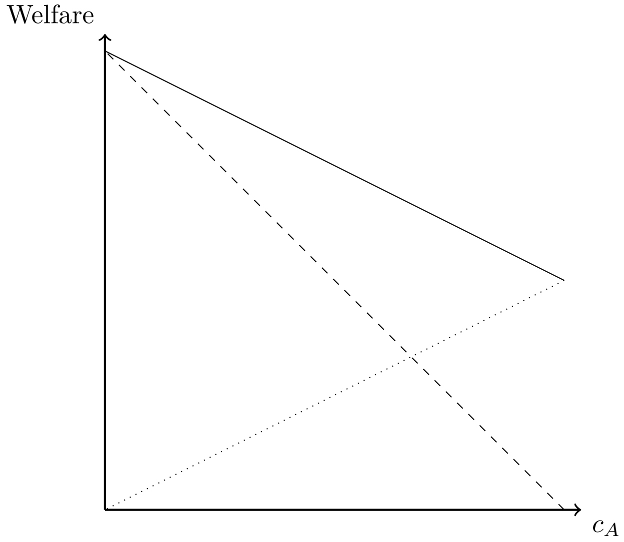
These findings have significant policy implications, particularly concerning potential subsidies for AM technology. Subsidies, whether through reducing marginal costs of AM technology or lowering customization costs, result in an increase in total surplus. However, consumers do not benefit; instead, they are adversely affected. The AM firm appropriates the surplus generated, thereby raising its market power. This increased market power enables the AM firm to raise prices, potentially driving other firms out of the market and leaving consumers worse off.

2.5.2 Welfare implications of AM entry

The previous subsection demonstrated a decline in consumer surplus (and an increase in total surplus) with a rise in the competitive advantage of AM technology. In light of this finding, the question arises whether consumers benefit from the entry of AM technology. Therefore, I now compare consumer surplus and total surplus in market structure II with the outcomes of market structure I (as derived in section 2.3.2).

Exogenous market entry of TM firms Comparing the consumer surplus in market structure II with a given number of TM firms with the benchmark market outcome yields

Figure 2.2: Welfare in market structure II



the following result.

Proposition 4: *(i)* $CS^{II}(N) > CS^{I}(N-1)$. *(ii)* $CS^{II}(N) > CS^{I}(N)$.

The proposition indicates an increase in consumer surplus for an exogenous number of TM firms caused by the adoption of AM technology. This finding comes in two versions. Part (i) says that, if I fix the total number of firms in the market, and one firm switches from TM to AM technology, then consumers benefit. Part (ii) shows that, if I fix the number of firms operating under TM technology, the entry of a new firm using the AM technology raises consumer surplus. In both cases, consumers benefit from AM entry.

Endogenous market entry of TM firms Considering endogenous entry of TM firms, I compare the consumer surplus in market structure I (2.3.3) with market structure II (2.5.1). This comparison yields:

$$\begin{aligned} & CS^{I} \lesseqgtr CS^{II} \\ \Leftrightarrow \qquad & \omega \gtreqless \frac{10-13\sqrt{2}}{14}\sqrt{F_T t} \end{aligned}$$

Proposition 5: *Suppose $\omega_H \geq \omega \geq \omega_L$. With endogenous TM entry, AM adoption*

(i) increases consumer surplus if and only if $\omega < \frac{10-13\sqrt{2}}{14}\sqrt{F_T t}$. Otherwise, consumer surplus remains equal or declines.

(ii) increases total surplus.

The proposition asserts that total surplus in market structure II always surpasses total surplus in market structure I. Nevertheless, the proposition also states that the adoption of AM may not necessarily lead to an improvement in consumer surplus. To be more precise, consumer surplus increases only when the competitive advantage of AM technology is not excessively large. This insight is derived from the findings in Lemma 3 and Proposition 4, which demonstrate that consumer surplus attains its maximum when the competitive advantage (and market power) of the AM firm is at its lowest possible level.

Examining the proposition from another angle involves considering its implications for AM profits. In the traditional sector, where firms earn zero profits, the disparity between total surplus and consumer surplus represents AM profits. Consequently, when the competitive advantage of AM technology is substantial, the AM firm not only gains access to the additional total surplus but also manages to appropriate a larger portion of consumer surplus. This dynamic results in diminished consumer surplus, despite an overall increase in total surplus.

I observe that this finding stands in contrast to the welfare analysis conducted under the assumption of an exogenous number of TM firms. In Proposition 4, I demonstrated that consumer surplus increases with AM entry, assuming a constant number of TM firms. In contrast, this analysis reveals that this outcome can be reversed when considering the possibility of TM exit induced by AM entry, coupled with the potential for the AM firm to gain significant market power at the expense of consumers.

Previously, I stated that subsidizing production costs could negatively impact consumers. This conclusion was drawn under the assumption of viable AM entry, leading to competition between firms employing AM and TM technologies. However, I now assert that there exists a rationale for subsidies aimed at increasing consumer surplus despite this initial argument.

The subsequent proposition asserts that subsidies targeting fixed costs have the potential to enhance consumer surplus, particularly when they facilitate the entry of AM.

Proposition 6: *Suppose that $\omega < \omega_L$ such that no AM entry occurs absent AM subsidization. Let $\bar{S}$ be implicitly given by*

$$\frac{F_A - \bar{S}}{2} - \sqrt{2F_T t} + \frac{1}{2}\sqrt{2(F_A - \bar{S})\sqrt{2F_T t} + (F_A - \bar{S})^2} = \omega.$$

Then, if $\frac{10-13\sqrt{2}}{14}\sqrt{F_T t} > \omega > -\sqrt{2F_T t}$ a fixed-cost subsidy $S > \bar{S}$ increases consumer surplus.

Consider a situation where fixed costs are prohibitively high, preventing profitable entry for the AM firm without policy interventions ($\omega < \omega_L$). However, the competitiveness of the AM technology is such that the firm can attain a positive market share once entry is feasible ($\omega > -\sqrt{2F_T t}$). The proposition establishes that a government can increase consumer surplus by subsidizing fixed costs, given that ω is not excessively large, where $\frac{10-13\sqrt{2}}{14}\sqrt{F_T t} > \omega$ (derived from Proposition 5).

2.6 The effect of intensified competition for the AM firm

In my baseline model, I considered the entry of one AM firm. my results indicate substantial attainment of market power by this firm, especially when its competitive advantage is significantly high. The resulting profits from AM technology might attract more firms to adopt AM. Therefore, it is crucial to investigate the implications if the AM firm encounters intensified competition, such as from additional competitors with the same technology.

This section discusses the consequences of intensified competition for the AM firm on consumer surplus and its subsequent policy implications. To facilitate a manageable analysis, I employ a stylized, reduced-form framework. Here, I assume that some of the AM firm's customers can switch to an alternative product choice.

Formally, I introduce a second stage into the consumer decision process. In this new stage, a share of the AM firm's consumers $\lambda \in (0, 1)$ has the option to switch to an outside alternative. However, the AM firm has the possibility to retain its consumers by offering a discount of $\delta > 0$. The parameter δ is interpretable as the competitive pressure from other customized products, where higher values signify more intense competition faced by the AM firm. Alternatively, the intensity of competition can be measured by the share of contested consumers (λ).

Given this modification, the AM firm's profit function becomes

$$\pi_A = \left(1 - 2N\frac{p_A - p_T + \theta s}{t}\right)[\lambda(p_A - \delta) + (1 - \lambda)p_A - c_A] - F_A,$$

while the profit function of any TM firm as well as all other elements of the model are unchanged.[4]

[4]All derivations are relegated to the Appendix.

Following the same steps as in my baseline model, I calculate equilibrium prices and derive equilibrium entry levels. An immediate finding is that AM profits experience a reduction in the face of a more competitive environment, indicated by higher values of δ and λ. The following proposition unveils the resulting equilibrium market structure.

Proposition 7: *Suppose the AM firm needs to offer a discount of $\delta > 0$ to a share $\lambda > 0$ of its customers. Then, the following market structure emerges.*

(i) If $\omega > \omega_H(\delta\lambda)$: The AM firm holds a monopoly.

(ii) If $\omega_H(\delta\lambda) \geq \omega \geq \omega_L(\delta\lambda)$: Mixed market with AM and TM firms.

(iii) If $\omega < \omega_L(\delta\lambda)$: Only TM firms are active.

The critical levels $\omega_L(\delta\lambda)$ and $\omega_H(\delta\lambda)$ are increasing in δ and λ.

The market configuration follows a similar structure as in the baseline model. For intermediate levels of ω, both types of firms are active in the market. For high or low values of ω, only one type of firm stays in the market. What distinguishes this model is that the critical values, $\omega_H(\delta\lambda)$ and $\omega_L(\delta\lambda)$, are now contingent on the competitive pressure exerted by an additional potential AM firm, as parameterized by δ. Notably, both critical levels exhibit an increase with higher values of δ. This trend aligns with intuition. As increased δ values intensify competitive pressure on the AM firm, its profits diminish. This reduces the likelihood of market monopolization by the AM firm, thereby expanding the parameter values within which TM firms can survive. Moreover, as ω_L is increasing in δ and λ, AM entry is only viable for a smaller parameter range than in the baseline model.

Besides its impact on equilibrium entry levels, intensified competitive pressure on the AM firm has significant implications for the welfare outcomes, particularly regarding consumer surplus. There are two effects to consider. The first effect demonstrates that consumer surplus increases with the intensity of AM competition. This observation aligns with intuitive reasoning, as intensified competition often leads to lower prices for AM products, thus benefiting consumers. However, there exists a second effect. With the viability of AM entry dependent on more restrictive conditions, there is a higher likelihood that such entry may not occur, consequently reducing the parameter range wherein consumers can benefit.

Figure 2.3 summarizes the essence of my discussion considering whether consumers would benefit from the entry of AM firms compared to the market outcome with only TM firms. The

Figure 2.3: Impact of AM's competitive pressure and marginal cost on consumer surplus

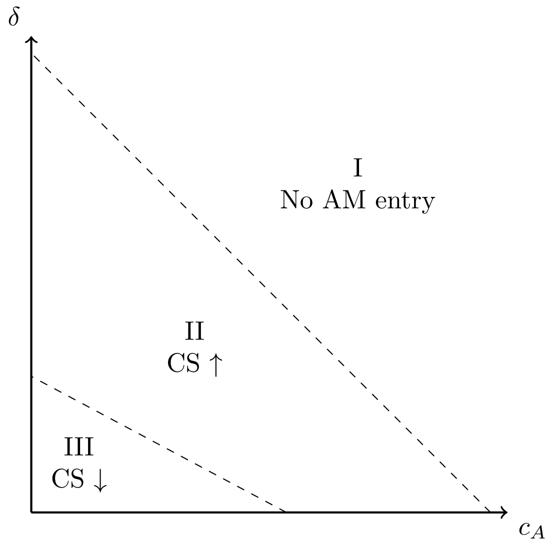


figure distinguishes three distinct areas: In area I, consumers would benefit from entry, but entry does not take place. In area II, consumers benefit from AM entry, and it successfully takes place. Finally, in area III, entry takes place but is detrimental to consumers. Consistent with the above discussion, the figure illustrates the interplay of positive and negative effects associated with promoting competition. On the one hand, an increase in δ diminishes the extent of area III, indicating a reduced likelihood of consumers being adversely affected by AM entry. On the other hand, as the conditions for AM entry become more restrictive, area I expands with higher values of δ.

Several new policy implications emerge from my findings. First, fostering competition expands the potential for consumer-surplus-enhancing adoption of AM technologies. In fact, if competition reaches a sufficiently intense level, consumers will consistently benefit from the entry of AM firms. Conversely, regulators must be aware of the fact that the adoption of the new technology becomes more costly when competition is promoted to the extent that entry might not occur. Therefore, promoting competition may require complementary measures such as increased subsidies to ensure the successful adoption of the new technology.

2.7 Managerial and policy implications

This study demonstrates how the adoption of AM affects market competition between firms producing standardized products with TM technology and firms producing customized products with AM technology. my model results have useful implications for managerial decision-making regarding technology adoption, pricing strategies, and product positioning and for policymakers aiming to implement welfare-maximizing policies in the manufacturing industry.

2.7.1 Managerial recommendations

Managers in the manufacturing sector contemplating AM adoption should assess various market characteristics, e.g. consumer preferences for individualized products, the competition with other firms with AM, and consumer ease of customization. In conformity with expectations, AM unleashes its highest potential in markets where consumers have a high need for customized products and a low level of competition with other customized products. Moreover, consumers' efforts to convey product preferences affect the demand for customized products and should, therefore, be taken into account. This exertion could include the obtainment of a digital imprint, e.g. the head shape for a customized helmet, or time to explain the product specifications to the manufacturer. Therefore, privacy concerns may play an important role. Another dimension of the adoption decision is the cost structure of AM. The marginal cost difference between the production with AM and TM technology determines the profitability of AM. Among other factors, the marginal costs include material cost, printing speed, and development of the CAD models. While marginal costs of AM not only influence the profitability of AM but also the competition with traditional manufacturers, AM's fixed costs only affect the moment when it becomes profitable for firms to adopt AM.

The adoption of AM and the supply of customized products influence firms' pricing strategies for both AM adopters and traditional manufacturers. While firms with AM can consider to impose a price premium for customized products, they should also account for consumers' associated customization efforts and the competition from other customized products. In response to fiercer price competition, traditional manufacturers should strategically reduce product prices to maintain competitiveness. Yet, the magnitude of the decline depends on the competition between firms with AM technology. The higher the competition intensity, the lower the required price reduction for standardized products.

Due to high prices for customized products, firms with AM should target consumers who prefer product variants with strong diverging specifications compared to standardized products. Therefore, the direct competitors for traditional manufacturers are shifting from other manufacturers with standardized products to manufacturers with customized products.

As a consequence, the emphasis on strategic product positioning for standardized products diminishes in significance.

2.7.2 Policy recommendations

Policymakers should distinguish between static effects (comparative statics in market structure II) and dynamic effects (adoption of AM technology) in order to identify optimal policy instruments. Table 2.1 provides an overview of the impact of different policy programs on welfare.

Table 2.1: Policy programs and welfare implications

		Static effects		Dynamic effects	
Policy	Program	CS	TS	CS	TS
Subsidies	↓ Marginal cost	−	+	+	+
	↓ Fixed cost	0	+	+	+
	↓ Customization cost	−	+	+	+
Regulations	↑ Competitive environment	+	−	−	−

Notes: This table reports the effect of policy programs on consumer surplus (CS) and total surplus (TS), distinguished by static and dynamic effects. The arrows (↓ and ↑) indicate the direction of cost changes caused by a policy program. ↓ denotes a cost decline and ↑ denotes a cost increase. The symbols +, −, and 0 indicate welfare changes: + denotes a positive effect, − denotes a negative effect, and 0 denotes no effect.

Considering dynamic effects, policymakers should facilitate the adoption of AM in order to enhance total surplus. In markets where consumers have a high need for customized products and the production fixed costs of TM technologies are relatively expensive, AM adoption additionally increases consumer surplus. As long as AM's cost efficiency and market power is not too high, consumers will benefit from the offer of customized products. In order to facilitate an earlier adoption of AM, policymakers should grant market leeway or market power to firms involved in AM. If AM's cost efficiency is rather low and competition high, the risk of AM rejection for the production of customized products reduces the likelihood of AM adoption. The subsidization of any AM-related costs supports the adoption of AM and, therefore, consumer surplus and total surplus.

From a static perspective, a growing competitive cost advantage compared to TM technologies will enlarge the demand for customized products and cease the supply of some standardized products. Consumers' opportunity to consume expensive customized products does not compensate for the decline of low-priced standardized goods and is harmful to consumers. Therefore, a decline in AM's marginal costs or consumers' customization costs will reduce consumer surplus. In order to counteract this effect and strengthen firms with standardized products, policymakers could foster competition between AM firms. A change in AM's fixed cost does not affect consumer surplus per se. Conversely to consumer surplus, total surplus benefits from lower marginal cost and customization cost because a superior AM technology restricts excessive entry (compare with Salop (1979)). Hence, a more competitive environment for firms with customized products would reduce total surplus. A subsidization in AM's fixed cost will reduce the aggregate sum of all fixed costs and thus increase total surplus.

Table 2.1 emphasizes heterogeneous outcomes of the discussed policy programs for consumer surplus considering static and dynamic effects. Only the subsidization of AM's fixed cost depicts the potential of a Pareto improvement. In terms of total surplus, a reduction of AM-specific costs (marginal cost, fixed cost, and customization cost) and less competition for firms with AM have a positive impact.

2.8 Future research

There remain open questions for future research. So far, the competition intensity and market concentration between firms with AM technology are unclear. On the one hand, relatively low fixed costs could incentivize market entry and, thus, a higher level of competition. On the other hand, potential scale effects from the usage and development of digital input designs could increase the market power for some firms. The consequences of generative artificial intelligence, such as generative design software, on market dynamics would be especially interesting to explore since it might substantially affect the production of AM in the future.

In my model, I consider AM's feature to flexibly produce any product variant and assume no quality differences between standardized and customized products. However, a central advantage of AM is adding product functionalities and manufacturing products that cannot be produced with TM technologies, e.g., complex geometries. Extending my analysis by a quality dimension would be an interesting avenue for future studies and would change the circumstance that only one firm adopts AM.

3 | Technology mapping using web text mining: The case of additive manufacturing

Summary

The diffusion of new technologies is crucial for realizing the social and economic benefits of innovation. However, tracking and mapping technology diffusion is often constrained by the limited availability of observable data on technology adoption. This study presents a novel methodology that uses website texts to train a multilingual language model ensemble, enabling the mapping of technology diffusion in additive manufacturing (AM) technology. I identify relevant actors and their roles in the diffusion process, highlighting the importance of manufacturers, retailers, information providers, and service providers. The spatial distribution of adoption intensity suggests that regional AM adoption is influenced by experienced lead users and the presence of technical universities. In addition, overall adoption intensity varies by sector and firm size. These results suggest that web text mining offers a useful and novel tool for technology mapping, complementing existing patent- or survey-based measures.

This chapter is based on joint research with Robert Dehghan, Sebastian Schmidt, Elisa Rodepeter, Andreas Stömmer, Kaan Uctum, Jan Kinne, David Lenz and Hanna Hottenrott.

3.1 Introduction

New technologies are a key driver of sustainable economic development and have contributed to the substantial rise in living standards observed since the first industrial revolution (Aghion et al., 2021). Furthermore, technological innovation plays an important role in enhancing the competitiveness and performance of firms (Audretsch and Feldman, 1996; Crepon et al., 1998; Aghion et al., 2009). Consequently, policymakers and practitioners are interested in understanding the emergence of new technologies. However, it is not only the invention that matters but also the adoption and diffusion of innovation (Hall, 2006).

Tracking the adoption of new technologies is, however, not straightforward. Researchers typically rely on patent application data to measure, analyze, and localize inventive activity (Moster, 2013; Pose-Rodriguez et al., 2020). Although patent data provides valuable insights, it captures only patentable inventions, potentially overlooking innovation and diffusion in other domains (Hall, 2020).

Identifying relevant patents for interdisciplinary technologies like additive manufacturing (AM) poses challenges, as patents may be classified under different technology classes (Pose-Rodriguez et al., 2020). Moreover, understanding the diffusion of new technologies requires insights into different actors involved in the diffusion process. Beyond manufacturers and users, other stakeholders contribute by providing information, thereby raising customer awareness and reducing adoption resistance among potential users and intermediaries. Besides patent data, firm surveys on new products, processes, and services can complement patent-based measures by providing additional information. Yet, surveys are often limited to smaller samples and may miss significant diffusion patterns (Salazar and Holbrook, 2004).

Firms use websites to promote their products and services and to inform the public about important events. Therefore, firm websites serve as valuable sources for tracking corporate activities, which is facilitated by the fact that almost every firm has its own website (Kinne and Axenbeck, 2020). In this study, I apply a novel methodology for mapping technology diffusion using website text analysis. Our approach builds on the recent work of Kinne and Lenz (2021), who analyzed the reactions of German firms to the coronavirus pandemic through web-based data. This methodology builds on advances in research on natural language processing to measure firm activity, such as innovation, via web mining

In this chapter, the terms *3D printing* and *additive manufacturing* are used interchangeably to refer to the same technology.

and deep learning (Gök et al., 2015; Kinne and Lenz, 2021).

In this analysis, I used text data from firm websites to distinguish among different contributors to AM diffusion. For data collection, a web scraper identified topic-specific keywords within text paragraphs on firm websites. By manually labeling a subset of these paragraphs, I created a training dataset based on the contextual use of keywords. This labeled data was then used to train a model ensemble, which I applied to firms with registered web domains in Germany, Switzerland, and Austria as listed in the ORBIS firm database (approximately 1.3 million firms). The model generated predictions on the degree of firm engagement at a granular regional level, along with classifications of the types of involvement in AM activities. This study identified four categories of involvement: *Manufacturers*, *Service Providers*, *Retailers*, and *Information Providers*. Using this detailed data, I mapped the diffusion of AM across Germany, examining adoption intensity across various sectors and regions.

The findings reveal several adoption hotspots, indicating that local adoption intensity is influenced by two main factors: proximity to technical universities and the presence of established manufacturing firms. Both factors appear to foster a more intensive use of AM, potentially through channels such as access to skilled human capital, opportunities for application, and customer base development. These results are in line with prior research underlining the importance of science-industry co-location in driving innovation, particularly in emerging technologies (Hausman, 2022; Cohen et al., 2002).

3.2 Methodology

The main objective of this study is to systematically map the diffusion of AM technology through the use of available information, employing a transparent and reproducible methodology. For this purpose, I use firm-level data obtained from corporate websites and the ORBIS database.[3] The steps of the approach are outlined in the following subsections.

3.2.1 Identification of keywords

To identify firms engaged in AM technology, I identified a list of keywords related to AM. While a uniform and standardized terminology for AM technologies does not yet exist, firms commonly reference technical terms derived from industry standards such as ASTM 52900 and VDI 3405. These standards provide a nomenclature for various AM technologies and

[3]The web-based analysis was conducted by ISTARI.AI GmbH.

their applications. Due to the continuous evolution of AM, I added terms identified in recent research papers and publications. The complete list of keywords used in the search, along with their respective sources, is provided in the appendix (see Table 3.1).

3.2.2 Identification of types

The initial dataset contained approximately 1.3 million economically active firms in Germany listed in the ORBIS database. This dataset included corporate URLs as well as firm characteristics such as the number of employees and incorporation dates. Due to limited financial resources, only 25 domains per website were scraped, including the main domain and 24 sub-domains, prioritizing them based on their URL hierarchy and length. Firm types were defined through an iterative process involving several feedback loops. In May 2021, the initial dataset was created by searching corporate websites for the selected keywords. This process yielded 103,000 data points, each containing the URL of the website where the keyword appeared, the specific keyword, and the paragraph in which it was found. When a URL contained multiple keywords, multiple data points were recorded.

In the first step, a randomly distributed subset of 750 data points was distributed evenly among five researchers. Each researcher analyzed the paragraphs and the overall websites to propose an initial classification of the data. During the first feedback round, the researcher consolidated these insights and agreed on seven classification types: *Manufacturer*, *Service*, *AM for own Products*, *Consulting & Education*, *Retail*, *Information*, and *Others*. The defined firm types were subsequently used to manually label a training dataset. For this purpose, 3,000 data points were randomly selected from the initial dataset. Labels were assigned based on a keyword, the corresponding paragraph, and the URL. To minimize bias originating from prior knowledge about the firms, this subset of data points was distinct from the subset initially used to define the types of firms. The given paragraph served as the decisive factor in assigning labels. Multiple researchers also carried out the labeling process for this data set.

The labeled dataset was used to train the prediction model. Through several feedback loops, the prediction results were evaluated using a test dataset to assess model performance. It was observed that the model encountered challenges in differentiating between closely related categories and their associated keywords. As a result, adjustments were made to the keywords and labels. Eleven keywords that did not precisely identify AM technologies—often appearing in unrelated contexts—were identified and removed from the keyword list. The appendix table A.2.1 provides a comparison of the initial and final keywords. Data points generated from keywords appearing only in menus, signatures, or other non-content sections of websites were removed from the dataset, reducing its size from 103,000 to 32,000 data points. In addition, the models exhibited low accuracy in distinguishing between the labels *Service*, *Consulting & Education*, and *AM for Own Products*. To address this issue, these labels were combined into a single category, *Service Provider*. The label *Others* was dropped due to its low frequency, resulting in four final types: *Manufacturer*, *Service Provider*, *Retail*, and *Information*. A detailed description of these types is provided in Table 3.1.

Table 3.1: Labels for website classification

Definition	**Initial classification**	**Final classification**
Manufacturer of AM machines or equipment	Manufacturer	Manufacturer
Offers personalized AM services Uses AM technologies in own production Offers AM consulting, training, etc.	Service Provider AM for own Products Consulting & Education	Service Provider
Sells AM machines, material, spare parts, etc.	Retail	Retail
Provides information about AM technologies	Information	Information
Miscellaneous purposes	Others	–

Notes: This table presents the identified types of AM adopters, describing their initial and final classifications along with corresponding definitions.

3.2.3 Model creation

Using the manually labeled dataset, the startup ISTARI.AI GmbH trained a machine learning model to automatically classify AM-related web content into the four predefined types. The final classification system consisted of an ensemble of 10 individual models. Each model was trained on a unique subset of data, allowing it to learn different patterns and become specialized in differentiating the defined types. This diversity in training ensured that each model approached classification with slightly different reasoning. During inference, each model casts a vote, and the type receiving the majority of votes became the final prediction. Ensemble models improve the reliability and quality of results, as single models can over-fit or under-fit the training data, leading to unwanted edge cases and overall subpar performance (Vaswani et al., 2017). The ensemble approach allowed to calculate confidence scores for predictions: the more models agreed on an outcome, the higher the confidence in the decision. To further improve performance, the architecture of each constituent model was optimized through a neural architecture search (Jin et al., 2019).

The constituent models used semantic vectors as inputs, derived by encoding the relevant paragraphs with pre-trained sentence transformers (Reimers and Gurevych, 2019). Pre-trained models offer the advantage of possessing fundamental language understanding (Malte and Ratadiya, 2019), requiring only a comparatively small amount of training data and minor adaptations to address new use cases. In addition to the relevant text, several firm and website meta-information were also encoded and concatenated into a single high-dimensional semantic vector. In this study, a 1,920-dimensional semantic vector represented the relevant information for each firm.

Since a firm's website typically consists of multiple sub-pages, each labeled individually, a single firm could be assigned multiple types, such as *Information* and *Retail*. To classify the entire firm, a hierarchy system was introduced. The final classification corresponded to the highest-ranking label assigned to the firm, as shown in Table 1. For instance, a firm offering AM services while also manufacturing AM machines was ultimately classified as *Manufacturer*.

3.3 Results

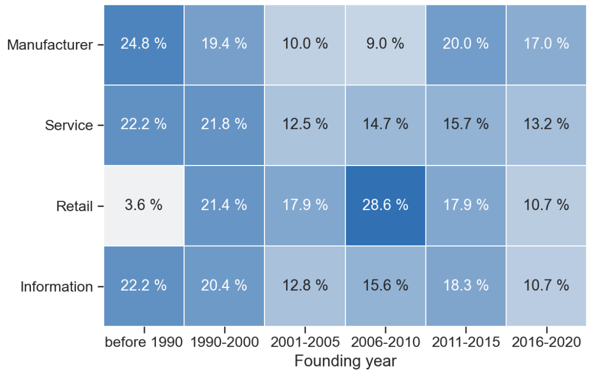
This section presents the findings in two stages. First, I analyze the characteristics of firms engaged in AM and classify them according to their respective types. Second, I examine the geographical distribution of AM firms, identifying hotspots and linking their occurrence to the locations of key manufacturing clusters and universities.

3.3.1 Firm characteristics

When analyzing the roles of firms involved in AM adoption and diffusion, the findings reveal that the majority of firms (total: 6,473) operated as service providers (71.9%). In addition, 19.7% of firms primarily focused on providing information. Manufacturers represented 8.0% of the total, while retail accounted for only 0.4%.

Dividing the engaged firms into six classes based on their age, I observed that both very young and relatively old firms were active in manufacturing and service provision. In contrast, retail activities were mainly driven by medium-aged firms. Interestingly, information providers tended to be relatively well-established, suggesting that experience and credibility play a significant role in this domain (see Figure 3.1).

Figure 3.1: Age of AM firms



When categorizing engaged firms by size based on employee numbers, I observed that small (10–49 employees) and micro firms (1–9 employees) represented the largest shares across all four classes, which is in line with the overall distribution of firm sizes. Large firms (more than 250 employees) had the highest representation in manufacturing, while micro-sized firms dominated the retail category (see Figure 3.2).

Figure 3.2: Size of AM firms

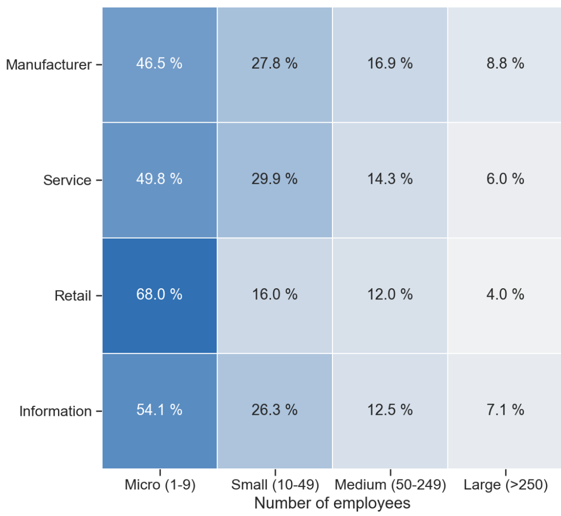


Figure 3.4 provides detailed insights into the industrial sectors where engagement with AM technology is most prevalent.[4] The highest share of AM-engaged firms was identified

[4]See Table A.2.3 in the Appendix for details on sector classification. Sub-sectors were aggregated into 31 main categories for group-related activities. For example, the category 'Electronics / optics' corresponds to NACE class C26 and includes the manufacturing of electrical equipment such as electric motors, machinery,

in material development sectors, such as synthetics (5.4%) and metals (4.8%). Significant shares were also observed in sectors producing electronics and optical products (3.2%), mechanical engineering (2.9%), and chemicals (2.6%). Some sectors were mainly engaged in AM service provision, such as the pharmaceutical industry (100%), repair and installation services (89.5%), and metal manufacturing (87.9%). This finding aligns with the observation that AM is frequently applied in producing spare parts, appliances, medical devices, and drugs (Pose-Rodriguez et al., 2020). I found the highest relative proportion of manufacturers in the mining sector (25.0%), followed by textile and clothing (18.8%) and transportation manufacturing (20.0%). Moreover, I observed that sectors with high shares of information providers related to AM included media and publishing firms (56.1%) and interest groups (45.7%). This finding likely reflects the importance of information diffusion as a means to reduce adoption barriers for end users. Furthermore, Engagement in AM within the retail category is most prevalent in the textile and clothing sector (6.2%), as well as in wholesale (1.8%) and retailing (1.7%), as expected.

3.3.2 Geographical diffusion

Figure 3.7a illustrates the geographical distribution of firms engaged in AM technology based on the listed addresses in the ORBIS database. A concentration of these firms was observed in major cities such as Berlin, Munich, and Hamburg. In addition, relatively high absolute numbers were identified in North Rhine-Westphalia, particularly around Cologne, as well as in the southwest of Germany, including Baden-Wuerttemberg. The high agglomeration near Cologne likely reflects the region's diverse industrial base, spanning sectors such as mining, consumer products, clothing, and design. Moreover, the areas around Hanover and Dresden stood out for their relatively high number of engaged firms. This geographical pattern likely reflects the overall business activities in these regions. For instance, the presence of Bremen and Kiel may be linked to the ship manufacturing industry, while the southern regions appear more focused on automotive manufacturing.

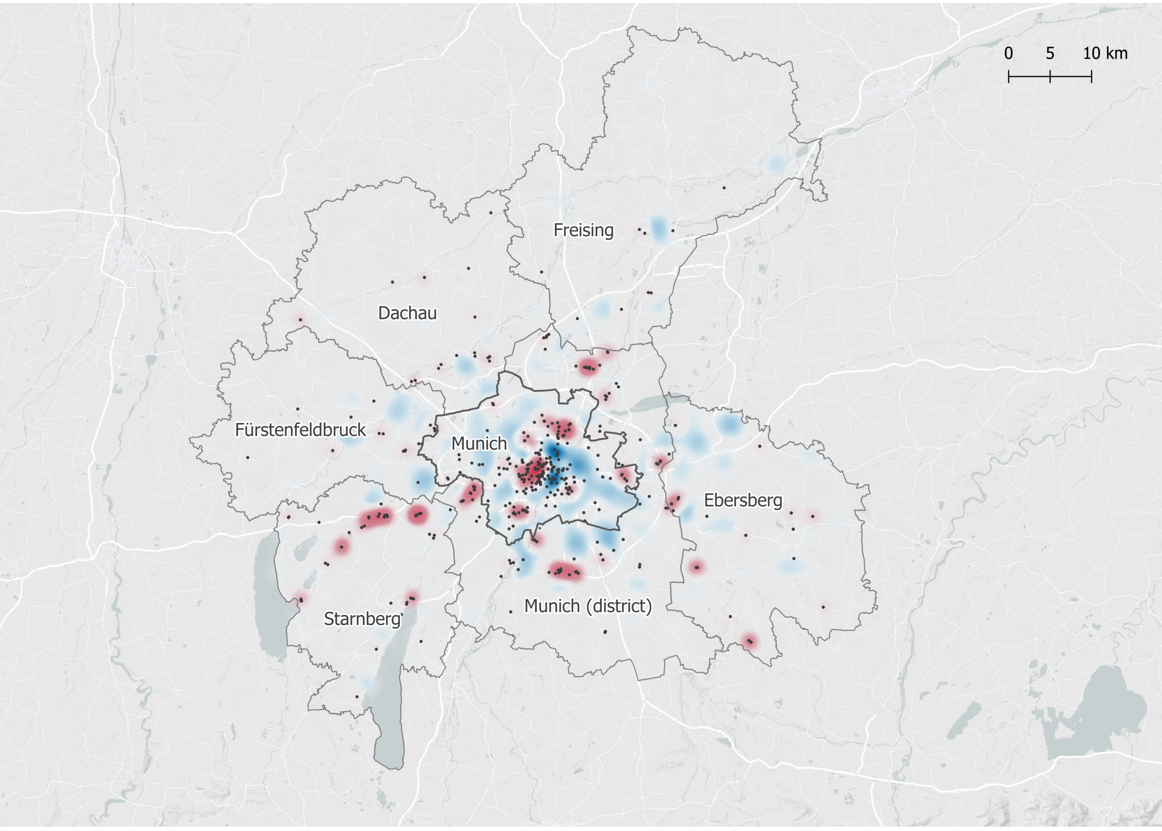
Even more informative is the depiction in Figure 3.7b, which illustrates the number of AM-active firms relative to the total number of firms in each region. This visualization highlights that the relative intensity of engagement is highest in the south and southwest of Germany. In addition, adoption hotspots are observed in central Germany and certain areas in the north. The red squares in the figure indicate the top 10 locations with the highest

and appliances.

relative AM engagement intensity. The three most engaged regions were Jena (Thuringia), Tuttlingen (Baden-Wuerttemberg), and Starnberg (Bavaria). Six out of the ten biggest clusters are located either in Baden-Wuerttemberg or in Bavaria. Only two of the hotspots are not located in southern Germany (Olpe and Jena).

A closer examination of the Munich area (see Figure 3.3) reveals several micro-hotspots within and around the city. Starnberg, ranked among the top 10 hotspots, is home to the headquarters of EOS, one of the largest manufacturers of AM machines and equipment. Several other high-tech firms are located in the south and southeast of Munich, including Airbus and Infineon Technologies. In Munich, the city district hosts the headquarters and AM Campus of the car manufacturer BMW. Other major corporations, such as Siemens AG (ranked among the top 3 applicants for AM patents) and MTU Aero Engines (ranked among the top 10 patent applicants), are also located in this area (cf. (Pose-Rodriguez et al., 2020), Table 4.1).

Figure 3.3: AM intensity in Munich



Notes: This figure shows firms adopting AM, represented by black dots. Regions with a high concentration of adopting firms are shown in red, while those with lower intensity are depicted in blue.

Jena, a comparatively smaller city than Munich, appears to have its AM engagement driven by users from the optical industry, which has traditionally been strong in the region. In contrast, Tuttlingen and Pforzheim, other high-engagement locations, are known for their manufacturing industries, including suppliers for the automotive sector, medical engineering, and the production of parts and materials used in industrial applications, such as jewelry.

An examination of the overall distribution of manufacturing firms (see Figure 3.7c) suggests that the diffusion and adoption of AM technology are linked to the prevalence of traditional manufacturing firms. This hypothesis is supported by the hotspot in Frankenthal (Pfalz), near Ludwigshafen on the Rhine, home to BASF, a chemical corporation and holder of many AM patents.

Another pattern visible in Figure 3.7d is the proximity of technical universities (TUs) to highly engaged locations. This is particularly evident in Figure 3.3, where the most prominent downtown hotspot coincides with the location of the Technical University of Munich (TUM). Moreover, the Munich University of the Federal Armed Forces (*Bundeswehruniversität*) is located in the southeast of the city, an area that is congruent with observed high-intensity zones. This pattern is not unique to Munich and can also be observed in Karlsruhe and Aachen, associated with the Karlsruhe Institute of Technology (KIT) and the Rheinisch-Westfaelische Technische Hochschule Aachen (RWTH Aachen), respectively. Furthermore, smaller universities of applied sciences, such as the Coburg University of Applied Science and Arts in less densely populated regions, likely contribute to relatively high adoption intensities in their surrounding areas.

A more differentiated analysis could be made when comparing the four types: *Manufacturer*, *Service*, *Retailer*, and *Information.* Regions with a higher density of traditional manufacturing firms demonstrated stronger engagement in manufacturing (see Figure 3.8a) and retail (see Figure 3.8b). In contrast, locations in close proximity to technical universities show higher activity in AM services (see Figure 3.8c) and information provision (see Figure 3.8d). Information provision often appeared in areas with a strong manufacturing base, such as Lichtenfels, where General Electric holds a majority share in Concept Laser. GE's expansion of activities in this region has attracted suppliers and service providers, contributing to a local ecosystem. In the identified top 10 locations, all types of activities are present, suggesting that clusters emerged where manufacturing, applications, and information provision coexisted. However, some areas with relatively high engagement intensity

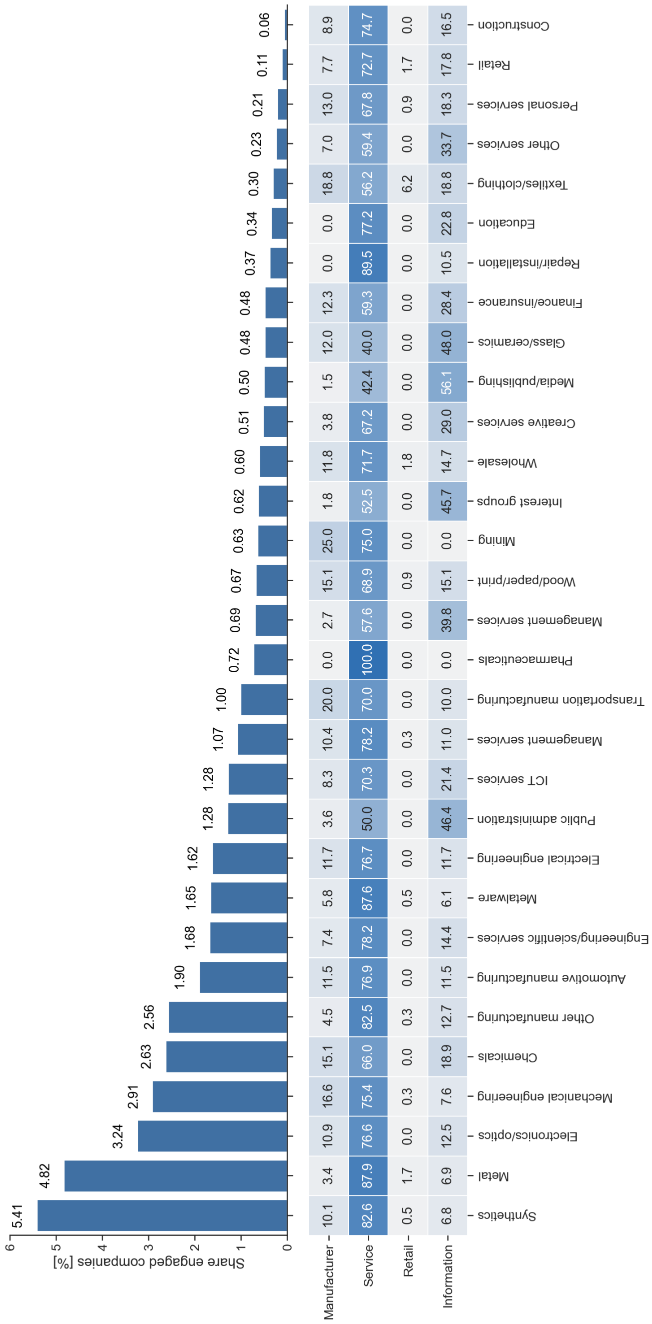


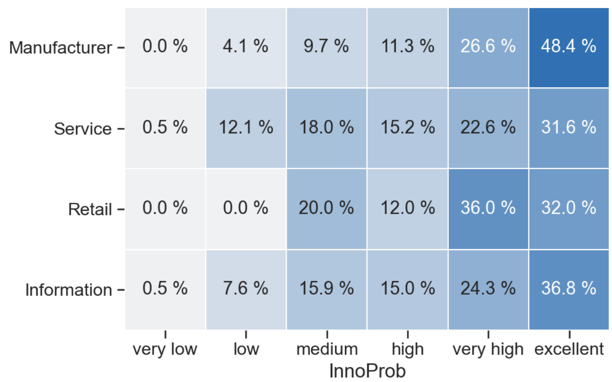
Figure 3.4: Sector distribution of AM firms

were mainly active in retail. Agglomerations are observed in both north and south of Berlin, as well as in northern Germany, indicating that factors such as inexpensive storage space and accessibility to export markets might influence location choices.

3.3.3 Validation

To validate the type identification, a consistency test was conducted to assess the overall innovativeness of firms by category. The assumption was that if the identification of new technology adopters and diffusers were accurate, these firms would also exhibit higher levels of innovativeness. The test uses the InnoProb indicator, a metric developed by Kinne and Lenz (2021), which assigns an innovation probability to firms based on a model trained with Community Innovation Survey data. Figure 3.5, engagement in AM technology correlated with higher degrees of innovativeness across the identified types. Overall, 57.7% of firms engaged in AM were classified as innovative (InnoProb ≥ 0.4), with manufacturers showing the highest proportion at 74.9%. This indicates that the identified firms were likely to have recently introduced a product or service innovation. The pattern was consistent across all four types, with particularly strong results for information providers and manufacturers.

Figure 3.5: Innovation performance of AM firms



The findings regarding the use of AM by sector align with those reported by Pose-Rodriguez et al. (2020). This EPO study, based on patent application data from the PAT-STAT database, documents sectoral trends in patenting and highlights the prevalence of AM in transport manufacturing, industrial tooling, healthcare, optics applications, and consumer goods. Geographically, my mapping overlaps with some of the findings in Pose-Rodriguez et al. (2020) (e.g., see Figure 38 in their paper), while also identifying additional regions not captured in patent data. There was significant overlap in identified hotspots, with both analyses highlighting Munich, the Munich district, Berlin, Hamburg, and Starnberg. However, relying solely on patent screening may underestimate the importance of locations like Jena or regions that are less manufacturing-intensive.

3.4 AM and sustainability

Besides measuring the adoption of new technologies, web text mining allows for the evaluation of firms' self-representation regarding sustainability, which often aligns with their actual practices (Schmidt et al., 2022). Given the potential of AM technology to enhance environmental sustainability and support the circular economy (Sauerwein et al., 2019; Despeisse et al., 2017), this analysis explores how AM firms portray their sustainability efforts.

To identify firms with sustainability engagement, I followed the approach of Schmidt et al. (2022). For labeling purposes, five categories were assigned with the following ordinal ranking: *Frontrunner*, *Enabler*, *Engaged*, *Information*, and *Not Engaged*. However, for this analysis, I grouped the first four categories into one. For the creation of the keyword list, the terms were restricted to the ecological dimension of sustainability (for the keyword list, see (Schmidt et al., 2022)). I considered a sustainability intensity > 0 as indicative of a firm with sustainability engagement.

For the analysis, I looked at a population of 1,782,172 firms in Germany, Austria, and Switzerland. 207,368 (11.6%) of these firms had a sustainability intensity > 0, thus, being classified as 'sustainability-engaged firms'. In the overall population, I identified 8,170 AM firms (6,473 in Germany, 713 in Austria, and 984 in Switzerland). This corresponded to 0.46% of the firm population (0.48% in Germany, 0.40% in Austria, and 0.38% in Switzerland). 2,500 (30.6%) of the AM firms were sustainability-engaged, which was a much higher number than the 11.6% in the overall firm population. The distribution of sustainability scores was highly skewed to the right for all sustainability-engaged firms (median: 0.275, max: 6.935), as well as for all sustainability-engaged AM firms (median: 0.383, max: 4.154).

The vast majority of AM firms were classified in the *Service* category (71.4%, cf. Table 3.2). Only a small fraction of firms acted as *Manufacturers*, while there was barely any in the *Retail* category. The distribution among the categories did not differ significantly between all AM firms and sustainable AM firms. However, the share of *Manufacturers* was slightly higher for sustainable AM firms.

Table 3.2: AM firms per adoption type

Category	**All**	**Sustainable**	**Share**
Manufacturer	643 (7.87%)	232 (9.28%)	36.1%
Service Provider	5,831 (71.37%)	1,664 (66.56%)	28.5%
Retail	35 (0.43%)	9 (0.36%)	25.7%
Information	1,661 (20.33%)	595 (23.80%)	35.8%

Notes: This table presents an overview of the total number of AM firms (labeled 'All') and the total number of AM firms with sustainability engagement (labeled as 'Sustainable') per adoption type. The proportion of each adoption type is shown in brackets. 'Share' represents the proportion of sustainability-engaged AM firms relative to the total number of AM firms within each category.

Considering the firm size, most of the AM firms were actually small firms, while only 247 were classified as very large. However, for these very large firms, 64.8% were indeed sustainability-engaged firms. Only 23.8% of the small firms were sustainability-engaged. However, in the overall firm population, merely 9.4% of small firms and 42.5% of very large firms were sustainability-engaged.

Table 3.3: AM firms per firm size category

Firm size	**All**	**Sustainable**	**Share**
small	3,785 (0.101)	902 (0.000)	23.8%
medium	2,161 (0.095)	700 (0.000)	32.4%
large	1,180 (0.087)	573 (0.150)	48.6%
very large	247 (0.085)	160 (0.568)	64.8%

Notes: This table presents an overview of the total number of AM firms (labeled 'All') and the total number of AM firms with sustainability engagement (labeled as 'Sustainable') per firm size. The median intensity is represented in brackets. The staff headcount categories follow the SME definition established by the European Commission. 'Share' represents the proportion of sustainability-engaged AM firms relative to the total number of AM firms within each category.

Most of the identified AM firms were rather young, as 61% were founded after the turn of the millennium (cf. Table 3.4). Consequently, the percentage of firms founded in the 1990s or earlier was higher for the subset. Overall, an earlier founding year was associated with a higher relative share of sustainability-engaged firms and higher intensity. This trend, however, was in line with the population of all firms in the DACH region. Therefore, I could not conclude a link between sustainability and the age of AM firms.

In a further step, I looked at the spatial distribution of sustainable AM firms. The 10 NUTS3 regions with the highest number of sustainable AM firms were Berlin (113), Munich (city) (90), Hamburg (81), Zurich (67), Bern (57), Vienna (55), Dusseldorf (50), Stuttgart (48), Munich (district) (42) and Frankfurt (36). This mostly corresponded with

Table 3.4: AM firms per decade of founding

Decade	All	Sustainable	Share
2020s	66 (0.8%)	15 (0.6%)	22.7%
2010s	2,658 (33.5%)	730 (29.5%)	27.5%
2000s	2,121 (26.7%)	617 (24.9%)	29.1%
1990s	1,550 (19.5%)	509 (20.6%)	32.8%
1980s	652 (8.2%)	230 (9.3%)	35.3%
before 1980	896 (11.3%)	399 (16.1%)	44.5%
Total	7,943 (100%)	2,473 (100%)	31.1%

Notes: This table presents an overview of the total number of AM firms (labeled 'All') and the total number of AM firms with sustainability engagement (labeled as 'Sustainable') per decade of founding. The proportion of each adoption type is shown in brackets. 'Share' represents the proportion of sustainability-engaged AM firms relative to the total number of AM firms within each category.

the NUTS3 regions with the highest overall number of AM firms and economic centers in the DACH region. Figure 3.6 aggregates the number of firms on the NUTS3 level and normalizes them with the overall number of AM firms in the respective region. Only NUTS3 areas with more than 10 AM firms were considered for this analysis. Accordingly, the map mainly reflects established economic and demographic centers of the research area.

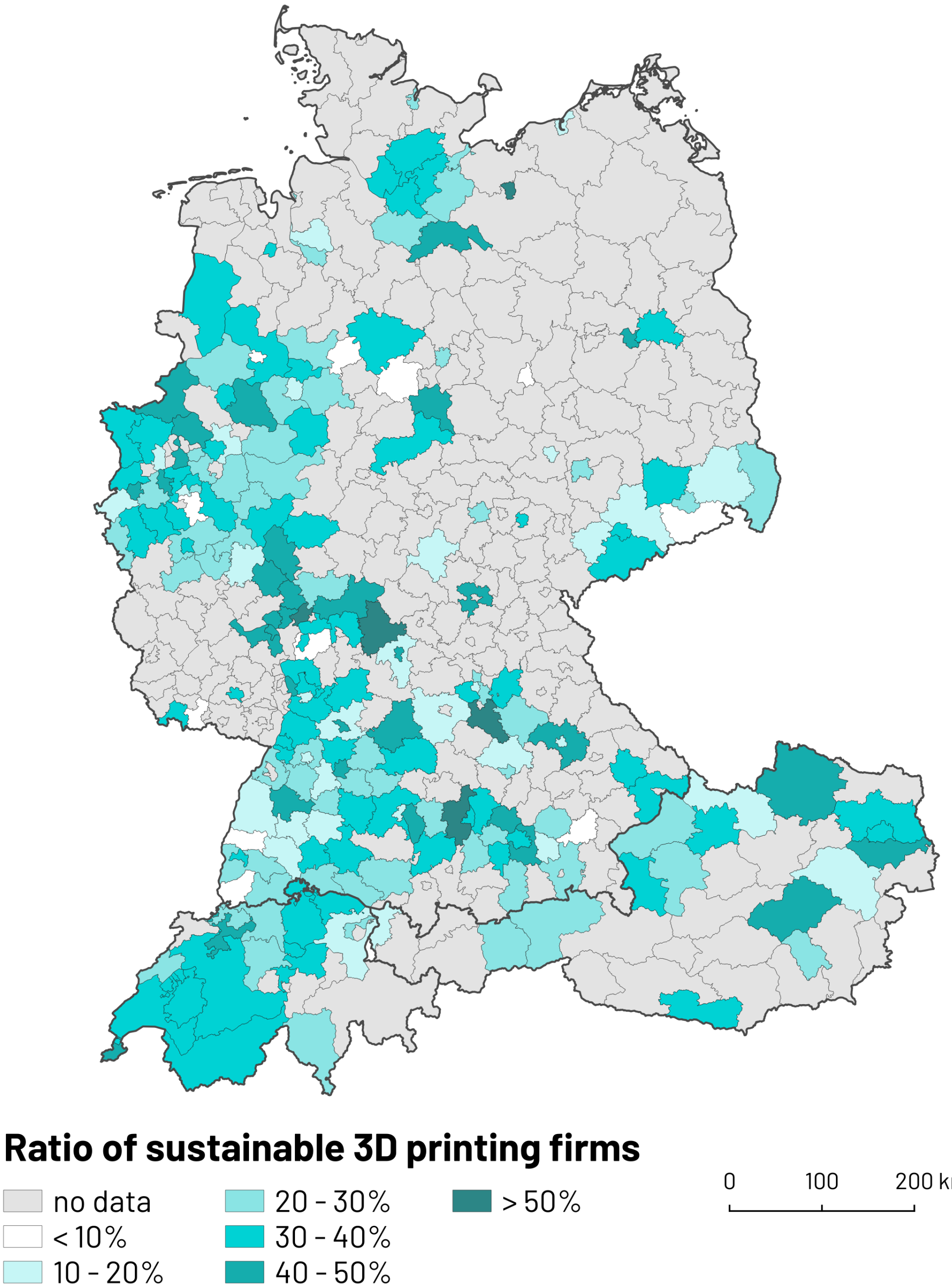
I also calculated the Moran's I for the ratio, employing a Queen contiguity approach for the underlying spatial weights matrix. The resulting value of 0.00029 was not statistically significant (p=0.458), indicating no spatial autocorrelation, i.e. the absence of spatial clustering. However, this might have been influenced by the low number of the remaining regions.

3.5 Discussion & conclusion

This study demonstrates a website text-based approach to analyzing adoption of new technology. Using machine learning, this method identifies firms engaged in specific technologies that are not easily captured by traditional indicators such as patents. Moreover, it distinguishes between different types of firm engagement, capturing activities related to the diffusion of new technology rather than its invention. These novel indicators can provide valuable insights for policymakers and other stakeholders by offering additional information about individual technologies.

For the case of AM, the analysis revealed geographical patterns of technology use and diffusion. Linking adoption intensity to firm characteristics highlighted the important role of young and small firms. Moreover, I found that regions with a strong manufacturing

Figure 3.6: Ratio of sustainability-engaged AM firms



base exhibited higher levels of activity. Interestingly, the majority of AM-engaged firms were classified as *Service Provider*. Locations close to technical universities showed higher adoption intensities, suggesting that academic research organizations and basic research play a critical role in fostering new technologies and providing a skilled workforce trained in relevant fields.

Regarding sustainability, AM firms were almost three times more inclined to present themselves as sustainability-engaged in comparison to the overall firm location in the DACH region. I found that larger and older companies were more inclined to be sustainability-engaged, which was consistent with the overall firm population. Furthermore, I observed that companies classified as *Manufacturer* and *Information* contained a higher share of sustainability-engaged companies than *Service Provider*. This may indicate that manufacturers and information providers understand the technological possibilities for sustainable activities. Service firms, on the other hand, do not seem to fully exploit AM's ecological potential, as their share of sustainability-engaged companies was considerably smaller.

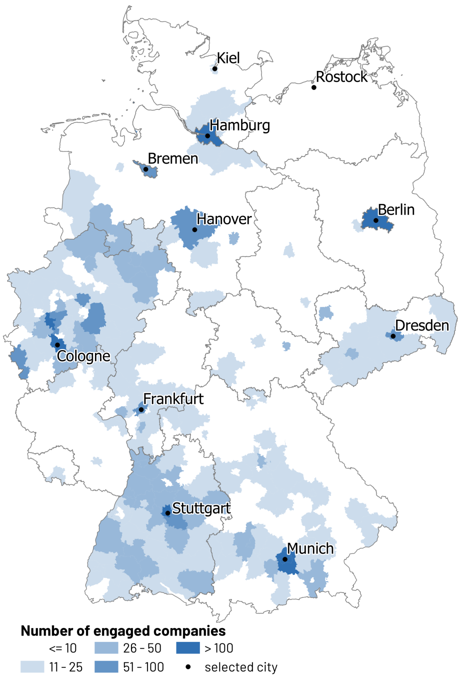
This analysis provides only descriptive results. Therefore, future studies could use econometric models to uncover statistically significant relationships. Investigating causal relationships between location factors, such as universities, and AM adoption would be particularly interesting and could extend recent research on the topic (Hausman, 2022). Furthermore, comparing these results to analyses based on patent data could enrich innovation research and contribute to the development of robust indicators. Lastly, more research on the relationship between web-based measures and other innovation indicators at the firm level would enhance our understanding of the distinct dimensions captured by these approaches for mapping technology diffusion (Kinne and Axenbeck, 2020).

This website text-based approach is a promising complementary indicator to measure the adoption and diffusion of new technologies.[5] While this study made efforts to validate the results internally and externally, there are potential limitations in the generalizability of the assigned labels. The accuracy of the classification was heavily influenced by the consistency of labeling in the initial training dataset, particularly by how clear the assignment of each data point to its respective category was to the labeling team. Furthermore, although using firm websites provides near-universal coverage, very small or newly established firms that do

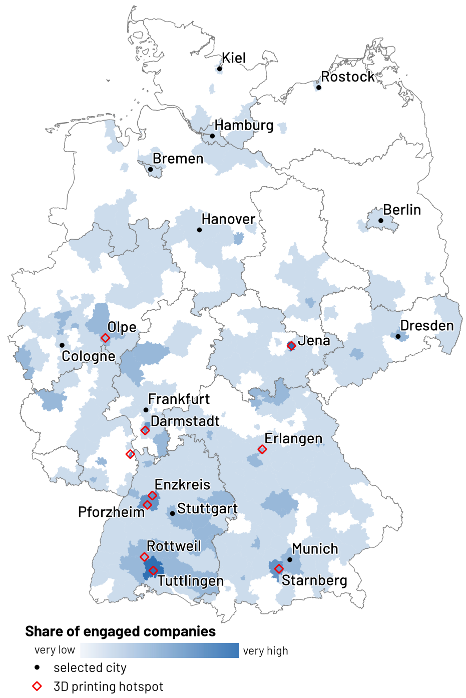
[5] In a subsequent study, I explored the potential of web mining to identify firms adopting blockchain technology (Gschnaidtner et al., 2024).

not yet have a website may have been excluded from the analysis (Kinne and Lenz, 2021). On the other hand, limiting the number of scraped sub-pages per website may introduce a retrieval bias, potentially underestimating the role of large firms with large websites. It is also important to consider that firms may strategically design their websites (incentive bias), such as startups emphasizing content to attract investors. Moreover, it is important to note that the analysis was conducted at a fixed point in time. As a result, understanding adoption dynamics over time will require repeated analyses in the future.

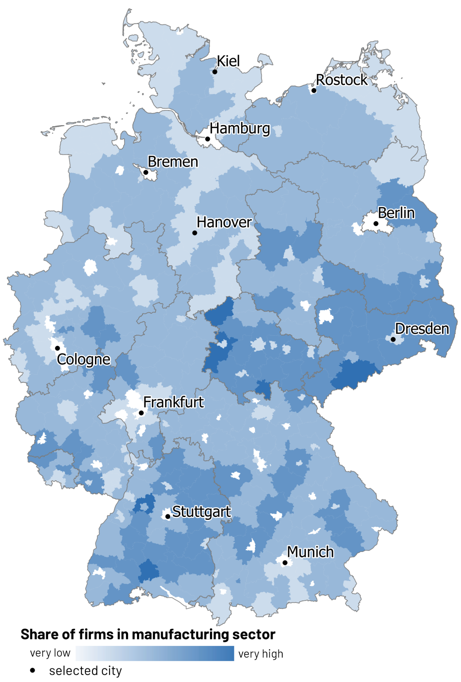
Figure 3.7: AM intensity and facilitators



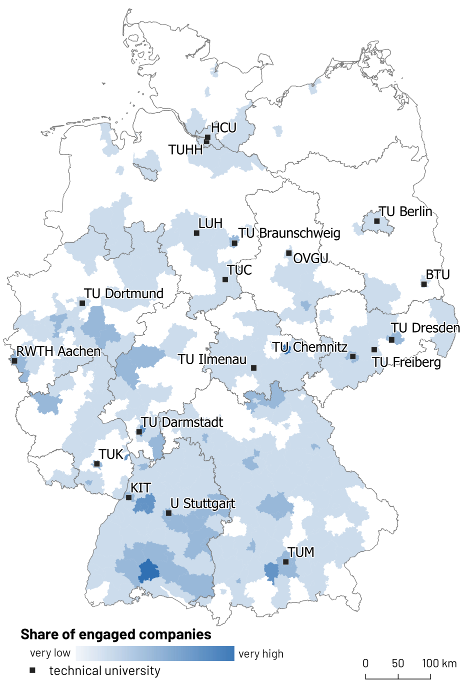
(a) Absolute intensity



(b) Relative intensity

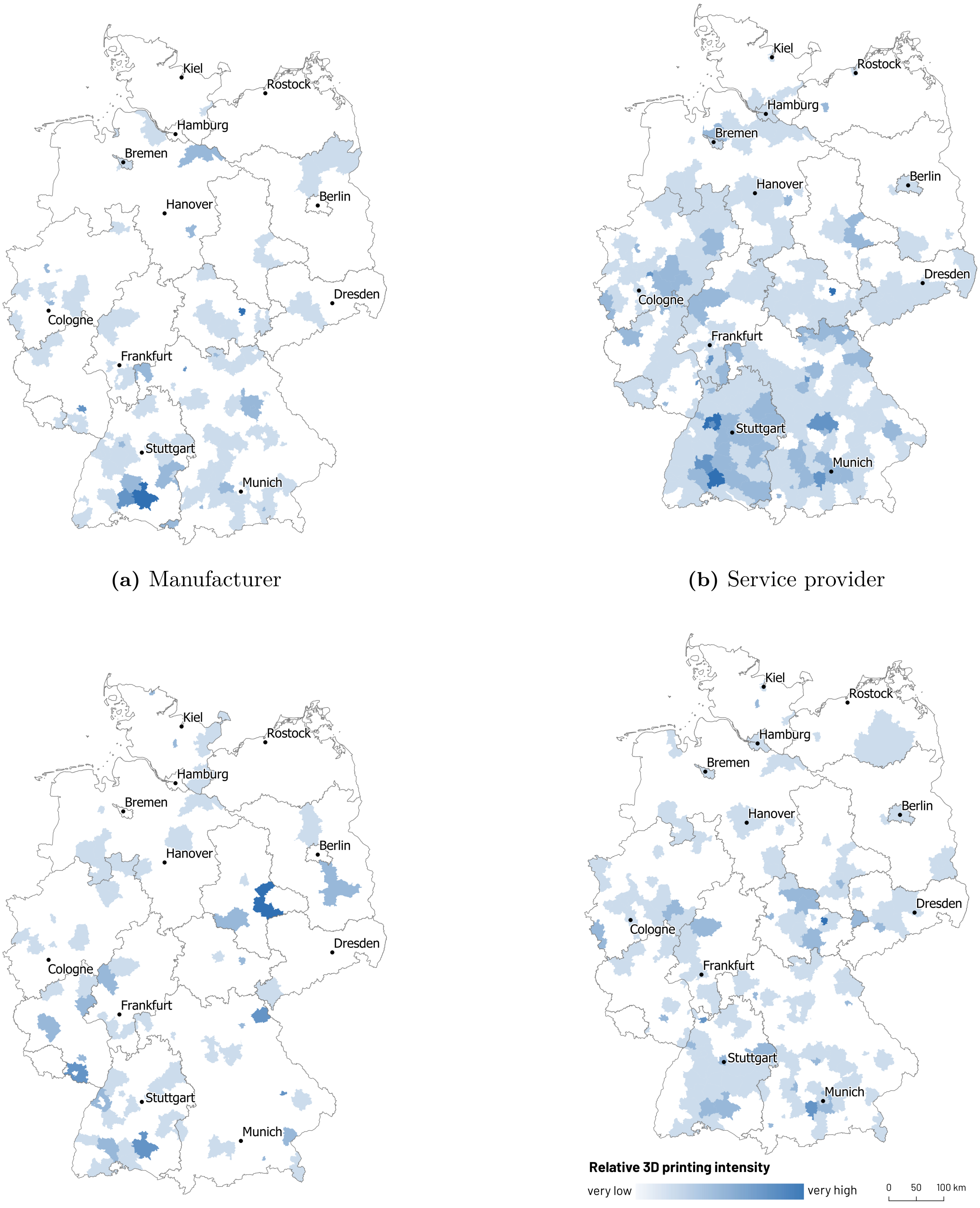


(c) Total manufacturing industry



(d) Technical universities

Figure 3.8: Relative AM intensity differentiated by categories



(a) Manufacturer

(b) Service provider

(c) Retail

(d) Information

4 | Clusters of Excellence and science spillovers to industry: Evidence from additive manufacturing

Summary

Public research funding provides an important policy instrument to foster the link between scientific advancement and industrial and technological progress. However, the (most) effective design of such funding schemes remains a subject of ongoing debate. In this chapter, I investigate the impacts of competitive geographically localized forum grants (Clusters of Excellence) in additive manufacturing research awarded under the German Excellence Initiative from 2006–2012. Using synthetic difference-in-differences estimation, I show that Excellence Clusters increased scientific output in funding-relevant domains especially, but not exclusively, in the right-tail of the scientific impact distribution—as measured by article citations—relative to non-funded applicants in similar areas of scholarly agglomeration. While this did not positively impact patenting by surrounding firms at the extensive margin, I find evidence for knowledge spillovers from scientific excellence to local industry, reflected in a significant increase in high-impact ('hit') corporate patents specific to additive manufacturing technology. Moreover, top scientific publications originating from Excellence Clusters received significantly more prior art citations from technically related industry patents worldwide. My findings support the effectiveness of forum-based funding programs for top science and provide dual implications for research and industrial policy.

This chapter is based on joint research with Hanna Hottenrott and Thomas Schaper.

4.1 Introduction

Universities are substantial drivers of economic growth. Being the principal breeding grounds of scientific knowledge and open loci of science transfer, they provide important spillovers to the broader economy (Jaffe, 1989; Mansfield, 1995; Henderson et al., 1998; Cohen et al., 2002; Bikard and Marx, 2020; Hausman, 2022). Moreover, the growing importance of science-based industries stresses the link between scientific knowledge and commercial applications (Audretsch and Stephan, 1996; Gittelman and Kogut, 2003; Fleming and Sorenson, 2004; Krieger et al., 2024), in particular between scientific excellence and technological progress in industry (Hicks et al., 2000; Iaria et al., 2018; Poege et al., 2019; Schaper et al., 2023). A key question for science policy is, therefore, whether the production of scientific knowledge that is of relevance for business and society can be fostered through targeted research funding (Scherer and Harhoff, 2000; European Commisson, 2024b). The literature in the economics of science and innovation has established that competitive research funding can increase scientific output (Jacob and Lefgren, 2011b; Carayol and Matt, 2004; Hottenrott and Lawson, 2017; Heyard and Hottenrott, 2021), that the type of funding matters for the type of output (Azoulay et al., 2011; Myers, 2020; Veugelers et al., 2022), and that public research and development (R&D) grants spur industry patenting (Azoulay et al., 2019). However, it remains unclear which specific design of funding schemes would yield the highest returns, both in terms of scientific advances and industry spillovers.

This chapter contributes to a better understanding of this link by studying the impacts of Germany's Clusters of Excellence program, a funding tool aimed to support geographically localized forum-based cutting-edge research in specific fields of science. This program was introduced in 2006 and funded more than 106 Excellence Clusters until 2024[2]. It is one of the central pillars within the German Excellence Initiative – a large-scale funding scheme for German universities administered by the German Research Foundation (DFG) with the goal of strengthening their competitiveness on a national and international level (Schiermeier, 2017; Möller et al., 2016; Schubert et al., 2017). As a part of this funding program, Clusters of Excellence aims to foster the agglomeration of frontier scientific human capital through financing groups of researchers who dedicate joint research efforts to a specific topic (Deutsche Forschungsgemeinschaft, 2015). In this analysis, I focus on Excellence Clusters in the broader

[2]A comprehensive list of all Clusters of Excellence, detailing their research focuses, participating institutions, and funding structures under Germany's Excellence Strategy, is available on the GEPRIS platform of the German Research Foundation. See https://gepris.dfg.de/gepris/OCTOPUS accessed on 09/01/2025.

area of additive manufacturing (AM). Researchers in this technology domain have received multiple grants, and it is a technology field that is a) science-based and b) was in its infant diffusion stage in the industry during the first funding period (Campbell et al., 2023). It is also one of the Key Enabling Technologies (KET) as defined by the European Commission (European Commisson, 2012). Spurring knowledge spillovers from science to industry is therefore crucial to promote further technological progress and the diffusion and development of new applications to businesses and consumers in this area.

In this chapter, I address the question of whether there are significant scientific as well as broader economic returns to excellence research funding in localized clusters. In particular, I investigate whether Excellence Clusters create more important and impactful scientific results relative to the control group and to what extent these would spill over (more) to industrial inventions related to the clusters' research scope. The expectations about the direction of the impact of targeted research funding on industrial innovation are ambiguous. On the one hand, funding may increase the quality of R&D by co-located firms due to knowledge spillovers from scientific output and agglomeration effects (Jaffe, 1989; Bikard and Marx, 2020). However, it is not obvious that basic research funding results in transferable knowledge (Colen et al., 2022). Moreover, Excellence Cluster funding might foster cooperation between universities and firms, thereby reducing the incentives for firms to invest in their own research, which in turn reduces firms' inventiveness.

Studying the effects of Excellence Cluster funding in a research area like additive manufacturing is challenging for multiple reasons. First, AM research is not a field on its own, but rather a meta-area of discoveries and inventions spanning multiple domains. At the same time, no domain or field is exclusive to AM-related science and technology alone. This makes it difficult to map and trace output in this area empirically. To overcome this issue, I classify all scientific articles in the Elsevier SCOPUS database and all patents granted by the United States Patent and Trademark Office (USPTO) based on the semantic contents of their article abstracts and patent text-bodies using expert-curated vocabularies of keywords and word/class-combinations specific to AM. This allows us to measure the exact publications and patent grants, their respective origins, types, and impacts, in the area of additive manufacturing worldwide.

The second challenge relates to the statistical inference of (isolated) effects of Excellence Clusters: the grant application process is highly competitive, and a successful application requires the involvement of top scientists as well as collaboration with eminent peers in related disciplines. The award of a cluster grant is therefore driven by ex-ante scientific excellence and distinguishing its marginal impact from selection effects is non-trivial. To tackle this challenge, I provide matched case-control-based evidence derived from a synthetic difference-in-differences estimation (Arkhangelsky et al., 2021), carefully comparing locations with cluster funding to a weighted, dynamic counterfactual of university locations that had received funding from another large funding scheme from the DFG, the so-called Collaborative Research Centers (CRC). To test the robustness of my results, I further restrict the synthetic counterfactual to include only locations that had successfully submitted a first-round proposal and had been invited to go to the second and final round of evaluation but were ultimately not selected for funding.

When comparing scientific publications and industry patenting in clusters versus non-funded CRC regions, both before and during the funding period, I find that in Clusters of Excellence, the overall number of scientific publications related to AM increased following the cluster grant. In addition, my results reveal a relatively larger increase in top publications, defined as those entering the upper percentile of year-field citation distributions. These effects are driven by publications of academic institutions (universities and public research organizations), rather than by industry authors or joint publications with industry. Following the rise in relevant research output, particularly in excellent/top science, the results show an increase in highly cited patents in AM technology by surrounding firms in cluster regions. At the same time, there was no rise in general patenting activity in these areas. Finally, further results show that the AM publications in funded locations were more likely to be cited in AM-patents.

4.2 Research funding & knowledge spillovers

Scientific research has long been understood as an important driver of knowledge and innovation (Cohen et al., 2002; Mansfield, 1995; Nelson, 1959). The growing importance of science-based technologies highlights the role played by scientific knowledge (Krieger et al., 2024; Fleming and Sorenson, 2004; Narin et al., 1997). However, as stressed already by Nelson (1959), the incentives to engage in the creation of research results are fundamentally impacted by the limited appropriability of knowledge. Thus, while investments in knowledge creation are pivotal for societies, the levels of investment by individuals and private organizations may be below the social optimum. This basic insight has led to a strong focus on the economics of science and, particularly, the role of publicly funded research (Stephan, 2012). In this discussion, it is a central question of how to increase incentives for knowledge creation and sharing to promote knowledge diffusion from science to industry to eventually benefit society (Jaffe, 1989; Hausman, 2022).

One prominent policy tool for promoting scientific research is grant competitions for allocating public research funding (Hottenrott et al., 2021; Oancea, 2019; Froumin and Lisyutkin, 2015; Azoulay et al., 2011; Stephan, 1996). The idea behind such funding instruments is that - unlike in the case of block grants - they incentivize competition among scientists and allocate scarce funding resources to those ideas and investigators likely with the highest returns. Given the rising use of competitive funding allocation instruments, for instance, in continental European national funding systems (Krücken et al., 2021), it appears crucial to understand not only whether funding competitions indeed result in additional and relevant research and produce desired knowledge spillovers, but also which types of funding schemes may be particularly effective in this.

4.2.1 Types & effects of grant-based funding instruments

Grant-based science funding instruments usually aim to fund scientists, groups of scientists, or entire institutions. Unlike block funding, research grants are typically awarded on the basis of a specific project proposal and undergo a peer-review process, which leads to an evaluation-based decision. The scientific quality of the proposed project and the characteristics of the applicants are typically relevant criteria for a positive evaluation. In most of such funding designs, the award process is administered by a funding agency and relies on collaboration with the scientific community, which supports the review and assessment process. The idea of such a competitive funding process is that researchers need to dedicate effort towards the application and that the 'best' proposals 'win'. Adopting the theoretical framework of Simmel (1908), such contests can be viewed as triads with the focal applicant being described as 'ego', the competitors as 'alter' and the funding agency constituting a third party ('tertius') that takes the role of a prize-giver. Such a competitive design is thought to ensure funding allocation to projects that are most likely to generate relevant outcomes (through peer review) and to encourage individual scientists to remain motivated and productive over the life-cycle by participating and succeeding in these contests (Stephan, 1996; Meulen, 1998; Schubert, 2009).

Researchers have studied the impact of such grant-based instruments on knowledge production at multiple levels. At the individual level, most commonly, scientists are granted funding for clearly specified research projects in which they take the role of a principal investigator. Such projects are typically smaller in scale and span a period of one to four years (Hottenrott and Lawson, 2017; Heyard and Hottenrott, 2021). Studies evaluating the outcomes from such individual grants typically find small increases in research outcomes following the funding (Arora and Gambardella, 2005; Jacob and Lefgren, 2011a, 2011b; Heyard and Hottenrott, 2021) but also stress that the sources of funding and the overall amount matters (Azoulay et al., 2011; Hottenrott and Lawson, 2017; Myers, 2020). Several of these studies show a positive effect of funding on scientific output.

At the institutional level, funding is typically allocated to the university or a larger part of it. Such funding is often not dedicated to specific research projects but rather supports larger infrastructure investments or institutional developments. Some authors have recently studied the impact of such institutional funding in the context of the German Excellence Initiative on aggregate, institutional-level scientific output (Gawellek and Sunder, 2016; Schubert et al., 2017). While, overall, their results suggest no to moderate positive aggregate effects on research outcomes, there is strong variability among findings across studies, depending on specific samples and methods employed. Schubert et al. (2017), using fixed effects panel regressions, do not find a strong impact of the EI on publication performance once accounting for time-invariant heterogeneity across universities, yet a significant positive impact of Clusters of Excellence on university-wide publications in engineering sciences. In addition, there is quite some evidence on the impact of similar funding instruments in other countries. For example, have researchers investigated China's 985 project (Zhang et al., 2013; Zong and Zhang, 2019), Russia's 5–100 project (Agasisti et al., 2020; Turko et al., 2016), or Taiwan's World Class University project (Fu et al., 2020). Yet, they found mixed performance effects from these initiatives. Obviously, funding at the institution may affect not only research outcomes but also university characteristics more generally. Concerning the impact of the EI on students, Bruckmeier et al. (2017) as well as Ayoubi et al. (2014) find that EI-funded universities manage to attract more students and that students perceive the quality of teaching and supervision as better.

More recently, funding at the team, group, or forum level has gained more attention, particularly team-level outcomes. Here, grants are awarded to groups of researchers, labs, or regional, collaborative clusters. Studies investigating such team-level grants are still rare, but Encaoua et al. (2000) find a positive link between science funding and research output also for research teams, while Carayol and Matt (2004), for example, do not find a significant link between science funding and team productivity. Bornmann (2016) documents a discipline-specific effect on co-authorship networks and publication performance from German 'Clusters of Excellence' (see next section for details) limited to solely the natural sciences. At the same time, a study by Möller et al. (2016) suggests that large-scale, group-level funding can have a substantial impact on measurable outputs. They estimate, based on aggregate bibliometric data, that about half of the increase in Germany's publication performance in the years after 2007 can be attributed to publications by the 'Clusters of Excellence'. Thus, the findings for teams are less clear than those for individuals. Based on these insights, it appears that team-funding effects are less clearly positive. On the one hand, collaboration within teams and the pooling of complementary skills may enhance motivation, creativity, research productivity, and quality of outcomes. On the other hand, teamwork comes with coordination and communication costs, disclosure of ideas to others, and conflicts. Moreover, most groups or teams in academia are fluid in the sense that there are considerable fluctuations and funding periods are usually limited. The latter characteristic could actually promote knowledge diffusion through increased mobility. Likewise, the involvement of different individuals could contribute to both knowledge creation and knowledge diffusion. Because of this ambivalence and fundamental difference as compared to individual grants, such group-level funding instruments are, therefore, particularly interesting, and previous insights are still very limited.

4.2.2 Clusters of Excellence

Clusters of Excellence as a science funding instrument were introduced in Germany as part of the so-called Excellence Initiative (EI). With the introduction of the EI, the German federal government took a stance to the promotion of top-level research through the competitive allocation of large grants, thereby aiming to improve the international standing of German research institutions and making Germany a more attractive location for top researchers. Besides Germany, several other countries have implemented similar science funding programs and generally moved towards larger-scale and performance-based allocation of science funding (Salmi, 2016; Hottenrott et al., 2021).

The German EI was introduced in 2005 with the first funding round (2006-2012) distributing €1.9 billion and the second round (2012-2017) assigned another €2.7 billion (Deutsche Forschungsgemeinschaft, 2015).

The EI assigned funding through three funding lines. First, universities could apply to establish graduate schools (up to €2.5 million per year). Graduation schools provide a structured education program for doctoral students and a place of interdisciplinary and cross-faculty scientific exchange to promote young researchers. They improve the cooperation within the university and with non-university research institutions. Second, Clusters of Excellence fund collaborative research in specific, often interdisciplinary, domains (up to €8 million per year). Clusters of Excellence are allocated to large researcher consortia with up to 25 principal investigators to foster expertise on specific topics to promote frontier research. Lastly, universities that were successful in these pillars of the EI could also apply for funding at the institutional level (institutional strategy) for developing the general university-level infrastructure without having to define particular research projects (up to €12.5 million per year). Thus, this funding line aims to strengthen the institution and its research (and education) as a whole.

This study focuses on the Clusters of Excellence as the central funding pillar. In this context, it can be expected that funding has positive effects on research excellence as well as knowledge spillovers from science to industry due to their pan-organizational design. Such clusters can be quite large and comprehensive as they can span and involve several universities and partners such as from the large research association (Leibniz Association, Max-Planck Association, Helmholtz Association, Fraunhofer Association) or industry.

The first funding round covered the period between 1^{st} November 2006 and 31^{st} October 2012 and contained two tendering rounds (2006 and 2007). In this phase, the total funding volume comprised 1.9 billion euros. 60% of this amount was allocated to 37 Clusters of Excellence. The second and third funding rounds took place between 2012 and 2017, as well as 2019 and 2024, respectively. Besides the direct effects on knowledge production and research outputs, it is a relevant and interesting question whether, assuming that the funding results in additional knowledge, it also generates spillovers to actors not directly involved in the research. Often, such spillovers are referred to as justification for promoting cutting-edge research. Scientific research funded by the EI may create such spillovers due to increased collaboration and exchange, as well as researcher mobility between organizations and teams. The local nature of most such clusters, i.e., relevant actors located within a certain spatial range, may foster such spillovers within the region but may also limit the spillovers that reach other research locations and firms.

4.2.3 Localization of knowledge spillovers

Previous literature has long argued that knowledge spillovers are highly localized due to agglomeration advantages (Jaffe et al., 1993; Saxenian, 1996), the role of tacit Knowledge, i.e. the complexity of inventions create human capital characterized by 'natural excludability' Zucker et al. (1998), and labor mobility within certain proximity (Palomeras and Melero, 2010). Based on these insights, cluster funding intentionally focuses on local collaboration with the objective of facilitating knowledge spillovers within the cluster team. Adams and Griliches (1996), for example, show that co-location in interpersonal links between scientists and firms is contingent on the characteristics and role (intensity of connection and importance of task) of the scientists – suggesting a complex interdependence and heterogeneity in the relationship between spillovers, network and geography.

Research on science-industry interactions has also focused traditionally on the spatial dimension of clustering of spillovers. Jaffe (1989) provides time-series evidence that university research generates a positive spillover effect on corporate R&D investment and patenting of firms located in the same U.S. state. Moreover, research has addressed institutional arrangements that facilitate science-industry spillovers, some of which relate to some dimensions of clustering. Bikard and Marx (2020) show, based on variation within twin discovery[3] pairs, that geographic hubs where universities and industry co-located are not only a strong predictor for spillovers in terms of patent-to-article citations, but they also function as amplifiers of the geographic reach of spillovers. Furthermore, Belenzon and Schankerman (2013) shows, based on citation links, that firm patent citations to university patents are strongly clustered within state borders. However, they also document that this localization is much less sharp and widely released for firm patent citations to university publications.

The literature on absorptive capacity through firm collaboration with (star) scientists (e.g., Cockburn and Henderson (1998) and Zucker et al. (1998)) highlights the importance of the network dimension. Such networks form through direct collaboration, but also employee mobility or informal exchanges Fudickar and Hottenrott (2019).

[3]Twin discoveries refer to papers with the same or very similar knowledge emerging in multiple locations

4.2.4 Research gap & contribution

Only a few papers have investigated the effects of Excellence Cluster funding on localized industry spillovers. Closely related to my analysis are the studies by Bergeaud et al. (2023) and Krieger (2024).

Bergeaud et al. (2023) examine knowledge spillovers from the French Excellence Cluster program (Laboratoire d'Excellence) to industry. They measure spillovers depending on the spatial and scientific proximity and show that the increase in science funding led to a significant increase in firms' R&D activities and to additional R&D outputs as measured in patents and the establishments of plants. Using a dynamic difference-in-differences approach, the authors find that funded commuting zones experienced an increase in R&D labor spending, the number of patents, and the establishment of new plants by new firms compared to non-funded zones after a few years. They also show that spillovers are stronger if firms are in close spatial and scientific proximity to the academic institution. In terms of knowledge spillover channels, their results suggest that R&D outsourcing through public-private partnerships, labor mobility from the private to the public sector, and informal contacts explain their findings.

Adding to these insights on the Excellence Cluster funding in France, Krieger (2024) studies the effect of the clusters funded by the German EI on regional innovativeness. He investigates firm-level data collected via the Community Innovation Surveys (Mannheim Innovation Panel) and uses difference-in-differences analyses to show that being located close to a cluster site results in a significant increase in the probability of introducing new products. The additional finding that the effects are considerably larger in regions with several clusters hints at the importance of scale and scope for the effectiveness of knowledge spillovers. Overall, the findings highlight the importance of regional context, as the impact of funding varies significantly across different regions. The results further suggest that regions with more established universities and higher funding levels are better positioned to leverage additional funding resources with potentially higher spillovers for innovation.

While these insights stress the value of 'cluster funding' as a science policy instrument, it remains unclear whether these effects are driven by scaling through more university funding and therefore more human capital and collaboration opportunities or by a quality effect through pushing research within clusters closer to the research frontier, or a combination of the two. In addition, we still know little about the nature of the innovations benefiting from Excellence Clusters — it is not straightforward that top science, insofar as produced by Clusters of Excellence, would automatically translate into top technology, which will likely be largely dependent on the (development of) top-science absorptive capacity of local industry. This study adds to this line of research by explicitly differentiating between scaling (more publications) and quality effects (more relevant research as indicated by citations). By differentiating between scientific publications and patents as outcomes and by distinguishing university authors from industry-based authors, I further aim to study the link between science funding and the origin of the research output. These analyses add to the findings by Bergeaud et al. (2023) and Krieger (2024) by investigating both the number and the relevance of inventions generated in close vicinity to funded clusters. Importantly, I can also trace the actual relevance of publication for patenting activity. By focusing on a single technology, I study whether technology-related clusters indeed foster cutting-edge research, as evidenced by an increase in highly cited publications, and whether there are spillovers to the industry in terms of high-impact inventions rather than merely appropriation by industry. Thereby, I also re-shift the focus from private to the social returns of Excellence Clusters.

4.3 Empirical context: additive manufacturing

Additive Manufacturing relates to a group of production technologies. These technologies transform digital models into physical three-dimensional objects by adding a material layer upon layer. AM consolidates technologies from different fields, such as computer-aided design (CAD), computer numerical control (CNC) machining, and laser technology (Cavallo et al., 2023). Hence, its development depends heavily on the progress of various research areas in natural and engineering sciences such as optics, material science, and mechanical engineering. AM can therefore be considered as a science-based technology, with a strong connectivity between basic research and technical progress (Meyer-Krahmer and Schmoch, 1998; Ahmadpoor and Jones, 2017). Universities and research organizations play a crucial role in the development of AM technology and applications, e.g., the Massachusetts Institute of Technology invented the direct shell production casting and inkjet printing technology. Hideo Kodama from Nagoya Municipal Industrial Research Institute was a pioneer in AM technology who studied and published a method to print objects in 3D. With his patent application in 1980 (Kodama, 1981), he belongs to the first inventors of stereolithography and thus AM technology (Campbell et al., 2023). Overall, academic institutions submitted 7% of all patent applications filed with the EPO in 2022 and 12% of all international patent families (IPFs) in technology classes associated with AM (Cavallo et al., 2023). It is, therefore, not surprising that various startups and larger AM firms are located in close proximity to universities. One example of such an agglomeration is the Boston area, which has firms such as Desktop Metal, Formlabs, and Markforged. Given Germany's engineering research and high-tech manufacturing tradition, it is perhaps not surprising that in the course of the EI, a substantial number of grants were devoted to AM-related initiatives.

Initially, the main application of AM had been rapid prototyping. This capability supports rapid iteration of ideas and opens new possibilities for product development, such as designing complex geometries (Gebhardt and Hötter, 2016). It thus serves as an effective tool for testing and refining new concepts with lower investment costs. Over the last years, the applications have shifted more towards end-product manufacturing. Nowadays, AM is a key technology for the production of customized products, e.g. different types of implants in the healthcare sector (Campbell et al., 2023).

Since it is a science-based technology that has found various applications in industry, I can reasonably expect that progress in research on AM may also spill over to industrial applications. Moreover, scientific advances in this area will likely leave traces in patent documents (namely, in prior art references and text), which allows us to measure the use of this knowledge in codified output (Ahmadpoor and Jones, 2017; Iaria et al., 2018; Schaper et al., 2023). A second reason for my focus on AM-related clusters is that, in this area, I am able to map science and technology developments with the use of expert-curated vocabularies of specific keywords that allow for the precise identification of publications and patents related to this complex of knowledge.

4.4 Data & measures

The following analyses are based on a comprehensive dataset including information about science funding, scientific publications, patents, and regional demographic and industry characteristics for Germany for the period 2001 to 2013.

Science funding information, including research area, applicant and participating institutions, and the funding period for the Clusters of Excellence and Collaborative Research Centres (CRC) has been gathered from the GEPRIS database provided by the DFG. GEPRIS is a publicly available database indexing all funded research projects by the DFG, including information about the funding terms, the principal investigators and their institutions, and summaries of the content and aim of the funded projects. For the Clusters of Excellence, all first funding round clusters of the German EI in the years 2006 and 2007 are considered. I identify whether a cluster is related to AM based on the cluster descriptions in which the usage or investigation of AM technology is (at least implicitly) mentioned. In total, there are four universities in three different regions with relevant clusters (Aachen, Hanover, and Erlangen). While the regions of Aachen and Hanover received funding in 2006, Erlangen received funding in 2007. Furthermore, I collected information on all CRCs starting between the years 1995 and 2005. These are collected to construct a comparison group and identify AM-relatedness accordingly. I further obtain a list of unsuccessful cluster applications from the DFG, which will serve as an alternative control group (Deutsche Forschungsgemeinschaft, 2006, 2007). The entire county in which the receiving universities and research organizations are located are considered as recipients. This speaks to the fact that researchers from the same university are not all working under the same address and may move across university buildings or change affiliation names even if the affiliation remains the same. For the purpose of this study, scientific output is proxied by publications in scientific journals. In a first empirical setup, the data collection comprised all ExC or CRC-involved publications based on the county in which the applicant university is located.

The primary source for publication data is the Elsevier SCOPUS database, which provides identifiers for articles, journals, authors, and affiliations, as well as publication years and, importantly, abstract text for more than 50 million scholarly articles worldwide. To identify relevant publications (i.e., related to AM), I conduct a semantic search of article abstracts with German affiliations, based on technology-specific keywords, extrapolated from established standards such as ISO/ASTM 52900 and VDI 3405, as well as recent literature (see Appendix A.3.4). This yields a publication sample of 16,272 publications related to AM in Germany between 2001–2013. Publications are assigned to the ExC and CRC locations based on the affiliation address information of the authors as listed on the publications.[4] This results in a total of 1,568 publications in the ExC locations and 5,587 in the sixteen CRC locations during the period 2001-2013. In addition, information about ExC applicants who were unsuccessful and also had a CRC to construct is used as an alternative control

[4]Publications with multiple assigned locations are counted separately for each assigned location.

group. For these four locations, there are a total of 1,376 publications.[5]

In order to quantify scientific excellence and cumulative impact on scientific research, articles in SCOPUS are linked via digital object identifiers (DOI) to citations and field information in Microsoft Academic Graph (MAG) (Sinha et al., 2015). For the latter, I rely on 284 machine-learning-based scientific concepts provided at the article level and trained on the MAG corpus, which is aggregated to 145 Clarivate Web of Science (WOS) Subject Categories as my main field classification, using a manually validated crosswalk (cf. Wang and Schaper, 2024.

To measure industrial inventions, AM-specific patents are identified among all patents filed at the USPTO during the period 2001–2013. USPTO patents cover the largest share among all patent offices of inventions worldwide (also for Germany), and have the advantage of providing public full-text data, as well as several curated meta-data on inventors and, in particular, links to science. My primary data source for patent data is the EPO PATSTAT global (2022 autumn edition) database. I link it to PatentsView in order to retrieve additional information for USPTO patents, particularly from PatentsView (specifically, full-texts and geocoded inventor and applicant locations). In order to identify AM-related patents, I adopt the approach and search key based on combinations of IPC/CPC classes and expert-curated technical terms from Pose-Rodriguez et al., 2020, querying the 'summary of the invention' sections in the full-text of all U.S. patents. Finally, I rely on the dataset provided by Marx and Fuegi, 2020, which identifies patent prior art references from all USPTO patents since 1975 to scientific articles in MAG, whereby they can be linked back directly to both the patents and the publications sample.

To study the effects of funding from the Excellence Cluster grants that were awarded in the first round of the program on research and inventions in 2006/2007, I constructed a panel data set on the basis of counties within Germany for the years 2001 - 2013. I restrict the observation period from six years prior to the first round of ExC funding to a maximum of seven years post-treatment.[6] To measure how funding affects scientific output and industry patenting outcomes in the empirical analysis, I construct the following variables:

[5]A list of regions with respective science funding programs is listed in Appendix A.3.3.

[6]More recent years are excluded because of the confounding effects from a second funding round in 2012 where some of the control units received funding and others applied but were unsuccessful.

Number of publications. This is the count of scientific publications within a county in a given year. A publication is assigned to a county if at least one author-affiliation address listed on the paper is located in the specific county. Two separate counts are computed: one for AM-related publications and one for non-AM-related publications.

Number of publication citations is the sum of total citations to scientific publications from a given year in a county, measured over an 8-year window, differentiating between citations to AM- vs. non-AM publications.

Hit publications. This counts the number of publications in a county that enter the top 5% of most cited papers in a given WOS field-year cohort, considering all publications worldwide. This is a widely used indicator to quantify 'high-gain-science' and scientific breakthroughs (cf. Wang et al., 2013; Ahmadpoor and Jones, 2017; Wang et al., 2017).

Number of patents. This is the count per year of corporate patents with at least one inventor location in a given county. Like in the case of scientific publications, this variable is split into AM- and non-AM-related patents. The timing of patents is based on the worldwide first application date (priority date). Information about corporate applicants is based on the PATSTAT Standardized Names (PSN) sector classification.

Number of patent citations is the sum of 8-year patent forward citations within the USPTO to patents (AM- vs. non-AM) from the focal year in a given county. Forward citations are a widely recognized and established metric in the literature for evaluating patent quality (Trajtenberg, 1990; Harhoff et al., 1999). These citations serve as a measure of technological impact, indicating how frequently an invention is used as a foundation for subsequent patents. For each focal patent, I consider forward citations over an 8-year window based on priority filing years.

Hit patents. This counts the number of patents in a given county in each year that belong to the top 5% highly-cited patents worldwide in their CPC-class-year 8-year citations distribution, based on a patent's first-listed CPC class (subgroup-level). This is a binary indicator for top-impact (or technological breakthrough) and has been widely used in the literature (e.g., Trajtenberg, 1990; Ahmadpoor and Jones, 2017; Pezzoni et al., 2022).

To normalize patent output, I collected population data for each county for the year 2005, i.e. the pre-treatment year, from the German Federal Statistical Office (DESTATIS).

Table 4.1 shows these indicators for the ExC and CRC locations for the pre-treatment period as for the rejected cluster locations. The differences in means between the ExC and other prior CRC locations are not statistically significant for the AM-publication measures, but I see that ExC locations have had more patents and more patent citations. There are also no significant differences in non-AM publications, but the number of non-AM patents is significantly higher in the treatment locations pre-treatment. In contrast, I do not find any significant differences in mean between ExC and rejected cluster locations for AM patent measures but for non-AM publications and non-AM patents. Table A.3.1 shows more details for additional publication, patent, and citation measures. Table A.3.2 shows correlations between my main variables for the pre- and post-treatment periods, respectively.

Table 4.1: Pre-treatment summary statistics

	ExC recipients	Other prior CRC		Only rejected clusters	
Variables	Mean	Mean	Diff.(p-val)	Mean	Diff.(p-val)
AM publications (peer-reviewed)	26.89	21.22	0.22	22.25	0.15
AM publication citations	495.78	421.67	0.51	456.92	0.72
Hit publications (in AM)	2.94	2.51	0.54	2.79	0.83
Industry AM patents	3.24	1.56	0.02	3.82	0.64
Hit patents (in AM)	0.05	0.06	0.87	0.12	0.31
AM patent citations	13.07	6.36	0.09	15.56	0.74
Non-AM publications	2190.83	2073.66	0.84	1856.54	0.04
Industry non-AM patents	142.72	37.03	0.00	66.05	0.01

Notes: This table presents group means for ‘ExC recipients’ (treatment group), ‘other prior CRC’ (control group), and only ‘rejected clusters’ (control group), alongside the results of group comparisons (t-tests). The sample covers regions (Kreis level) of funded universities during the pre-treatment phase (2001—2006). ‘ExC recipients’ are regions of universities awarded an excellence cluster. ‘Other prior CRC’ are regions with universities that received an AM-related CRC between 1995 and 2005 (excluding ‘ExC recipients’). ‘Only rejected clusters’ are regions with unsuccessful cluster applications. ‘Hit publications/patents’ denotes the number of top 5% most-cited publications or patents in a field year.

4.5 Empirical approach

4.5.1 Identification strategy

The main objective for the introduction of the Clusters of Excellence pertains to the advancement of the research frontier. Hence, the funding is expected to be allocated to top research groups that are close to the frontier. This implies that there is likely a strong positive selection of highly able and highly productive researchers into the funding scheme. Assuming that these researchers are not directly comparable to the ‘average’ researcher, the empirical model needs to account for this selection bias in my estimation of any treatment effects.

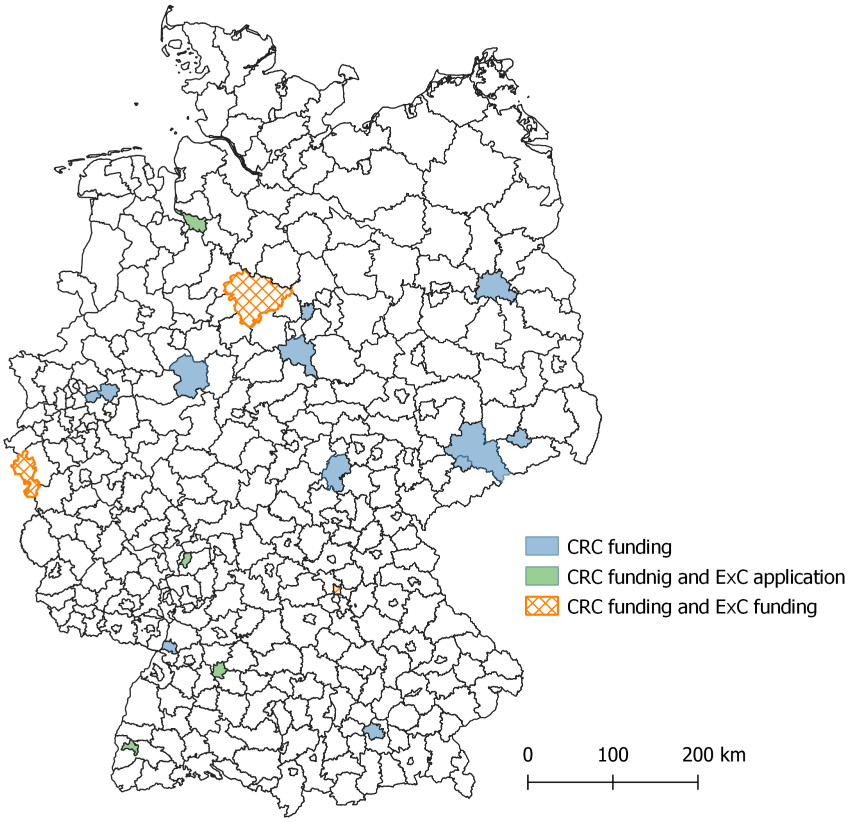
Therefore, I construct an appropriate counterfactual for funded clusters based on locations that host researchers performing at comparable levels prior to the cluster grants. Given the highly skewed nature and uneven distribution of research excellence, this approach ensures a non-parametric balancing of covariates, thereby reducing model dependence and extrapolation in the estimation.

All universities that had previously received a CRC grant in the field of AM in the years between 1995 and 2005 but that did not receive Excellence Cluster funding during the first funding serve as control units. CRCs are university-based research groups with a funding period of up to 12 years. They consist of a large number of projects and involve various partners from other research institutions and industry. As expected, all universities with Clusters of Excellence associated with AM received a CRC related to AM within this time span. I infer the link to AM semantically from the thematic focus section in the description of all 37 CRCs funded by the DFG included in the GEPRIS database (for a list of all CRC-funded regions, see Table A.3.3). These control cases are characterized by a strong focus on Mechanical & Production Engineering or Material Engineering & Science. This selection of control cases is grounded on the rationale that research concerning production methods and material properties was particularly salient within the domain of AM at the beginning of the 21st century. Figure 4.1 shows the spatial location of the 12 regions with only CRC funding (blue), four regions with rejected cluster applications (green), and three regions that receive Excellence Cluster funding (yellow).

4.5.2 Synthetic difference-in-differences estimation

The econometric analysis of my constructed sample entails further methodological challenges. First of all, the focus of my study on a very specific research area (i.e., AM) determines a relatively small sample size. This is potentially problematic for statistical inference—due to a lack of statistical power and the high likelihood of imprecise estimates—making it particularly difficult to reliably reject any null hypotheses. Second, even after refining the sample to only regions with similar characteristics regarding scientific research activities in AM, I still observe small but significant differences between treated and control groups, for instance, with regards to industry patenting activities (cf. Table 4.1). Moreover, the treatment and control units exhibit different trends pre-treatment which violates a key assumption in standard difference-in-difference analyses. Table 4.2 indicates different trends in university rankings, number of students in natural science and medicine, and depending on the con-

Figure 4.1: Regional distribution of treatment and control regions



Notes: This figure shows the regional distribution of funding for AM-related programs in Germany, defined at the Kreis level. It includes ExC recipients and applicants from the first round of the EI, as well as all granted CRCs between 1995 and 2005.

trol group for third-party funding and students in other fields. To address these challenges, I employ the synthetic difference-in-differences (SDID) estimation method as outlined in Arkhangelsky et al. (2021).

The SDID estimation is a combination of the synthetic control method and the conventional difference-in-differences estimation. It generates weights for the control units in order to match the trends of the treatment and control group in the pre-treatment period. Therefore, this method eliminates the need for observed parallel trends, by synthetically constructing a counterfactual with matching trends. In contrast to the Synthetic Control method, it moreover allows for a level difference between the treatment and control group.

In order to estimate the effect of ExC funding on scientific output and industrial in-

Table 4.2: Pre-treatment differences in academic characteristics

	ExC recipients	Other prior CRC		Only rejected clusters	
Variables	Mean	Mean	Diff.(p-val)	Mean	Diff.(p-val)
Third-party funds	109,342.8	79,905.42	0.11	82,477.74	0.00
Ranking	16.67	29.87	0.00	27.79	0.03
Students	27,337.39	25,202.92	0.71	20,782.17	0.00
Natural Science	16,015.39	12,461.25	0.16	10,833.92	0.00
Medicine	2,840.28	1,378.47	0.01	764.46	0.00
Engineering	6,376.5	4,568.47	0.04	4,461.42	0.13

Notes: This table presents group means for 'ExC recipients' (treatment group), 'other prior CRC' (control group), and 'only rejected clusters' (control group), alongside results of group comparisons (t-tests). The sample represents regions (Kreis level) of funded universities during the pre-treatment phase (2001-–2006). 'ExC recipients' are universities awarded an excellence cluster in AM. 'Other prior CRC' are universities that received an AM-related CRC between 1995 and 2005 (excluding 'ExC recipients'). 'Only rejected clusters' are regions with unsuccessful cluster applications.

ventions, I minimize the following equation by using the computational implementation described in Clarke et al., 2023.

$$\left(\widehat{\tau}^{SDID}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - ExC_{it}\tau)^2 \widehat{w}_i^{SDID} \widehat{\lambda}_t^{SDID} \right\}$$

In this minimization problem, $\widehat{\tau}^{SDID}$ represents the average treatment effect of the Excellence Cluster funding. The average treatment effect (ATT) corresponds to the change in the difference between means of the scientific output and industrial invention indicators during the periods before and after the treatment. ExC indicates with a binary variable whether the county accommodates a funded university. I assume a time lag of one year for treatment to become at least somewhat effective due to the implementation lag of cluster activities. This also applies to the time needed to actually produce the first results and any spillovers to industrial inventions to occur. Therefore, I consider the treatment year in 2007 and 2008 for ExC funding awarded in the funding round 2006/2007. The variables $\widehat{w}_i^{SDID}$ and $\widehat{\lambda}_t^{SDID}$ correspond to the optimal region and time weights for the control units. Y_{it} is the indicator of either the scientific output or industrial invention activities in county i and year t. The patent indicators are normalized to 100,000 citizens in order to take the county size into account (which also includes the number of firms and potential employees). α_i and β_t are the fixed effects for region and time, respectively.

4.6 Results

4.6.1 Scientific output

To evaluate the impact of Clusters of Excellence on scientific output at funded universities, I first analyze publication indicators. Table 4.4 and Table 4.3 summarize the results. I find a relative increase of 17.82 AM publications in counties with funded universities compared to regions with prior CRC funding in the years following treatment (see Table 4.4). This represents a 74% increase. Moreover, I observed a significant increase of about 663 total citations, which is equivalent to 140%. However, there are no significant differences in hit publications for AM. With a p-value of 0.056 is this result marginally insignificant. It is important to note that Table A.3.6 in the appendix shows an increasing publication effect relative to the mean when considering publications in the right tail of the citation distribution.

Table 4.3: Scientific publication output with 'only rejected clusters' as control group

	Synthetic difference-in-differences estimates					
	AM Publications			Non-AM Publications		
DV	(1) No. Pubs	(2) Cit w/ Pubs	(3) Hit Pubs	(4) No. Pubs	(5) Cit w/ Pubs	(6) Hit Pubs
$Cluster_t$	17.82^{***}	663.04^{***}	2.61^{*}	347.08^{*}	12,700	25.49
	(6.82)	(119.04)	(1.36)	(270.12)	(20,300)	(82.27)
Number of observations	91	91	91	91	91	91
DV mean	24.24	473.57	2.86	1,999.81	49,595.67	258.71

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on scientific publication output between 2001–2013 with the treatment years in 2007 & 2008 (depending on the university). In these analyses, the control group includes regions from all universities that received an AM-related CRC between 1995 and 2005 (excluding recipients of an ExC). "No. pubs" refer to the number of publications, 'cit w/ pubs' to publication citations, and "hit pubs" to hit publications. Hit publications are the number of top 5% most cited publications within a field year. Model (1)-(3) considers AM publications, while model (4)-(6) shows the results for non-AM publications. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Further analyses indicate that these effects are primarily driven by academic institutions (see Table 4.5). The results confirm that the observed impacts are not attributable to industry authors or joint publications, aligning with the funding's focus on academic institutions. In contrast to the effects on AM publications, I find no significant impact on non-AM publications (see Table 4.4 and Table 4.3). This suggests that funding effects are specifically topic-related. When repeating the analysis using the alternative control group (only rejected clusters), the results remain consistent. Interestingly, this analysis reveals a statistically significant increase in hit publications (113%) but no significant change in total citation counts. Overall, the findings suggest that funding influences the quality of publications more than quantity.

Table 4.4: Scientific publication output with 'Other prior CRC' as control group

	Synthetic difference-in-differences estimates					
	AM Publications			Non-AM Publications		
DV	(1) No. Pubs	(2) Cit w/ Pubs	(3) Hit Pubs	(4) No. Pubs	(5) Cit w/ Pubs	(6) Hit Pubs
Cluster_t	15.17^{**}	702.66	2.91^{**}	226.73	1,330	74.80
	(5.92)	(518.55)	(1.46)	(263.16)	(13,400)	(111.62)
Number of observations	247	247	247	247	247	247
DV mean	22.11	433.37	2.58	2,092.16	53,469.13	217.83

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on scientific publication output between 2001–2013 with the treatment years in 2007 & 2008 (depending on the university). In these analyses, the control group includes regions from all universities who applied for an AM excellence cluster but did not receive it. 'No. pubs' refer to the number of publications, 'cit w/ pubs' to publication citations, and 'hit pubs' to hit publications. Hit publications are the number of top 5% most cited publications within a field year. Model (1)-(3) considers AM publications, while model (4)-(6) shows the results for non-AM publications. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.2 Industrial inventions

To investigate the effects of Excellence Cluster funding on industrial applications, I examine patenting activity by firms. Table 4.6 presents results for the number of patents, patent citations, and the number of 'hit' patents located within the same county as the treatment and control universities. The findings reveal a significant decline in the overall number of AM patents. However, the results show a significant positive effect on high-impact AM innovations. In particular, there is an annual average increase of 0.24 AM hit patents per 100,000 citizens, representing a 400% increase relative to the dependent variable (DV) mean. In addition, AM patent citations increase by 44.83 per year on average, in total a 604% rise compared to the DV mean. These results highlight a shift toward the production of higher-quality or more influential AM innovations rather than a broad increase in AM patent quantity. In contrast, non-AM patenting exhibits a different pattern. While the total number of non-AM patents increases, the number of non-AM hit patents remains unchanged. Moreover, non-AM patents receive significantly fewer citations. Table 4.7 presents results for the same analysis using the alternative control group based on rejected cluster locations. The effect sizes for this analysis are slightly smaller relative to the sample mean of the dependent variable. Despite the reduced sample size, most coefficients remain statistically significant,

Table 4.5: Scientific publication output in categories

	Synthetic difference-in-differences estimates					
	AM Publications			Non-AM Publications		
DV	(1) No. Pubs	(2) Cit w/ Pubs	(3) Hit Pubs	(4) No. Pubs	(5) Cit w/ Pubs	(6) Hit Pubs
All publications						
Cluster_t	15.17^{**}	702.66	2.91^{**}	226.73	1,330	74.80
	(5.92)	(518.55)	(1.46)	(263.16)	(13,400)	(111.62)
Publications from academia						
Cluster_t	16.91^{***}	768.95	3.21^{***}	162.08	-515	10.91
	(5.02)	(523.71)	(1.07)	(281.42)	(12,300)	(62.53)
Publications from industry						
Cluster_t	-0.61	-83.72	-0.08	-0.95	-309	0.82
	(0.99)	(27.30)	(0.08)	(40.43)	(1.14)	(11.93)
Publications from a collaboration between academia and industry						
Cluster_t	0.34	-38.18^{*}	-0.08	19.17	-696.89	-0.37
	(1.15)	(20.93)	(0.08)	(28.14)	(1,900)	(8.02)
Number of observations	247	247	247	247	247	247

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on scientific publication output between 2001–2013 with the treatment years in 2007 & 2008 (depending on the university). In these analyses, the control group includes regions from all universities that received an AM-related CRC between 1995 and 2005 (excluding recipients of an ExC). 'No. pubs' refer to the number of publications, 'cit w/ pubs' to publication citations, and 'hit pubs' to hit publications. Hit publications are the number of top 5% most cited publications within a field year. Model (1)-(3) considers AM publications, while model (4)-(6) shows the results for non-AM publications. The analyses are divided into all, academic, industrial, and collaborative publications. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

except for the total number of AM patents.

Overall, these findings suggest an impact of proximity to universities with Excellence Cluster funding on industrial innovation. While the total number of patents does not change and may even decline, the relevance and influence of patents—as reflected by hit patents and citation counts—improve substantially. This shift toward higher-quality innovations could indicate a deeper integration of cutting-edge knowledge into industrial applications, particularly in AM technologies.

Table 4.6: Industry patent output with 'other prior CRC' as control group

	Synthetic difference-in-differences estimates					
	AM Patents			Non-AM Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
DV	No. Pats	Cit w/ Pats	Hit Pats	No. Pats	Cit w/ Pats	Hit Pats
Cluster_{t-1}	-0.87^{**}	44.83^{***}	0.24^{***}	9.49^{**}	-262^{***}	-0.1
	(0.44)	(4.93)	(0.08)	(3.29)	(42.21)	(0.28)
Number of observations	247	247	247	247	247	247
DV mean	1.83	7.42	0.06	53.72	243.43	1.52

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on industry patent output between 2001–2013. Considering a time lag of one year, the treatment years are 2007 & 2008 (depending on the university). In these analyses, the control group includes regions from all universities that received an AM-related CRC between 1995 and 2005 (excluding recipients of an ExC). 'No. pats' refers to a number of patents, 'cit w/ pats' to patent citations, and 'hit pats' to hit patents. Hit patents are the number of top 5% most cited patents within a field year. Model (1)-(3) considers AM patents while model (4)-(6) shows the results for non-AM patents. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.7: Industry patent output with 'only rejected clusters' as control group

	Synthetic difference-in-differences estimates					
	AM Patents			Non-AM Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
DV	No. Pats	Cit w/ Pats	Hit Pats	No. Pats	Cit w/ Pats	Hit Pats
Cluster_{t-1}	0.02	44.70^{***}	0.13^{***}	17.93	-346^{***}	-0.55
	(1.02)	(11.89)	(0.05)	(11.14)	(112.93)	(0.39)
Number of observations	91	91	91	91	91	91
DV mean	3.57	14.49	0.09	98.91	455.84	2.88

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on industry patent output between 2001–2013. Considering a time lag of one year, the treatment years are 2007 & 2008 (depending on the university). In these analyses, the control group includes regions from universities that applied for an AM excellence cluster but did not receive it. 'No. pats' refers to the number of patents, 'cit w/ pats' to patent citations, and 'hit pats' to hit patents. Hit patents are the number of top 5% most cited patents within a field year. Model (1)-(3) considers AM patents, while model (4)-(6) shows the results for non-AM patents. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.6.3 Spillovers from publications to inventions

The finding that there are more local AM patents in funded locations suggests that inventive activity also benefits from the funding. It is, however, unclear whether these patents are indeed based on insights from scientific publications that resulted from funded research. To get a more direct measure of knowledge spillovers, the following analysis investigates references to scientific articles in patent documents as an indicator for direct use of use scientific insights. This approach has been used in prior research such as Ahmadpoor and Jones, 2017; Poege et al., 2019. The idea is that inventors (need to) cite relevant scientific research that informs or constitutes the basis of their invention (Callaert et al., 2014; Roach and Cohen, 2013; Tijssen, 2001). Therefore, scientific papers cited in patent documents reflect a direct application of scientific insight. Table 4.8 and Table 4.9 show the results of the SDID estimations. I find a significant positive effect of cluster funding on the SNPRs from AM patents to AM publications within the top 10th percentile of the citation distribution. In particular, cluster funding increases citations by 12.33 (a 104% increase) compared to the 'other prior CRC' control group and by 18.89 (a 119% increase) in the 'only rejected clusters' control group. However, no significant effect is observed when considering all AM publications or those within the top 5th percentile of the citation distribution[7]. I do not find any significant effects for non-AM SNPRs.

Table 4.8: Scientific non-patent references with 'other prior CRC' as control group

	Synthetic difference-in-differences estimates					
	AM SNPRs			Non-AM SNPRs		
DV	(1) All Pubs	(2) Top 10% Pubs	(3) Top 5% Pubs	(4) All Pubs	(5) Top 10% Pubs	(6) Top 5% Pubs
Cluster_{t-1}	15.69	12.33^{***}	4.57	-129	-78.73	-33.20
	(10.45)	(3.85)	(4.36)	525.21	355.92	185.28
Number of observations	247	247	247	247	247	247
DV mean	21.42	11.89	9.39	1500.52	921.07	692.80

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on the number of scientific non-patent references between 2001–2013. Considering a time lag of one year, the treatment years are 2007 & 2008 (depending on the university). The models consider publications of different percentiles in the citation distribution. In these analyses, the control group includes regions from universities that applied for an AM excellence cluster but did not receive it. 'No. pats' refers to the number of patents, 'cit w/ pats' to patent citations, and 'hit pats' to hit patents. Hit patents are the number of top 5% most cited patents within a field year. Model (1)-(3) considers AM patents, while model (4)-(6) shows the results for non-AM patents. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[7]It is important to note that SNPRs are rare occurrences, which complicates the identification of statistically significant effects, particularly for a limited sample size of publications.

Table 4.9: Scientific non-patent references with 'only rejected clusters' as control group

	Synthetic difference-in-differences estimates					
	AM SNPRs			Non-AM SNPRs		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Top 10%	Top 5%	All	Top 10%	Top 5%
DV	Pubs	Pubs	Pubs	Pubs	Pubs	Pubs
Cluster$_{t-1}$	6.13	18.89***	9.12	-193	-110	-56.21
	(6.20)	(7.07)	(6.14)	272.68	131.98	114.93
Number of observations	91	91	91	91	91	91
DV mean	22.03	15.85	12.33	1238.98	776.41	585.90

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on the number of scientific non-patent references between 2001–2013. Considering a time lag of one year, the treatment years are 2007 & 2008 (depending on the university). The models consider publications of different percentiles in the citation distribution. In these analyses, the control group includes regions from universities that applied for an AM excellence cluster but did not receive it. 'No. pats' refers to the number of patents, 'cit w/ pats' to patent citations, and 'hit pats' to hit patents. Hit patents are the number of top 5% most cited patents within a field year. Model (1)-(3) considers AM patents, while model (4)-(6) shows the results for non-AM patents. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.7 Discussion & conclusion

This paper examines the impact of large-scale, collaborative, and thematically focused local research funding on research outcomes and the subsequent knowledge spillovers into technological innovation. Using AM as a representative science-based technological field, this chapter presented a detailed examination of the effects of the first round of the German EI, which allocated – among others – funding to three AM-related research clusters.

The analysis shows the evolution of research outputs and patenting activity in the funded locations over the initial seven-year funding period, benchmarking these developments against comparable control locations. Based on synthetic difference-in-difference estimations, the results suggest a positive and significant link between targeted research funding and the quality—or visibility—of scientific outputs produced in funded regions. This improvement is predominantly attributable to publications authored by university researchers.

Moreover, the data reveal an increase in the number of highly cited AM patents originating from the funded locations compared to the control regions, which shared a similar scientific profile before the funding intervention. These findings show that the EI not only enhanced local research capabilities but also catalyzed measurable and statistically significant advancements in the translation of scientific knowledge into high-impact technological outputs.

The observation that funded locations produced both high-impact publications and patents indicates that the benefits of funding extended beyond academic research, fostering spillovers into practical applications. Interestingly, while the total number of publications and patents remained comparable across funded and control locations, the funded regions demonstrated a significant increase in top-cited outputs—referred to here as 'hit-publications' and 'hit-patents'. This suggests a shift towards higher visibility and impact rather than merely higher output. This results contrast with the findings by (Carayol and Maublanc, 2025), who estimated average effects at the principal investigator level over all disciplines. Further research may, therefore, study heterogeneity depending on disciplines and individual versus aggregate effects in more detail.

For patents, the effect is more pronounced with hit patents in funded AM-related clusters despite no observable growth in the total volume of patenting. These findings align with prior research highlighting the ability of targeted research funding to stimulate high-quality, frontier-pushing outputs (Hottenrott and Lawson, 2017; Heyard and Hottenrott, 2021). At a minimum, the results demonstrate that the scientific outputs in funded regions are more visible and relevant than those from comparable non-funded settings working on similar topics.

Interestingly and somewhat counter to expectations, the funding did not appear to drive an increase in collaborative publications between academia and industry, nor did it impact the number or quality of publications with industry-affiliated authors. However, the findings suggest that there are direct knowledge flows from AM-related academic research in funded locations to AM-related patents filed by private firms, as indicated by patent citations to these publications. This suggests that the spillovers from science to industry were particularly strong in technological areas directly linked to the funded research, supporting the notion that targeted funding can bridge the gap between scientific discovery and private-sector innovation.

The analysis presented in this chapter establishes a link between science funding and the advancement of frontier research, with measurable spillovers into industrial applications, as evidenced by the increase in firm AM-related hit patents. These findings contribute to the broader literature on the critical role of public science funding in driving economic and technological progress (Krieger, 2024; Bergeaud et al., 2023).

This study centered on the case of AM technology, a representative example of a key enabling technology chosen for its suitability in tracing knowledge spillovers through publications and patents. The codified nature of knowledge transfer in engineering and technology fields like AM allows for more direct observation of these dynamics. By contrast, in other disciplines—such as the social sciences or life sciences—knowledge transfer mechanisms are often less codified, making it more challenging to track spillovers systematically. These differences highlight the importance of disciplinary context when evaluating the impact of science funding on knowledge transfer and innovation outcomes.

In principle, however, it can be argued that research funding may also yield real-world impacts in other disciplines, even if the mechanisms of spillover are less readily observable. Unlike the tangible paper trails left by publications and patents in fields like engineering and technology, spillovers in other disciplines—such as the social sciences or life sciences—may manifest in less codified or less easily measurable forms. Addressing this challenge presents an opportunity for future research, which could explore alternative data sources and methodological approaches to capture the broader and often intangible impacts of research funding across diverse disciplinary contexts.

Moreover, while the analysis covers an extended time period, it does not explicitly address the long-term impacts beyond the initial funding period. Certain effects may only materialize over a longer horizon, for example, through the mobility of researchers, such as doctoral graduates who transition into new academic or industrial roles, or through collaborations initiated during the funding period that yield tangible outcomes years later. Future research could explore these delayed effects to better understand the sustained influence of research funding on scientific and technological ecosystems.

Nevertheless, the results underline that large-scale research funding can generate measurable impacts extending beyond the immediate circle of funded researchers, thereby contributing to the broader (and local) innovation ecosystems. In addition to advancing the research frontier, targeted research funding emerges as an effective instrument of innovation policy, capable of fostering knowledge spillovers and strengthening regional technological capabilities.

The analysis presented here is subject to several limitations. First, while I use AM as a case study to demonstrate the existence of funding effects within a specific technological field, it remains unclear whether similar effects extend to other areas. Investigating the economic returns in fields beyond the funded technology class would be a valuable avenue for future research, potentially offering a more comprehensive understanding of the broader scope of funding spillovers to industry. Furthermore, the extent of spillovers may vary across disciplines, influenced by factors such as the size of the research community, the maturity of the topic, and the characteristics of the local innovation ecosystem.

Another limitation lies in my ability to assess the geographic dimensions of knowledge spillovers. Future studies could investigate the resulting scientific publications and patents, paying closer attention to co-authorship and inventor networks to better map the flow of knowledge. It would also be particularly insightful to distinguish between patents involving university researchers (or even principal investigators from the main funded clusters) and those developed by unaffiliated inventors. Such analyses could help clarify the pathways through which targeted research funding translates into broader technological and economic impacts.

The underlying mechanisms driving the observed effects also need further discussion. Funding programs like the EI carry significant prestige, which may partially account for the increased visibility of research from funded locations. This prestige could enhance the diffusion and recognition of new insights, as both researchers and their universities may leverage the cluster funding to more effectively market their work.

In addition, it is challenging to disentangle the effects of new, enhanced, or expanded collaborations from the mere infusion of additional resources into pre-existing partnerships. Similarly, distinguishing research directly funded by the grant from other research conducted by the same principal investigators or by other researchers in the same field and location remains a methodological challenge. These ambiguities highlight the need for future studies to explore the pathways through which such funding mechanisms generate their impacts.

5 | Democratization of innovation: Do FabLabs contribute to the emergence of ventures in additive manufacturing?

Summary

Previous research stresses the role of community workshops, such as makerspaces, hackerspaces, and fabrication laboratories (FabLabs), in driving innovation. However, the specific impact of FabLabs on entrepreneurship remains unclear. In this study, I investigate the relationship between the establishment of FabLabs and the creation of additive manufacturing (AM) ventures. Using a staggered difference-in-differences approach, I find a 16 percentage point increase in the linear probability of AM startups in regions with a newly established FabLab. This effect is greater than that observed for makerspaces and hackerspaces. Moreover, I identify positive significant effects on startups focusing on hardware and application development. In contrast, the results show no significant effects for software and material-based startups. Furthermore, I do not find evidence for an effect on AM-specific patents suggesting that FabLabs support applications rather than driving new inventions in AM. These findings underline the role of community workshops in fostering entrepreneurship and offer valuable insights for policymakers.

5.1 Introduction

Innovation policies are essential tools for boosting regional entrepreneurship and economic development. Existing literature highlights the role of various knowledge intermediaries, such as coworking spaces (Roche et al., 2024), science parks (Armanios et al., 2017), accelerators (Yu, 2020), and incubators (Lukeš et al., 2019), as effective policy instruments for fostering innovation. Recently, there has been increasing scientific and policy interest in the economic impact of community workshops, particularly regarding entrepreneurship, (Van Holm, 2015, 2017; Halbinger, 2020). There are different types of community workshops, such as hackerspaces (Moilanen, 2012), makerspaces (Dougherty, 2012), and fabrication laboratories (FabLabs) (Gershenfeld, 2005). These workshops are community-driven physical spaces that offer shared resources and tools to facilitate idea exchange, technological tinkering, and project collaboration, thereby enabling innovation and entrepreneurial activity. The users of these spaces range from individuals to small firms, but their impact on innovation is debated. Many users are hobbyists without entrepreneurial intentions (Bao, 2024; Halbinger, 2018). While recent studies report a positive effect of makerspaces on entrepreneurial activities and subsequent commercialization outcomes in the United States (Bao, 2024) and a positive link between hackerspaces and information and communication technology (ICT) startups in Germany (Cuntz and Peuckert, 2023), the impact of FabLabs on entrepreneurship remains insufficiently explored.

In this chapter, I contribute to the literature by investigating the role of FabLabs in fostering entrepreneurship in Germany, with a focus on additive manufacturing (AM). So far, evidence for the relevance of open-source communities for AM startups is mainly anecdotal. In addition, AM technology is used in every FabLab as it plays a central role in rapid prototyping - one of the primary objectives of FabLabs. This chapter addresses three research questions: First, does the establishment of FabLabs affect AM venture creation? Second, is this effect stronger compared to makerspaces and hackerspaces? Third, do FabLabs facilitate the development of AM technology, its applications, or both?

In theory, the effects of FabLabs are ambiguous, partly due to the diversity among community workshops and the multidimensional roles FabLabs play within local and global contexts. Although hackerspaces, makerspaces, and FabLabs share similar organizational structures and purposes, they emerged from distinct historical contexts, have different thematic orientations, and lack standardized definitions (Van Holm, 2014). While hackerspaces traditionally focus on topics related to information and communication technologies (ICT), makerspaces emphasize hardware development (Dougherty, 2012; Van Holm, 2014). Therefore, it is not surprising to see a correlation between regional entrepreneurial activities and the thematic foci of these spaces. In particular, recent studies identified a link between ICT startups and hackerspaces (Cuntz and Peuckert, 2023) as well as hardware startups and makerspaces (Bao, 2024). In addition to those inter-space distinctions, there are various factors, such as the variety of tools, access costs, and community size, that differ within most space types (Mersand, 2021).

A FabLab can be considered a specialized type of makerspace, distinguished by its support and management from the *Fab Foundation*[1], a global institution. In contrast to makerspaces, FabLabs are instructed to follow the specific rules outlined in the *Fab Charter*[2]. These rules mandate the presence of designated digital fabrication tools, the provision of operational, educational, technical, and logistical support, and open access for individuals. By following the *Fab Charter*, FabLabs maintain a unified organizational structure, a standardized minimum configuration of digital tools, and connections to a global community.

Hypothesis 1: *The establishment of a new FabLab increases the linear probability of AM venture creation in the region.*

Building on prior research (Cuntz and Peuckert, 2023; Bao, 2024), FabLabs are suggested to promote regional entrepreneurial activity through two primary channels: providing access to tools and facilitating access to knowledge. An essential factor in the commercialization of ideas is the ongoing process of experimentation and iteration of the product (Contigiani and Levinthal, 2019). However, this process can be resource-intensive, especially in terms of monetary costs (Yang et al., 2020). A core component of most community workshops is the provision of fabrication tools. These tools can include machines for textiles, sewing, woodworking, metalworking, milling, electronics, computers for digital fabrication, AM machines, and others (Kemp, 2013). Access to such tools reduces the costs of prototyping and experimentation. By lowering these barriers, community workshops enable rapid and cost-effective product iterations, empowering individuals and small firms to develop and commercialize

[1]The *Fab Foundation*, established in 2009 as part of MIT's Center for Bits and Atoms FabLab program, supports the global expansion of the FabLab network, which now includes over 1,750 labs across more than 100 countries. The foundation's activities include facilitating education through the Fab Academy, promoting the establishment of new FabLabs, providing resources and knowledge-sharing platforms, and connecting promising community ventures with funding opportunities. For more information, see www.fabfoundation.org

[2]The *Fab Charter* is available at the following link: https://fab.cba.mit.edu/about/charter/ accessed on 09/01/2025.

their products. While the range of tools varies across makerspaces and hackerspaces, every FabLab is required to offer a standardized set of digital tools. This standardization may improve tool availability for FabLab users compared to makerspace users, thus expanding their options for prototyping and production (Browder et al., 2019). Consequently, this could increase entrepreneurial activities.

Knowledge generation and exchange are critical factors for early-stage startups (Assenova, 2020), and these resources are sometimes facilitated by makerspaces. Research has shown that the co-location of diverse individuals fosters informal interactions and unintentional knowledge sharing, leading to knowledge spillovers among users (Baruffaldi and Poege, 2024; Sandvik et al., 2020; Fudickar and Hottenrott, 2019). Entrepreneurs may benefit from these interactions, where shared challenges and common technological tools encourage the cross-pollination of ideas. While the community size of makerspaces and hackerspaces is mostly limited to the local region, the *Fab Foundation* connects FabLabs worldwide, providing access to a global community. This global network may enhance knowledge spillovers between FabLab users. Some makerspaces and hackerspaces function as hubs of learning by offering educational opportunities that build technical competencies in using available technologies (Keune and Peppler, 2019). In contrast, every FabLab provides structured courses on a wide range of topics, offering more extensive learning opportunities compared to the average makerspace or hackerspace. In summary, FabLabs enhance access to tools and knowledge more effectively than makerspaces and hackerspaces, potentially fostering entrepreneurship to a greater extent.

Hypothesis 2: *The effect of FabLabs on new ventures is larger than that of makerspaces and hackerspaces.*

AM machines are integral components of makerspaces, hackerspaces, and FabLabs. As a flexible manufacturing technology, AM enables rapid prototyping and facilitates the creation of objects that are not feasible with traditional manufacturing methods (Gibson et al., 2014; Weller et al., 2015). Beyond fostering the development of new applications, some users within these spaces focus on designing AM machines inspired by the replicating rapid prototyping (RepRap) project, an open-source hardware initiative aimed at advancing AM machine development (Savvides, 2021). Anecdotal evidence highlights the importance of the RepRap community and hackerspaces in enabling MakerBot Industries, LLC to develop and commercialize their desktop AM machines (West and Kuk, 2016).

Hypothesis 3: *The establishment of a FabLab increases the linear probability of ventures focused on the development of AM technologies, such as hardware or software, as well as those aiming to use AM for the creation of new applications.*

In order to test the hypotheses, I employ the staggered difference-in-differences method proposed by Callaway and Sant'Anna (2021) to identify changes in the linear probability of AM venture creation in regions that have adopted at least one FabLab. For this analysis, I constructed a hand-collected dataset that includes information on makerspaces, hackerspaces, FabLabs, and AM ventures at the regional level in Germany, comprising 416 community workshops and 175 startups. The findings show that the establishment of a FabLab is linked to a 16% higher linear probability of AM venture creation in a region. This impact exceeds the effects observed for makerspaces (10%) and hackerspaces (no effect). Furthermore, the results indicate a positive effect on startups with a focus on hardware and applications, while I find no significant effects for those specialized in software or materials-based innovation. When considering other measures of innovation, such as patenting activity, I do not find significant effects.

5.2 Empirical strategy

To examine the impact of FabLab adoption on AM entrepreneurship, this study uses a difference-in-differences (DID) approach, combining information from multiple data sources.

5.2.1 Research design

I apply the staggered DID estimation described in Callaway and Sant'Anna (2021). This DID approach estimates the differences in outcomes between a treated and a control group while accounting for differences in outcomes before the treatment. In the context of this chapter, treated locations are regions where FabLabs were established, whereas the control group comprises regions without FabLabs during the sample period.

This approach identifies causal treatment effects when the treatment occurs exogenously. Although the decision to locate a FabLab in a specific location is likely strategic from a regional development perspective, it should not be driven by individual inventors or startup founders. From their perspective, the establishment of a FabLab can be considered exogenous. However, the adoption may still be influenced by underlying regional characteristics. Although I account for various regional factors, I cannot fully rule out the potential for selection bias, particularly regarding factors that are not observable in publicly available data. To estimate the effect of FabLabs, I solve the following equation.

$$V_{it} = \alpha_{it} + \beta W_{it} + \gamma X_{it} + c_i + \delta_t + \epsilon_{it}$$

In this optimization problem, V_{it} is a dummy variable indicating the presence of an AM venture in region i during year t, while W_{it} denotes the existence of a FabLab in the same region and year. The coefficient β captures the average treatment effect. The vector X_{it} includes time-varying firm-level controls, c_i and δ_t account for region and time fixed effects, respectively, and ϵ_{it} represents the error term. I used the same approach to identify the effect of makerspaces and hackerspaces.

5.2.2 Sample and data sources

The sample includes 96 functional urban areas (FUAs) in Germany, covering the period from 2000 to 2019. I compiled a comprehensive dataset that integrates information on FabLabs, patents, startups, and regional characteristics.

I collected data on FabLabs, including their names, addresses, and websites, from a platform[3] provided by the *Fab Foundation*. I obtained data on makerspaces from the German association Verbund Offener Werkstätten e.V. I refined the makerspace dataset by removing repair cafes, art spaces, and FabLabs. Information on hackerspaces was obtained from hackerspaces.org. Finally, I manually added the founding year for each FabLab, makerspace, and hackerspace to the dataset as indicated on their websites. FabLabs are mutually exclusive from other types of workshops, whereas makerspaces and hackerspaces overlap.

I measure entrepreneurship using data on AM-specific startups. The startup list, which includes names, websites, and categories, was sourced from AM Ventures Management GmbH, a venture capital firm specializing in investments in AM startups. I manually added the founding year for each startup to the dataset based on their names and websites. The dataset categorizes startups into four groups: hardware, software, material, and application. ‘Hardware’ encompasses the development of equipment for production and post-processing, while ‘software’ includes solutions across the digital value chain. ‘Material’ refers to the production, refinement, or research and development of metals, polymers, ceramics, and composites. Finally, ‘application’ covers products specifically designed for or produced using AM technologies.

[3] See www.fablabs.io accessed on 09/01/2025.

For regional control variables, I collected data from the INKAR database provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). This data includes population, measured in the number of citizens between 15 and 65 years of age, and regional development, measured in gross domestic product. Moreover, I enriched the dataset with AM-specific publications and patents to account for academic and industrial activities. To identify AM-related publications, I searched for AM-specific keywords in the abstracts of scientific articles with German affiliations from the Elsevier SCOPUS database. These keywords are derived from industry standards such as ISO/ASTM 52900 and VDI 3405, as well as recent literature (see Appendix A.4.2). For AM patents, I used the patents identified by the European Patent Office (EPO) (Pose-Rodriguez et al., 2020) based on the inventor's location.

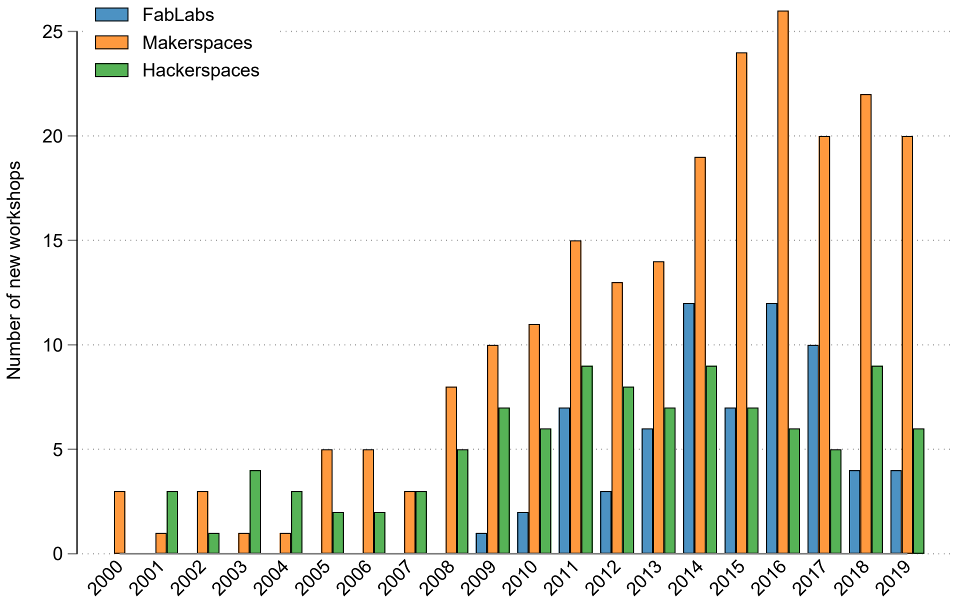
5.2.3 Summary statistics

As of 2019, a total of 416 workshops were operating in Germany, 76 of which were FabLabs. Between 2000 and 2019, the number of FabLabs within FUAs increased from 0 to 68. During the same period, the number of makerspaces grew from 30 to 251, while hackerspaces expanded from 14 to 116. Figure 5.1 illustrates the annual adoption of new spaces within FUAs. It is important to note that 47 workshops are classified as both hackerspaces and makerspaces.

The first FabLab in Germany was established in 2009 at RWTH Aachen University. Between 2009 and 2016, there was a continuous increase in the number of FabLabs, followed by a decline starting in 2017. Makerspaces, on the other hand, existed prior to 2000 but experienced only modest growth until 2008. After that, the establishment of new makerspaces increased significantly. A similar trend is observed for hackerspaces, although their rise after 2008 was less pronounced. The development of community workshops in Germany may have been influenced by various events such as the beginning of the maker movement in 2005 and the introduction of the first desktop AM machine in 2009 (Jones et al., 2011; West and Kuk, 2016).

Figure 5.2 illustrates the regional distribution of FabLabs, makerspaces, and hackerspaces across Germany in 2019. These community workshops were located in 77 FUAs. While there is a concentration in major cities, such as Berlin and Munich, some were found in rural regions. FabLabs were established in 37 FUAs, makerspaces in 69 FUAs, and hackerspaces in 60 FUAs. 29 FUAs had at least one FabLab, one makerspace, and one hackerspace.

Figure 5.1: Establishment of community workshops



Notes: This figure shows the annual adoption of makerspaces, hackerspaces, and FabLabs in Germany between 2000 and 2019.

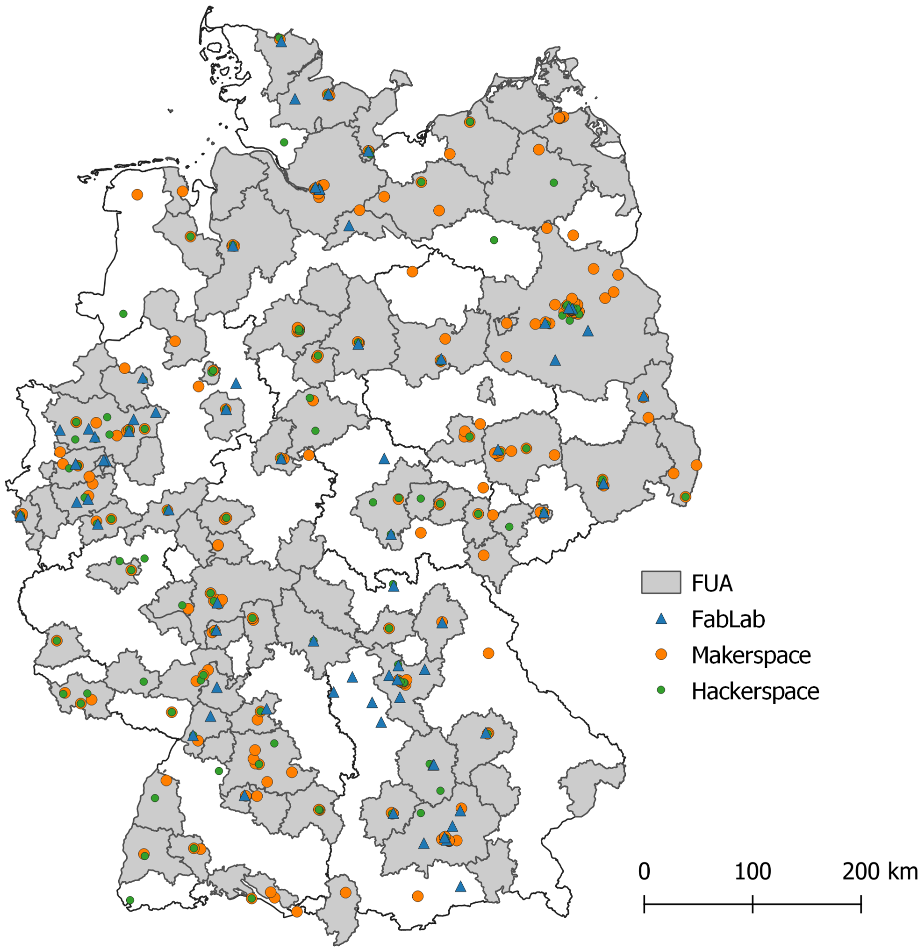
The sample of AM-specific ventures consists of 175 startups located across 42 FUAs. Among these, 59 focus on hardware, 36 on software, 18 on materials, and 62 on applications. Given the small sample size, I estimate the linear probability of AM venture creation rather than analyzing their count.

5.3 Results

Table 5.1 presents the estimation results for the relationship between the regional adoption of community workshops and the emergence of AM startups. Row 1 reports the estimated impact of having at least one community workshop in a region compared to regions without any such workshops. The results indicate that the adoption of each type of community workshop is associated with an increased chance of launching at least one AM startup. On average, the linear probability increases by 0.07 for makerspaces, 0.14 for hackerspaces, and reaches the highest effect of 0.23 for FabLabs.

When analyzing specific startup categories, the effects vary across workshop types. Makerspaces are associated with a 0.17 increase in the linear probability of material startups. Hackerspaces show broader impacts, with increases of 0.13 for software startups, 0.31 for

Figure 5.2: Regional distribution of community workshops



Notes: This figure shows the distribution of makerspaces, hackerspaces, and FabLabs established in Germany until 2019 with regions represented as FUAs (Functional Urban Areas).

material startups, and 0.11 for application startups. FabLabs, in contrast, show significant effects on hardware startups (0.15), material startups (0.08), and application startups (0.15). Consistent with previous studies (Cuntz and Peuckert, 2023; Bao, 2024), the results suggest that software startups benefit primarily from hackerspaces, while hardware startups are influenced by FabLabs, where users gain access to tools.

Table 5.1: The impact of community workshops on AM startups without controls

	Staggered difference-in-differences estimates				
	(1)	(2)	(3)	(4)	(5)
DV: Startups	All	Hardware	Software	Material	Application
FabLab (ATT)	0.23^{***}	0.15^{**}	0.09	0.08^{**}	0.15^{**}
	(0.06)	(0.05)	(0.06)	(0.03)	(0.05)
Num. of obs.	1,920	1,920	1,920	1,920	1,920
Makerspace (ATT)	0.07^{**}	0.04	0.02	0.17^{*}	0.05
	(0.02)	(0.02)	(0.02)	(0.07)	(0.03)
Num. of obs.	1,540	1,540	1,540	1,540	1,540
Hackerspace (ATT)	0.14^{**}	0.08	0.13^{**}	0.31^{**}	0.11^{*}
	(0.04)	(0.04)	(0.05)	(0.10)	(0.05)
Num. of obs.	1,740	1,740	1,740	1,740	1,740
Controls	X	X	X	X	X
Fixed effects	✓	✓	✓	✓	✓

Notes: This table reports the estimates from a regional FabLab adoption on the foundation of AM startups between 2000–2019. Controls include the number of citizens between 15 and 65, the number of AM publications, AM patents, and gross domestic product. The standard errors are in parentheses and the significance levels are defined as the following: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.2 presents the results incorporating several control variables to address selection effects related to the location of community workshops. These control variables include the number of citizens aged 15 to 65, the number of AM publications, the number of AM patents, and gross domestic product. The findings reveal a significant effect of FabLabs (0.16) and makerspaces (0.10) on AM startups, while the effect for hackerspaces becomes insignificant, suggesting that their adoption may be driven by regional characteristics.

Interestingly, the difference in effect size between FabLabs and makerspaces diminishes but remains larger for FabLabs. A visualization of the dynamic effect relative to the treatment period is illustrated in Figure A.4.1 (Appendix). The influence of FabLabs on hardware startups (0.10) and application startups (0.10) persists, whereas any effects on specific startup categories disappear for makerspaces and hackerspaces[4]. I do not find any effects for software or material startups. These results suggest that FabLabs promote the development of AM

[4]It is important to note that no pre-treatment events were identified for the effect of hackerspaces on material startups due to the low number of AM startups in the material sector. As a result, this effect cannot be reliably interpreted.

technology by supporting the establishment of hardware-focused startups and encouraging its application through the creation of application-focused startups.

Table 5.2: The impact of community workshops on AM startups with controls

	Staggered difference-in-differences estimates				
	(1)	(2)	(3)	(4)	(5)
DV: Startups	All	Hardware	Software	Material	Application
FabLab (ATT)	0.16*	0.10*	-0.01	0.08	0.10*
	(0.06)	(0.04)	(0.05)	(0.06)	(0.05)
Num. of obs.	1,899	1,899	1,899	1,899	1,899
Makerspace (ATT)	0.10*	0.10	0.00	0.11	0.06
	(0.05)	(0.06)	(0.03)	(0.10)	(0.03)
Num. of obs.	1,513	1,513	1,513	1,513	1,513
Hackerspace (ATT)	0.06	0.01	0.07	0.23*	0.03
	(0.05)	(0.06)	(0.04)	(0.10)	(0.05)
Num. of obs.	1,610	1,610	1,610	1,610	1,610
Controls	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓

Notes: This table reports the estimates from a regional FabLab adoption on the foundation of AM startups between 2000–2019. Controls include the number of citizens between 15 and 65, the number of AM publications, AM patents, and gross domestic product. The standard errors are in parentheses and the significance levels are defined as the following:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To assess the impact of community workshops on innovation, I used AM-specific patents as an alternative measure. While the analysis without control variables shows a link between FabLabs, makerspaces, hackerspaces, and AM patent activity, these effects disappear when controlling for regional characteristics. This suggests that community workshops are predominantly located in regions with high ex-ante levels of AM activity (see Table A.4.1 in Appendix). For a comprehensive analysis of the impact on patents, see Kreyer (2025).

5.4 Discussion and conclusion

This chapter examined the impact of FabLab adoption on entrepreneurship, with a specific focus on changes in AM venture creation. Using a staggered difference-in-differences estimation, the analysis finds that regions establishing a FabLab experience a 16% higher linear probability of new AM-related startup creation. This effect exceeds those observed for makerspaces and hackerspaces, suggesting that FabLabs may have a greater direct impact on fostering entrepreneurship. A plausible explanation is the institutional structure of FabLabs, which includes minimum tool requirements, standardized educational offerings, and a global network connecting all FabLabs. This network fosters a large community and offers better opportunities for knowledge exchange compared to makerspaces and hackerspaces.

Furthermore, the data reveal a positive and significant link between FabLab adoption and the emergence of hardware and application startups. This finding indicates that FabLabs may promote both the advancement of AM technology and its application. These results have implications for future policy design. Although I control for various regional characteristics, I cannot entirely eliminate the endogeneity issue related to FabLab location. Thus, some of the estimated impact may still be explained by selection into regions with the highest potential to create AM startups.

The analysis presented in this chapter is subject to several limitations. Data on makerspaces and hackerspaces rely on self-reported sources, which may introduce selection bias. Since no systematic database exists to identify these spaces, future research could employ web scraping techniques to create a more comprehensive dataset. While this study achieves high internal validity by focusing on startups related to AM, it remains uncertain whether the findings generalize to other sectors. Expanding the scope to include all startups in future research could enhance the external validity of this study. Such an approach would also address the current limitation of a small sample size. Another promising avenue for research is to explore the role of access to tools, community exchange, educational offerings, funding opportunities, and the motivations of accidental entrepreneurs in the creation of new startups. Gaining a deeper understanding of these channels is crucial for policymakers to design effective programs that support these innovation hubs.

Policymakers should consider community workshops as policy instruments to democratize innovation and stimulate economic development in their regions. My findings thereby contribute to the innovation literature, which discusses institutions and various tools for initiating and promoting entrepreneurial activities, highlighting the role of community workshops in fostering regional entrepreneurship and advancing new technologies (Hottenrott and Richstein, 2020; Halbinger, 2018; Furman and Stern, 2011). Moreover, the results suggest that policymakers should not only support the establishment of new spaces but also focus on creating systems that connect these spaces to one another. Such networks can expand communities, facilitate knowledge exchange, and enhance spillover effects. Disadvantaged regions, in particular, could benefit from the broader community and collaborative opportunities provided by these connections.

6 | Conclusion

The goal of this dissertation was to analyze the impact of AM adoption on welfare (chapter 2), the current stage of diffusion (chapter 3), and relevant drivers for its adoption (chapter 4 and chapter 5) and thereby contribute to economic literature on the role of new technologies Goldfarb and Tucker (2019). In this chapter, I summarize the main findings from each study, discuss their policy implications, and finally provide an outlook on potential directions for future research.

6.1 Overview of main findings and policy implications

In chapter 2, I examined the effect of AM adoption on market structure and welfare. Using a game-theoretical model of spatial product differentiation, I analyzed how traditionally standardized product markets evolve when a firm adopts AM to produce customized products. The findings on the market structure show increased competition for traditional manufacturers, as indicated by a decline in the prices of standardized products and a reduction in the number of traditional manufacturers. In contrast, firms with AM technology charge a price premium, influenced by the consumer's customization costs, and position their customized products above the initial market equilibrium. Interestingly, the price of customized products is determined by the cost structure of traditional manufacturers. The reduction in traditional manufacturers is correlated with the market power of the AM firms, which, in turn, depends on the cost structure of the AM technology. The welfare results show an increase in total surplus. However, the impact on consumer surplus depends on the number of traditional manufacturers and can become detrimental to consumers if this number falls below a critical threshold. In an extended model, I demonstrated that this threshold is also influenced by the intensity of competition the AM firm faces.

The optimal policy recommendations to maximize welfare depend on whether firms in a market have already adopted AM technology or not. In markets with no AM usage, its adoption would increase total surplus. Furthermore, AM adoption also increases consumer surplus if this market exhibits a high demand for customized products and high fixed costs for TM technologies. However, in other cases, AM adoption could potentially reduce consumer surplus. Policymakers can encourage firms to adopt AM technology by implementing programs that lower the marginal or fixed costs of AM technology, reduce the effort required from consumers during the customization process, or allow a certain level of market power for adopting firms. In markets with AM usage, a reduction in AM's marginal costs, consumers' customization costs, or an increase in market power for AM firms enhances total surplus but simultaneously reduces consumer surplus. The only tool for policymakers to encourage AM adoption while avoiding negative consequences in markets where AM is already established is to implement programs that reduce the fixed costs of AM technology.

In chapter 3, I investigated the adoption and diffusion of AM technology in Germany. Inspired by the web scraping and deep learning approach by Gök et al. (2015) and Kinne and Lenz (2021), I applied a novel and alternative method to traditional innovation indicators, such as surveys and patents, to measure the adoption of AM technology. The results show that manufacturers, retailers, information providers, and service providers play significant roles in the AM diffusion process. Firm-level findings indicate that these firms are relatively young, small, and primarily belong to the manufacturing industry. At the regional level, the analysis reveals high AM technology adoption rates in areas with technical universities and established manufacturing industries. A comparison with EPO data (Pose-Rodriguez et al., 2020) reveals consistent adoption patterns between patents and web-mined firms. The study also identifies AM-intensive regions, which are not reflected in patent data. Furthermore, the analysis reveals that the identified AM firms more frequently represent themselves as environmentally sustainable compared to the average across the overall firm population.

The results of this study suggest that web mining could serve as a complementary indicator to traditional measures of technology adoption and diffusion. In addition to uncovering hidden innovation activities, web mining allows policymakers to monitor the development of AM adoption in real-time, enabling faster evaluation of the effectiveness of policy measures. Furthermore, the results underline the importance of universities in facilitating AM adoption. This could be attributed to two main factors. First, as a science-based technology, advancements in AM depend on basic research. Second, universities contribute to the regional supply of skilled labor with expertise in AM-relevant domains. Moreover, the findings on sustainability indicate that AM-using firms do not exploit the potential for enhancing environmental sustainability.

In chapter 4, I analyzed how science funding policies contribute to knowledge generation and inventions in the field of AM. In particular, I investigated the effect of competitive, geographically localized forum grants (excellence clusters) awarded during the first funding period of the German Excellence Initiative (2006–2012) with an AM focus on scientific output and corporate patents. By using the synthetic difference-in-differences method proposed by (Arkhangelsky et al., 2021), I found an increase in AM publications among funded applicants compared to non-funded ones. This effect is larger for high-impact publications defined as those entering the upper percentile of year-field citation distributions. Furthermore, the results indicate that this effect is driven by AM publications from academic institutions. In terms of potential knowledge spillovers to the industry, I found a significant increase in highly cited, AM-specific corporate patents, while no growth is observed for patents at the extensive margin. Moreover, I found no significant effects for publications and patents across all domains, suggesting that these effects are domain-specific.

These findings demonstrate the effectiveness of excellence clusters in supporting not only (academic) basic research but also (corporate) development in AM technology. This suggests that there was indeed a funding gap in cutting-edge research, which was reduced by cluster funding. Consequently, policymakers could use targeted research funding as a policy instrument to foster cutting-edge research in the AM domain and thereby support the development of high-quality AM inventions, which in turn enhance local ecosystems.

In chapter 5, I investigated how the establishment of knowledge intermediaries influences entrepreneurship in AM. I examined the impact of FabLabs on AM startups with a staggered difference-in-differences approach (Callaway and Sant'Anna, 2021) between 2000 and 2019 in Germany. The results indicate a 16% increase in the linear probability of new AM startups. This effect size is larger than those observed for makerspaces and hackerspaces. In terms of startup categories, I found a 10% increase in hardware startups and a 10% increase in application startups, while no significant effects were observed for software or material startups. The analysis using AM patents as an alternative measure of innovation also did not yield significant effects.

This analysis highlights the potential of community workshops as a policy instrument to promote regional entrepreneurship in AM. FabLabs, in particular, provide infrastructure and facilitate knowledge exchange through a global network, empowering people to pursue projects that advance AM technology and to develop innovative applications based on AM technology. Furthermore, the findings on FabLabs suggest that policymakers should focus not only on establishing new community workshops but also on supporting networks and exchanges between existing workshops in order to expand community size and enhance knowledge spillovers.

6.2 Limitations and future research

This dissertation could not cover all interesting and relevant questions due to limited data, time, and model restrictions. However, the results of this research raise new questions that can be explored in future research.

An interesting research avenue is to examine the effect of other AM-specific features on competition. In chapter 2, my research framework is simplified to specifically model AM's flexibility capabilities. However, AM is also characterized by other features, such as its capability to develop goods that cannot be produced with TM technologies. This capability might affect firms' innovation activities, the supply of new products, and in turn firms' pricing strategy. Especially the rise of generative artificial intelligence and its possible joint usage with AM increases the relevance of more research in this field.

Large language models enable researchers to use websites to develop innovation indicators, raising several questions about their potential and reliability. In Chapter 3, I provided a descriptive analysis of a web-based AM model. Future research could build on this by further validating the use of web-based innovation indicators, particularly in addressing potential biases, such as the strategic use of websites to signal information to stakeholders (incentive bias). Moreover, future research could benefit from scraping websites at different points in time to analyze dynamic effects. Given the evolution of AM, it may be necessary to constantly adjust the keywords to capture relevant developments.

In Chapters 4 and 5, I demonstrated a link between Excellence Cluster funding and FabLabs with high-quality patent filings and venture creation, respectively. However, the channels of these effects remain unclear. To uncover the knowledge flows between Excellence Cluster-funded universities and industries, future research could explore researcher mobility from academia to industry and the establishment of collaborations during the funding period. The role of FabLabs could be further investigated by extending the dataset to include information on community size, educational offers, and equipment across FabLabs, makerspaces, and hackerspaces. This data extension could help disentangle the effects of different channels. A better understanding of these channels would help policymakers develop effective mechanisms.

Europe faces major challenges in maintaining competitiveness, reversing the slowdown in economic growth, and maintaining its prosperity. A central issue is the innovation gap between Europe and leading players such as the United States and China. Addressing this gap requires substantial investments in digital technologies, including AM (Draghi, 2024a).

AM has the potential to improve sustainability and supply chain resilience in various industries. Its adoption could foster Europe's economic and industrial ecosystems by fostering innovation and improving productivity. Recognizing these benefits, the European Commission (Draghi, 2024b) and Germany's *Commission of Experts for Research and Innovation* (EFI) (Bertsche et al., 2023) have emphasized the need for targeted measures. These include improving the regulatory framework, strengthening infrastructure, and KETs through skill development and competency building.

Appendix

A.1 Mass customization with additive manufacturing: Blessing or curse for society?

Here, I provide the detailed derivations of the extended model presented in section 2.6. I follow the same steps as in the base model.

Maximizing the profit functions stated in the main text, I can derive equilibrium prices for a given number of TM firms:

$$p_T = \frac{1}{3}\left(\frac{t}{2N} - \omega + \delta\lambda\right) + c_T,$$
$$p_A = \frac{1}{3}\left(\frac{t}{N} + \omega + 2\delta\lambda\right) + c_A.$$

As consumers of the AM firm receive a discount, the effective price is:

$$p_A^{\text{eff}} = \frac{1}{3}\left(\frac{t}{N} + \omega - \delta\lambda\right) + c_A.$$

Customers of the AM firm are benefiting from intensified AM competition via lower prices.

Given these prices, the profit of the AM firm is:

$$\pi_A = \frac{2}{9}\frac{(t + N(\omega - \delta\lambda))^2}{Nt} - F_A,$$

which is decreasing in the extent of AM competition.

Inserting the equilibrium prices in the TM profit function, I can derive the number of TM firms:

$$N^{II} = \frac{t}{3\sqrt{2F_T t} + 2(\omega - \delta\lambda)}.$$

The number of TM firms increases with δ and λ. Increased pressure on the firm with AM places TM firms in an advantageous position enabling them to achieve higher prices and profits. Consequently, a larger number of TM firms enter the market.

Equilibrium prices are

$$p_T = \sqrt{\frac{F_T t}{2}} + c_t$$
$$p_A^{\text{eff}} = \sqrt{2F_T t} + c_T - \theta s - \lambda\delta$$

To derive Proposition 7 from the main text, note that given N^{II}, the AM firm derives non-negative profits when

$$\omega \geq \frac{F_A}{2} - \sqrt{2F_T t} + \delta\lambda + \frac{1}{2}\sqrt{2F_A\sqrt{2F_T t} + F_A^2} = \omega_L(\delta\lambda)$$

Entry by at least one TM firm occurs when

$$\omega \leq \frac{t}{2} - \frac{3}{\sqrt{2}}\sqrt{F_T t} + \delta\lambda = \omega_H(\delta\lambda).$$

Together, these two critical threshold levels imply the equilibrium market structure. Hence, a market structure with both AM and TM firms occurs only if $\omega_L \leq \omega \leq \omega_H$ as detailed in Proposition 7.

Given equilibrium entry, I can derive consumer surplus

$$CS^{II} = v - p_A^{II} - \delta\lambda - \theta s + N^{II}\left(\frac{F_T}{2} - \delta\lambda\sqrt{\frac{F_T}{t}}\right).$$

Then, the comparison with consumer surplus in market I yields:

$$\begin{aligned} & CS^I \lesseqqgtr CS^{II} \\ \Leftrightarrow \qquad & \omega \gtreqqless \frac{2(5 - 10\sqrt{2} + \sqrt{2t})\sqrt{tF_T}\lambda\delta + 8(\lambda\delta)^2 + (22 - 15\sqrt{2})tF_t}{(10 - 8\sqrt{2})\sqrt{tF_T} + 8\lambda\delta} \end{aligned}$$

As in the main model, AM entry only makes consumers better off if the competitive advantage of AM technology is sufficiently small. However, this critical level of ω is decreasing in the extent of AM competition, as measured by $\lambda\delta$. Therefore, the parameter space where consumer surplus is increasing becomes larger as AM competition intensifies.

A.2 Technology mapping using web text mining: The case of 3D printing

Table A.2.1: AM keywords for website search

Source: Standard VDI 3405		
Additive Manufacturing	Additive Fertigung	Rapid Manufacturing
Rapid Prototyping†	Rapid Tooling	Stereolithography
Stereolithografie	Laser Sintering	Laser-Sintern
Selective Laser Sintering	Selektives Laser-Sintern	Laser Beam Melting
Laser-Strahlschmelzen	Laser Forming	Laser Forming
Selective Laser Melting	Selective Laser Melting	LaserCUSING
Direct Metal Laser Sintering	Direktes Metall-Laser-Sintern	Electron Beam Melting
Elektronen-Strahlschmelzen	Fused Layer Manufacturing	Fused Layer Modelling
Fused Deposition Modelling	Filament Deposition	Strangablegeverfahren
Multi-Jet Modelling	Poly-Jet Modelling	3D-Printing
3D-Druck	Layer Laminated Manufacturing	Schicht-Laminat-Verfahren
Laminated Object Manufacturing	Digital Light Processing	Thermotransfer Sintering
Thermotransfer-Sintern		
Source: Standard ISO/ASTM 52900		
Binder Jetting	Freistrahl-Bindemittelauftrag	Directed Energy Deposition
Materialauftrag mit gerichteter Energieeinbringung	Material Extrusion	Materialextrusion
Material Jetting	Freistrahl-Materialauftrag	Powder Bed Fusion
Pulverbettbasiertes Schmelzen	Sheet Lamination	Schichtlaminierung
Vat Photopolymerization	Badbasierte Photopolymerisation	
Source: AMPower GmbH & Co. KG		
Metal Selective Laser Sintering	Laser Beam Powder Bed Fusion	Wire Feed Laser
Powder Feed Laser Energy Deposition	Continuous Fiber Sheet Lamination	Wire Arc†
Plasma Arc Energy Deposition	Electron Beam Powder Bed Fusion	Liquid Metal Printing
Fiber Alignment Area-Wise Vat Polymerization	Electron Beam Energy Deposition	Ultrasonic Welding†
Metal Filament Fused Deposition Modeling	Nanoparticle Jetting	Friction Deposition
Metal Pellet Fused Deposition Modeling	Metal Lithography	Powder Metallurgy Jetting
Continuous Fiber Thermoplastic Deposition	Electrographic Sheet Lamination	Thermal Powder Bed Fusion
Laser Powder Bed Fusion	Pellet Based Material Extrusion	Mold Slurry Deposition
Continuous Fiber Material Extrusion	Filament Based Material Extrusion	Coldspray
Area-Wise Vat Polymerization	Resistance Welding†	Thermoset Deposition
Continuous Fiber Thermoset Deposition	Elastomer Deposition	Vat Vulcanization
Source: Recent scientific articles from journals such as *Additive Manufacturing*, *Rapid Prototyping Journal*, *Materials*, etc.		
Laser Chemical Vapor Deposition	Continuous Liquid Interface Production	Laser Metal Fusion
Selektives Laserschmelzen	Selective Mask Sintering	Selektive Maskensintern
Laser Engineered Net Shaping	ARBURG Kunststoff-Freiformen	Laserpulverformung
Maskless Masoscale Material Deposition	Foam Reaction Prototyping	Tool-Less Fabrication†
Werkzeuglose Fertigung†	Generative Manufacturing	Generative Fertigung
Digital Composite Manufacturing	Laserstrahlschmelzen	Laser Consolidation
Laserkonsolidierung	Ultrasonic Consolidation	Ultraschallkonsolidierung
Freeform Fabrication	Freiformherstellung	Layer Manufacturing
Schichtbauverfahren	Additive Layer Manufacturing	Additive Schichtherstellung
Additive Layer Manufacturing	Additive Schichtherstellung	Additive Techniques†
Ultrasonic Additive Manufacturing	Additive Process†	Additive Fabrication
Digital Light Synthesis	Continuous Digital Light Manufacturing	Two-Photon Polymerization
Programmable Photopolymerization	Direct Shell Production Casting	Thermal Polymerization
Directed Light Fabrication	Light Initiated Fabrication Technology	Additive Techniken†
Ultraschalladditivherstellung	E-Manufacturing†	Hot Lithography
Holographic Interference Solidification	Fused Filament Fabrication	Schmelzschichtung
Masked Stereolithography	Laser Metal Deposition	Laserauftragsschmelzen
Lithography-Based Ceramic Manufacturing	Robocasting	Direct Metal Deposition
Beam Interference Solidification	Ballistic Particle Manufacturing	Bioprinting
Solid Ground Curing	Solid Foil Polymerisation	Film Transfer Imaging
Cold Spraying†	Selective Deposition Lamination	Kaltgasspritzen
Digital Manufacturing†	Digitale Fertigung	Direct Ink Writing
Stereolithography Apparatus		

Notes: This table lists all AM-related keywords for the search of corporate websites. The keywords originate from four sources: the standards VDI 3405 and ISO/ASTM 52900, the consulting firm AMPower GmbH & Co. KG, and technical terms from recent literature in journals like *Additive Manufacturing*, *Rapid Prototyping Journal*, and *Materials*. Keywords marked with † have been removed from the search.

Table A.2.2: Full names of the technical universities

Abbreviation	**Full Name**
BTU	Brandenburgische TU Cottbus-Senftenberg
HCU	HafenCity Universität Hamburg
KIT	Karlsruher Institut für Technologie
LUH	Leibniz Universität Hannover
OVGU	Otto-von-Guericke-Universität Magdeburg
RWTH Aachen	Rheinisch-Westfälische Technische Hochschule Aachen
TU Berlin	Technische Universität Berlin
TU Braunschweig	Technische Universität Braunschweig
TU Chemnitz	Technische Universität Chemnitz
TU Darmstadt	Technische Universität Darmstadt
TU Dortmundt	Technische Universität Dortmund
TU Dresden	Technische Universität Dresden
TU Freiberg	Technische Universität Bergakademie Freiberg
TU Ilmenau	Technische Universität Ilmenau
TUC	Technische Universität Clausthal
TUHH	Technische Universität Hamburg
TUK	Technische Universität Kaiserslautern
TUM	Technische Universität München
U Stuttgart	Universität Stuttgart

Notes: This table provides the full names of technical university abbreviations.

Table A.2.3: Industry classification

Industry Name	**NACE range**	**Description**
Mining	B	Mining and quarrying
Textiles/clothing	C13-C15	Manufacturing of textiles, wearing apparel, fur, carpets, leather
Wood/paper/print	C16-C18	Manufacturing of wood, wood, cork products (except furniture); manufacture of straw articles and plaiting materials
Chemicals	C20	Manufacturing of chemicals and chemical products
Pharmaceuticals	C21	Manufacturing of basic pharmaceutical products and pharmaceutical preparations
Synthetics	C22	Manufacturing of rubber and plastic products, packaging
Glass/ceramics	C23	Manufacturing of glass and glass, refractory products, clay building materials, tiles, flags, porcelain, cement, concrete
Metal	C24	Manufacturing of basic metals (iron, steel, ferro, lead, zinc and tin)
Metalware	C25	Manufacturing of fabricated metal products (incl. cutlery, tools), except machinery and equipment
Electronics/optics	C26	Manufacturing of computer, electronic, optical products, and peripheral equipment
Electrical engineering	C27	Manufacturing of electrical equipment (incl. electric motors, machinery & equipment, appliances)
Mechanical engineering	C28	Manufacturing of machinery and equipment (incl. tools)
Automotive manufacturing	C29	Manufacturing of motor vehicles, trailers and transport equipment
Transportation manufacturing	C30	Manufacturing of boats, trains, aircraft, spacecraft
Other manufacturing	C31-C32	Manufacturing of furniture, coins, games & toys, jewellery, medical and dental instruments and supplies
Repair/installation	C33	Repair and installation of machinery and equipment
Construction	F	Construction of buildings, roads, railways, bridges, civil engineering, demolition, drilling, roofing, other installations
Wholesale	G46	Wholesale on a fee or contract basis (including raw materials, animals, textile raw materials, household goods, etc.)
Retail	G47	Retail trade of food, fuel, ICT, electronics, cultural goods, media, toys, flowers, plants
Media/publishing	J58-J60	Publishing of books and others, video production, music recording and publishing, radio broadcasting
ICT services	J61-J63	Telecommunications, programming, information service activities, data processing, hosting, etc.; web portals
Finance/insurance	K	Financial and insurance activities, monetary intermediation, activities of holding companies,
Management services	M69-M70	Legal and accounting activities, including accounting, bookkeeping and auditing activities; tax consultancy
Engineering/scientific services	M71-M72	Architectural and engineering activities; technical testing and analysis, scientific R&D
Creative Services	M73	Advertising and market research, media representation, public opinion polling
Other services	M74-N82	Other activities in science, specialized designs, veterinarian, administration, rental, leasing, etc.
Public administration	O	Public administration and defence; compulsory social security; foreign affairs, defence, fire service
Education	P	Education, driving schools, higher education, educational support activities
Interest groups	S94	Activities of membership organizations, business associations, trade unions, political and religious organizations
Personal services	S95-S96 and T	Repair of computers and personal and household goods, repair of computers and communication equipment

Notes: This table outlines the industry classification based on NACE codes.

A.3 Clusters of Excellence and science spillovers to industry: Evidence from additive manufacturing

Table A.3.1: Extended summary statistics

	Clusters	Controls			
	ExC recipients	Other prior SFB		Only rejected clusters	
VARIABLES	Mean	Mean	Diff.(p-val)	Mean	Diff.(p-val)
AM publications from academia	24.17	18.21	0.12	19.67	0.12
AM publication citations from academia	427.89	369.75	0.55	395.67	0.73
AM hit publications from academia	2.67	2.18	0.43	2.5	0.80
AM publications from industry	1.33	1.5	0.82	1.54	0.73
AM publication citations from industry	41	23.23	0.31	34.71	0.83
AM hit publications from industry	0.06	0.14	0.44	0.13	0.46
Collaborative AM publications	2.39	2.28	0.91	2.04	0.53
Collaborative AM publication citations	66.56	43.60	0.41	58.13	0.84
Collaborative AM hit publications	0.06	0.06	0.92	0.04	0.84

Notes: This table presents group means for 'ExC recipients' (treatment group), 'other prior CRC' (control group), and only 'rejected clusters' (control group), alongside the results of group comparisons (t-tests). The sample covers regions (Kreis level) of funded universities during the pre-treatment phase (2001–2006). 'ExC recipients' are regions of universities awarded an excellence cluster. 'Other prior CRC' are regions with universities that received an AM-related CRC between 1995 and 2005 (excluding 'ExC recipients'). 'Only rejected clusters' are regions with unsuccessful cluster applications. 'Hit publications' denotes the number of top 5% most-cited publications in a field-year.

Table A.3.2: Pairwise correlation

Variables	AM publications	AM publication citations	Hit publications in AM	Industry AM patents	Hit patents in AM	AM patent citations	Non-AM publications	Industry non-AM patents
AM publications	1.00							
AM publication citations	0.88	1.00						
Hit publications in AM	0.85	0.92	1.00					
Industry AM patents	0.14	0.13	0.12	1.00				
Hit patents in AM	0.05	0.04	0.05	0.36	1.00			
AM patent citations	0.09	0.08	0.08	0.61	0.60	1.00		
Non-AM publications	0.86	0.81	0.77	0.13	0.04	0.07	1.00	
Industry non-AM publications	0.26	0.22	0.21	0.63	0.23	0.38	0.22	1.00

Notes: This table presents the pairwise correlation between my main variables. The sample represents the treatment and control regions in the pre-treatment phase (2001-2006).

Table A.3.3: Regional funding overview

Location	ExC project #	ExC rejection	CRC project #
Aachen	89, 128	-	289, 401, 442, 525, 532, 561
Berlin	-	-	281, 546, 605
Bochum	-	-	459, 526
Braunschweig	-	-	420, 599
Bremen	-	✓	570, 637
Chemnitz	-	-	283, 379, 457
Clausthal	-	-	390
Darmstadt	-	✓	392, 595, 666
Dortmund	-	-	459, 559
Dresden	-	-	609, 639
Erlangen	315	-	396
Freiberg	-	-	609
Freiburg	-	✓	499
Hanover	62	-	516, 599, 653
Illmenau	-	-	622
Karlsruhe	-	-	483, 588
Munich	-	-	582
Paderborn	-	-	614
Stuttgart	-	✓	404, 467, 543

Notes: This table shows an overview of regional science funding projects. 'Location' indicates the county of the funded university. 'ExC project #' are the project numbers of cluster projects with a focus on AM in the first round of the excellence initiative. In contrast to the other projects, ExC 315 started in the year 2007. 'ExC rejection' indicates all regions of universities with rejected excellence cluster applications. 'CRC project #' are the project numbers of collaborative research centers projects started between 1995 and 2005 in the fields of Mechanical & Production Engineering or Material Engineering & Science.

Table A.3.4: Keywords for semantic search

Source: Standard VDI 3405		
Additive Manufacturing	Additive Fertigung	Rapid Manufacturing
Rapid Prototyping	Rapid Tooling	Stereolithography
Stereolithografie	Laser Sintering	Laser-Sintern
Selective Laser Sintering	Selektives Laser-Sintern	Laser Beam Melting
Laser-Strahlschmelzen	Laser Forming	Laser Forming
Selective Laser Melting	Selective Laser Melting	LaserCUSING
Direct Metal Laser Sintering	Direktes Metall-Laser-Sintern	Electron Beam Melting
Elektronen-Strahlschmelzen	Fused Layer Manufacturing	Fused Layer Modelling
Fused Deposition Modelling	Filament Deposition	Strangablegeverfahren
Multi-Jet Modelling	Poly-Jet Modelling	3D-Printing
3D-Druck	Layer Laminated Manufacturing	Schicht-Laminat-Verfahren
Laminated Object Manufacturing	Digital Light Processing	Thermotransfer Sintering
Thermotransfer-Sintern		
Source: Standard ISO/ASTM 52900		
Binder Jetting	Freistrahl-Bindemittelauftrag	Directed Energy Deposition
Materialauftrag mit gerichteter Energieeinbringung	Material Extrusion	Materialextrusion
Material Jetting	Freistrahl-Materialauftrag	Powder Bed Fusion
Pulverbettbasiertes Schmelzen	Sheet Lamination	Schichtlaminierung
Vat Photopolymerization	Badbasierte Photopolymerisation	
Source: AMPower GmbH & Co. KG		
Metal Selective Laser Sintering	Laser Beam Powder Bed Fusion	Wire Feed Laser
Powder Feed Laser Energy Deposition	Continuous Fiber Sheet Lamination	Wire Arc
Plasma Arc Energy Deposition	Electron Beam Powder Bed Fusion	Liquid Metal Printing
Fiber Alignment Area-Wise Vat Polymerization	Electron Beam Energy Deposition	Ultrasonic Welding
Metal Filament Fused Deposition Modeling	Nanoparticle Jetting	Friction Deposition
Metal Pellet Fused Deposition Modeling	Metal Lithography	Powder Metallurgy Jetting
Continuous Fiber Thermoplastic Deposition	Electrographic Sheet Lamination	Thermal Powder Bed Fusion
Laser Powder Bed Fusion	Pellet Based Material Extrusion	Mold Slurry Deposition
Continuous Fiber Material Extrusion	Filament Based Material Extrusion	Coldspray
Area-Wise Vat Polymerization	Resistance Welding	Thermoset Deposition
Continuous Fiber Thermoset Deposition	Elastomer Deposition	Vat Vulcanization
Source: Recent scientific articles from journals such as *Additive Manufacturing*, *Rapid Prototyping Journal*, *Materials*, etc.		
Laser Chemical Vapor Deposition	Continuous Liquid Interface Production	Laser Metal Fusion
Selektives Laserschmelzen	Selective Mask Sintering	Selektive Maskensintern
Laser Engineered Net Shaping	ARBURG Kunststoff-Freiformen	Laserpulverformung
Maskless Masoscale Material Deposition	Foam Reaction Prototyping	Tool-Less Fabrication
Werkzeuglose Fertigung	Generative Manufacturing	Generative Fertigung
Digital Composite Manufacturing	Laserstrahlschmelzen	Laser Consolidation
Laserkonsolidierung	Ultrasonic Consolidation	Ultraschallkonsolidierung
Freeform Fabrication	Freiformherstellung	Layer Manufacturing
Schichtbauverfahren	Additive Layer Manufacturing	Additive Schichtherstellung
Additive Layer Manufacturing	Additive Schichtherstellung	Additive Techniques
Ultrasonic Additive Manufacturing	Additive Process	Additive Fabrication
Digital Light Synthesis	Continuous Digital Light Manufacturing	Two-Photon Polymerization
Programmable Photopolymerization	Direct Shell Production Casting	Thermal Polymerization
Directed Light Fabrication	Light Initiated Fabrication Technology	Additive Techniken
Ultraschalladditivherstellung	E-Manufacturing	Hot Lithography
Holographic Interference Solidification	Fused Filament Fabrication	Schmelzschichtung
Masked Stereolithography	Laser Metal Deposition	Laserauftragsschmelzen
Lithography-Based Ceramic Manufacturing	Robocasting	Direct Metal Deposition
Beam Interference Solidification	Ballistic Particle Manufacturing	Bioprinting
Solid Ground Curing	Solid Foil Polymerisation	Film Transfer Imaging
Cold Spraying	Selective Deposition Lamination	Kaltgasspritzen
Digital Manufacturing	Digitale Fertigung	Direct Ink Writing
Stereolithography Apparatus		

Notes: This table lists all AM-related keywords used for the semantic search of article abstracts with German affiliations. The keywords originate from four sources: the standards VDI 3405 and ISO/ASTM 52900, the consulting firm AMPower GmbH & Co. KG, and technical terms from recent literature in journals like *Additive Manufacturing*, *Rapid Prototyping Journal*, and *Materials*.

Table A.3.5: Placebo test on publication output

	Synthetic difference-in-differences estimates					
	AM Publications			Non-AM Publications		
DV	(1) No. Pubs	(2) Cit w/ Pubs	(3) Hit Pubs	(4) No. Pubs	(5) Cit w/ Pubs	(6) Hit Pubs
Cluster_t	5.60	52.24	-0.02	13.65	2,050	-8.32
	(4.78)	(154.24)	(0.90)	(202.92)	(7,660)	(58.51)
Number of observations	247	247	247	247	247	247
DV mean	11.21	137.47	2.22	1,225.88	22,078.85	251.30

Notes: This table reports the estimates from a placebo test on publication output. The test assumes a treatment in the year 2001 and considers a time span from 1996–2007. In these analyses, the control group includes regions from all universities that received an AM-related CRC between 1995 and 2005 (excluding recipients of an ExC). 'No. pubs' refer to the number of publications, 'cit w/ pubs' to publication citations, and 'hit pubs' to hit publications. Hit publications are the top 5% most cited publications within a field year. Model (1)-(3) considers AM publications, while model (4)-(6) shows the results for non-AM publications. Each regression is bootstrapped with 500 repetitions. The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3.6: Funding effect on publication outcome

	Synthetic difference-in-differences estimates				
DV	(1) All Pubs	(2) Top 50% Pubs	(3) Top 10% Pubs	(4) Top 5% Pubs	(5) Top 1% Pubs
Cluster_{t-1}	15.17^{**}	13.61^{***}	4.06^{**}	2.61^{*}	0.74^{*}
	(5.92)	(4.97)	(1.61)	(1.37)	(0.42)
Number of observations	247	247	247	247	247
DV mean	2.20	1.83	0.53	0.28	0.07

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on scientific publication output between 2001–2013. The models consider publications of different percentiles in the citation distribution. In these analyses, the control group includes regions from all universities that received an AM-related CRC between 1995 and 2005 (excluding recipients of an ExC). Considering a time lag of one year, the treatment years are 2007 & 2008 (depending on the university). The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3.7: Funding effect on patent outcome

	Synthetic difference-in-differences estimates				
DV	(1) All Pats	(2) Top 50% Pats	(3) Top 10% Pats	(4) Top 5% Pats	(5) Top 1% Pats
Cluster_{t-1}	-0.87^{**}	0.27	0.33^{***}	0.24^{***}	0.18^{***}
	(0.44)	(0.25)	(0.08)	(0.08)	(0.02)
Number of observations	247	247	247	247	247
DV mean	0.97	0.36	0.07	0.03	0.01

Notes: This table reports the estimates from the receipt of an excellence cluster in the field of AM on industry patent output between 2001–2013. The models consider publications of different percentiles in the citation distribution. In these analyses, the control group includes regions from all universities that received an AM-related CRC between 1995 and 2005 (excluding recipients of an ExC). Considering a time lag of one year, the treatment years are 2007 & 2008 (depending on the university). The standard errors are in parentheses, and the significance levels are defined as the following: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4 Democratization of innovation: Do FabLabs contribute to the emergence of ventures in additive manufacturing?

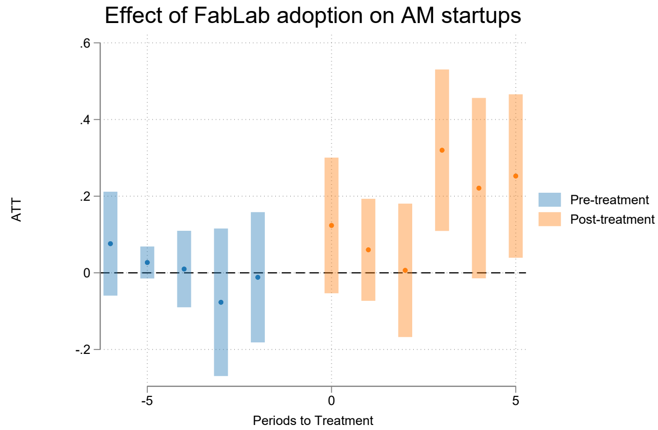
Table A.4.1: The impact of community workshop adoption on AM patents

DV: Patents	(1)	(2)
FabLab (ATT)	12.58*	0.68
	(5.69)	(4.11)
Num. of obs.	1,920	1,907
Makerspace (ATT)	2.65**	0.82
	(0.84)	(0.97)
Num. of obs.	1,540	1,519
Hackerspace (ATT)	6.00**	0.46
	(2.16)	(1.34)
Num. of obs.	1,740	1,672
Controls	X	✓
Fixed effects	✓	✓

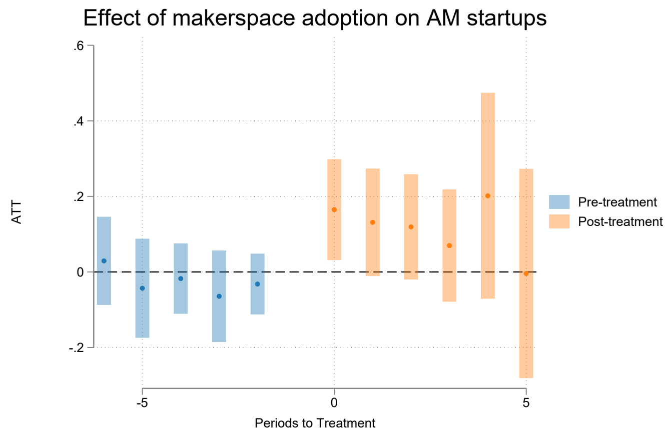
Notes: This table reports estimates from a regional community workshop adoption on AM patents between 2000–2019. Patents were retrieved from the EPO database (Pose-Rodriguez et al., 2020) based on the inventor's location. Controls include citizens between 15 and 65, the number of AM publications, and gross domestic product. The standard errors are in parentheses, and the significance levels are defined as the following:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure A.4.1: Event studies

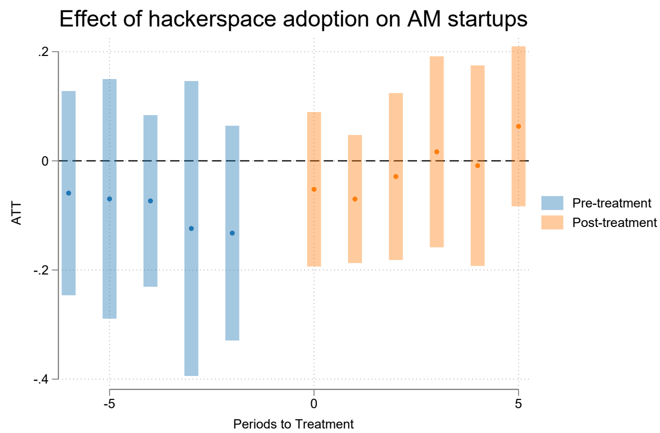
(a) FabLab



(b) Makerspace



(c) Hackerspace



These event study plots visualize the dynamic community workshop effects on AM startup creation estimated with the doubly robust estimator by (Callaway and Sant'Anna, 2021). The number of citizens between 15 and 65, number of AM publications, AM patents, and gross domestic product are included as control variables.

Table A.4.2: AM keywords

Source: Standard VDI 3405		
Additive Manufacturing	Additive Fertigung	Rapid Manufacturing
Rapid Prototyping	Rapid Tooling	Stereolithography
Stereolithografie	Laser Sintering	Laser-Sintern
Selective Laser Sintering	Selektives Laser-Sintern	Laser Beam Melting
Laser-Strahlschmelzen	Laser Forming	Laser Forming
Selective Laser Melting	Selective Laser Melting	LaserCUSING
Direct Metal Laser Sintering	Direktes Metall-Laser-Sintern	Electron Beam Melting
Elektronen-Strahlschmelzen	Fused Layer Manufacturing	Fused Layer Modelling
Fused Deposition Modelling	Filament Deposition	Strangablegeverfahren
Multi-Jet Modelling	Poly-Jet Modelling	3D-Printing
3D-Druck	Layer Laminated Manufacturing	Schicht-Laminat-Verfahren
Laminated Object Manufacturing	Digital Light Processing	Thermotransfer Sintering
Thermotransfer-Sintern		
Source: Standard ISO/ASTM 52900		
Binder Jetting	Freistrahl-Bindemittelauftrag	Directed Energy Deposition
Materialauftrag mit gerichteter Energieeinbringung	Material Extrusion	Materialextrusion
Material Jetting	Freistrahl-Materialauftrag	Powder Bed Fusion
Pulverbettbasiertes Schmelzen	Sheet Lamination	Schichtlaminierung
Vat Photopolymerization	Badbasierte Photopolymerisation	
Source: AMPower GmbH & Co. KG		
Metal Selective Laser Sintering	Laser Beam Powder Bed Fusion	Wire Feed Laser
Powder Feed Laser Energy Deposition	Continuous Fiber Sheet Lamination	Wire Arc
Plasma Arc Energy Deposition	Electron Beam Powder Bed Fusion	Liquid Metal Printing
Fiber Alignment Area-Wise Vat Polymerization	Electron Beam Energy Deposition	Ultrasonic Welding
Metal Filament Fused Deposition Modeling	Nanoparticle Jetting	Friction Deposition
Metal Pellet Fused Deposition Modeling	Metal Lithography	Powder Metallurgy Jetting
Continuous Fiber Thermoplastic Deposition	Electrographic Sheet Lamination	Thermal Powder Bed Fusion
Laser Powder Bed Fusion	Pellet Based Material Extrusion	Mold Slurry Deposition
Continuous Fiber Material Extrusion	Filament Based Material Extrusion	Coldspray
Area-Wise Vat Polymerization	Resistance Welding	Thermoset Deposition
Continuous Fiber Thermoset Deposition	Elastomer Deposition	Vat Vulcanization
Source: Recent scientific articles from journals such as *Additive Manufacturing*, *Rapid Prototyping Journal*, *Materials*, etc.		
Laser Chemical Vapor Deposition	Continuous Liquid Interface Production	Laser Metal Fusion
Selektives Laserschmelzen	Selective Mask Sintering	Selektive Maskensintern
Laser Engineered Net Shaping	ARBURG Kunststoff-Freiformen	Laserpulverformung
Maskless Masoscale Material Deposition	Foam Reaction Prototyping	Tool-Less Fabrication
Werkzeuglose Fertigung	Generative Manufacturing	Generative Fertigung
Digital Composite Manufacturing	Laserstrahlschmelzen	Laser Consolidation
Laserkonsolidierung	Ultrasonic Consolidation	Ultraschallkonsolidierung
Freeform Fabrication	Freiformherstellung	Layer Manufacturing
Schichtbauverfahren	Additive Layer Manufacturing	Additive Schichtherstellung
Additive Layer Manufacturing	Additive Schichtherstellung	Additive Techniques
Ultrasonic Additive Manufacturing	Additive Process	Additive Fabrication
Digital Light Synthesis	Continuous Digital Light Manufacturing	Two-Photon Polymerization
Programmable Photopolymerization	Direct Shell Production Casting	Thermal Polymerization
Directed Light Fabrication	Light Initiated Fabrication Technology	Additive Techniken
Ultraschalladditivherstellung	E-Manufacturing	Hot Lithography
Holographic Interference Solidification	Fused Filament Fabrication	Schmelzschichtung
Masked Stereolithography	Laser Metal Deposition	Laserauftragsschmelzen
Lithography-Based Ceramic Manufacturing	Robocasting	Direct Metal Deposition
Beam Interference Solidification	Ballistic Particle Manufacturing	Bioprinting
Solid Ground Curing	Solid Foil Polymerisation	Film Transfer Imaging
Cold Spraying	Selective Deposition Lamination	Kaltgasspritzen
Digital Manufacturing	Digitale Fertigung	Direct Ink Writing
Stereolithography Apparatus		

Notes: This table lists all AM-related keywords used for the semantic search of article abstracts with German affiliations. The keywords originate from four sources: the standards VDI 3405 and ISO/ASTM 52900, the consulting firm AMPower GmbH & Co. KG, and technical terms from recent literature in journals like *Additive Manufacturing*, *Rapid Prototyping Journal*, and *Materials*.

Bibliography

Adams, James D, and Zvi Griliches. 1996. *Research productivity in a system of universities.* National Bureau of Economic Research Discussion Paper No. w5833, Working Paper.

Adner, Ron, and Peter Zemsky. 2005. "Disruptive technologies and the emergence of competition." *The RAND Journal of Economics* 36 (2): 229–254.

Agasisti, Tommaso, Ekaterina Shibanova, Daria Platonova, and Mikhail Lisyutkin. 2020. "The Russian excellence initiative for higher education: A nonparametric evaluation of short-term results." *International Transactions in Operational Research* 27 (4): 1911–1929.

Aghion, Philippe, Céline Antonin, and Simon Bunel. 2021. *The power of creative destruction: Economic upheaval and the wealth of nations.* Harvard University Press.

Aghion, Philippe, Richard Blundell, Rachel Griffith, Peter Howitt, and Susanne Prantl. 2009. "The effects of entry on incumbent innovation and productivity." *The Review of Economics and Statistics* 91 (1): 20–32.

Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin, and John Van Reenen. 2016. "Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry." *Journal of Political Economy* 124 (1): 1–51.

Ahmadpoor, Mohammad, and Benjamin F Jones. 2017. "The dual frontier: Patented inventions and prior scientific advance." *Science* 357 (6351): 583–587.

Alexandrov, Alexei. 2008. "Fat products." *Journal of Economics & Management Strategy* 17 (1): 67–95.

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens, and Stefan Wager. 2021. "Synthetic difference-in-differences." *American Economic Review* 111 (12): 4088–4118.

Armanios, Daniel Erian, Charles E Eesley, Jizhen Li, and Kathleen M Eisenhardt. 2017. "How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources." *Strategic Management Journal* 38 (7): 1373–1390.

Arora, Ashish, and Alfonso Gambardella. 2005. "The impact of NSF support for basic research in economics." *Annales d'Economie et de Statistique,* 91–117.

Arvanitis, Spyridon, Gudela Grote, Andrin Spescha, Toni Wäfler, and Martin Wörter. 2017. "Digitalisierung in der Schweizer Wirtschaft: Ergebnisse der Umfrage 2016: Eine Teilauswertung im Auftrag des SBFI." *KOF Studies* 93.

Assenova, Valentina A. 2020. "Early-stage venture incubation and mentoring promote learning, scaling, and profitability among disadvantaged entrepreneurs." *Organization Science* 31 (6): 1560–1578.

Atzeni, Eleonora, and Alessandro Salmi. 2012. "Economics of additive manufacturing for end-usable metal parts." *The International Journal of Advanced Manufacturing Technology* 62:1147–1155.

Audretsch, David B., and Maryann P. Feldman. 1996. "R&D spillovers and the geography of innovation and production." *The American Economic Review* 86 (3): 630–640.

Audretsch, David B, and Paula E Stephan. 1996. "Company-scientist locational links: The case of biotechnology." *The American Economic Review* 86 (3): 641–652.

Ayoubi, Charles, Sandra Barbosu, Michele Pezzoni, and Fabiana Visentin. 2014. *Striving for excellence: University competition, quality perceptions, and ability sorting.* Cologne Graduate School Series 05-01, Working Paper.

Azoulay, Pierre, Joshua S Graff Zivin, Danielle Li, and Bhaven N Sampat. 2019. "Public R&D investments and private-sector patenting: Evidence from NIH funding rules." *The Review of Economic Studies* 86 (1): 117–152.

Azoulay, Pierre, Joshua S Graff Zivin, and Gustavo Manso. 2011. "Incentives and creativity: Evidence from the academic life sciences." *The RAND Journal of Economics* 42 (3): 527–554.

Balasubramanian, Sridhar. 1998. "Mail versus mall: A strategic analysis of competition between direct marketers and conventional retailers." *Marketing Science* 17 (3): 181–195.

Bao, Jiayi. 2024. "Do makerspaces affect entrepreneurship? If so, who, how, and when?" *Strategic Management Journal.*

Bar-Isaac, Heski, Guillermo Caruana, and Vicente Cuñat. 2023. "Targeted product design." *American Economic Journal: Microeconomics* 15 (2): 157–186.

Baruffaldi, Stefano, and Felix Poege. 2024. "Like stars: How firms learn at scientific conferences." *Management Science.*

Baumers, Martin, Phill Dickens, Chris Tuck, and Richard Hague. 2016. "The cost of additive manufacturing: Machine productivity, economies of scale and technology-push." *Technological Forecasting and Social Change* 102:193–201.

Baumers, Martin, and Matthias Holweg. 2019. "On the economics of additive manufacturing: Experimental findings." *Journal of Operations Management* 65 (8): 794–809.

Belenzon, Sharon, and Mark Schankerman. 2013. "Spreading the word: Geography, policy, and knowledge spillovers." *Review of Economics and Statistics* 95 (3): 884–903.

Ben-Ner, Avner, and Enno Siemsen. 2017. "Decentralization and localization of production: The organizational and economic consequences of additive manufacturing (3D printing)." *California Management Review* 59 (2): 5–23.

Bergeaud, Antonin, Arthur Guillouzouic, Emeric Henry, and Clément Malgouyres. 2023. *From public labs to private Firms: Magnitude and channels of R&D spillovers.* CEPR Discussion Paper 17487.

Berman, Barry. 2012. "3-D printing: The new industrial revolution." *Business horizons* 55 (2): 155–162.

Bernhardt, Dan, Qihong Liu, and Konstantinos Serfes. 2007. "Product customization." *European Economic Review* 51 (6): 1396–1422.

Bertsche, Irene, Guido Buenstorf, Uwe Cantner, Carolin Haeussler, Till Requate, and Friederike Welter. 2023. *Report on research, innovation, and technological performance in Germany.* Commission of experts for research and innovation.

Bikard, Michaël, and Matt Marx. 2020. "Bridging academia and industry: How geographic hubs connect university science and corporate technology." *Management Science* 66 (8): 3425–3443.

Bornmann, Lutz. 2016. "Is the promotion of research reflected in bibliometric data? A network analysis of highly cited papers on the clusters of excellence supported under the excellence initiative in Germany." *Scientometrics* 107 (3): 1041–1061.

Bouckaert, Jan. 2000. "Monopolistic competition with a mail order business." *Economics Letters* 66 (3): 303–310.

Bresnahan, Timothy F, and Manuel Trajtenberg. 1995. "General purpose technologies 'engines of growth'?" *Journal of Econometrics* 65 (1): 83–108.

Browder, Russell E, Howard E Aldrich, and Steven W Bradley. 2019. "The emergence of the maker movement: Implications for entrepreneurship research." *Journal of Business Venturing* 34 (3): 459–476.

Bruckmeier, Kerstin, Georg-Benedikt Fischer, and Berthold U Wigger. 2017. "Status effects of the German excellence initiative." *International Journal of Economics and Finance* 9 (3): 177–183.

Brynjolfsson, Erik, Yu Hu, and Michael D Smith. 2003. "Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers." *Management Science* 49 (11): 1580–1596.

Callaert, Julie, Maikel Pellens, and Bart Van Looy. 2014. "Sources of inspiration? Making sense of scientific references in patents." *Scientometrics* 98:1617–1629.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics* 225 (2): 200–230.

Campbell, Ian, Olaf Diegel, Ray Huff, Joseph Kowen, and Terry T Wohlers. 2023. *Wohlers report 2023 3D printing and additive manufacturing global state of the industry.* Wohlers Associates Inc.

Carayol, Nicolas, and Mireille Matt. 2004. "Does research organization influence academic production?: Laboratory level evidence from a large European university." *Research Policy* 33 (8): 1081–1102.

Carayol, Nicolas, and François Maublanc. 2025. "Can money buy scientific leadership? The impact of excellence programs on German and French universities." *Research Policy* 54 (2): 105155.

Cavallo, Frédéric, Judy Ceulemans, Benoit Gasner, Miguel Godino Martinez, Muzio Grilli, Yann Ménière, José Luis Meseguer Mayoral, et al. 2023. *Innovation trends in additive manufacturing: Patents in 3D printing technologies.* European Patent Office.

Chang, Myong-Hun. 1993. "Flexible manufacturing, uncertain consumer tastes, and strategic entry deterrence." *The Journal of Industrial Economics* 41 (1): 77–90.

Chava, Sudheer, Alexander Oettl, Manpreet Singh, and Linghang Zeng. 2024. "Creative destruction? Impact of e-commerce on the retail sector." *Management Science* 70 (4): 2168–2187.

Choong, Yu Ying Clarrisa, Hong Wei Tan, Deven C Patel, Wan Ting Natalie Choong, Chun-Hsien Chen, Hong Yee Low, Ming Jen Tan, Chandrakant D Patel, and Chee Kai Chua. 2020. "The global rise of 3D printing during the COVID-19 pandemic." *Nature Reviews Materials* 5 (9): 637–639.

Clarke, Damian, Daniel Pailañir, Susan Athey, and Guido Imbens. 2023. "Synthetic difference in differences estimation." *arXiv preprint arXiv:2301.11859.*

Cockburn, Iain M, and Rebecca M Henderson. 1998. "Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery." *The Journal of Industrial Economics* 46 (2): 157–182.

Cohen, Wesley M., Richard Nelson, and John P. Walsh. 2002. "Links and impacts: The influence of public research on industrial R&D." *Management Science* 48 (1): 1–23.

Colen, Linde, Rene Belderbos, Stijn Kelchtermans, and Bart Leten. 2022. "Reaching for the stars: When does basic research collaboration between firms and academic star scientists benefit firm invention performance?" *Journal of Product Innovation Management* 39 (2): 222–264.

Contigiani, Andrea, and Daniel A Levinthal. 2019. "Situating the construct of lean start-up: Adjacent conversations and possible future directions." *Industrial and Corporate Change* 28 (3): 551–564.

Crepon, Bruno, Emmanuel Duguet, and Jacques Mairesse. 1998. "Research, innovation and productivity: An econometric analysis at the firm level." *Economics of Innovation and New Technology* 7 (2): 115–158.

Cuntz, Alexander, and Jan Peuckert. 2023. "From hackers to start-ups: Innovation commons and local entrepreneurial activity." *Research Policy* 52 (2): 104675.

Delic, Mia, and Daniel R Eyers. 2020. "The effect of additive manufacturing adoption on supply chain flexibility and performance: An empirical analysis from the automotive industry." *International Journal of Production Economics* 228:107689.

Despeisse, Mélanie, Martin Baumers, Phil Brown, Fiona Charnley, Simon J Ford, Alysia Garmulewicz, S Knowles, et al. 2017. "Unlocking value for a circular economy through 3D printing: A research agenda." *Technological Forecasting and Social Change* 115:75–84.

Deutsche Forschungsgemeinschaft. 2006. *Ergebnis der Sitzung der Gemeinsamen Kommission am 20. Januar 2006.* Accessed: 09/01/2025.

———. 2007. *Ergebnis der Sitzung der Gemeinsamen Kommission am 12. Januar 2007.* Accessed: 09/01/2025.

———. 2015. *Forderatlas 2015: Kennzahlen zur offentlich finanzierten Forschung in Deutschland.* John Wiley & Sons.

Dewan, Rajiv, Bing Jing, and Abraham Seidmann. 2003. "Product customization and price competition on the internet." *Management Science* 49 (8): 1055–1070.

Diegel, Olaf, Joseph Kowen, and Terry T Wohlers. 2024. *Wohlers report 2024 3D printing and additive manufacturing global state of the industry.* Wohlers Associates Inc.

Dougherty, Dale. 2012. "The maker movement." *Innovations: Technology, governance, globalization* 7 (3): 11–14.

Draghi, Mario. 2024a. *The future of European competitiveness – A competitiveness strategy for Europe.* European Commisson.

Draghi, Mario. 2024b. *The future of European competitiveness – In-depth analysis and recommendations.* European Commisson.

Du Plessis, Anton, Chris Broeckhoven, Ina Yadroitsava, Igor Yadroitsev, Clive H Hands, Ravi Kunju, and Dhruv Bhate. 2019. "Beautiful and functional: A review of biomimetic design in additive manufacturing." *Additive Manufacturing* 27:408–427.

Eaton, B Curtis, and Nicolas Schmitt. 1994. "Flexible manufacturing and market structure." *The American Economic Review* 84 (4): 875–888.

Encaoua, David, Bronwyn H Hall, François Laisney, Jacques Mairesse, Ashish Arora, Paul A David, and Alfonso Gambardella. 2000. *Reputation and competence in publicly funded science: Estimating the effects on research group productivity.* Springer.

European Commisson. 2012. *A European strategy for key enabling technologies—a bridge to growth and jobs.* European Commisson.

———. 2024a. *Directorate-general for research and innovation, Horizon Europe, the EU research and innovation programme (2021-27) – for a green, healthy, digital and inclusive Europe.* Publications Office of the European Union.

———. 2024b. *Frontier research: The European challenge. High-level expert group report. Brussels: European Commission.* European Commisson.

Eyers, Daniel R., Andrew T. Potter, Jonathan Gosling, and Mohamed M. Naim. 2018. "The flexibility of industrial additive manufacturing systems." *International Journal of Operations and Production Management* 38 (12): 2313–2343.

Fleming, Lee, and Olav Sorenson. 2004. "Science as a map in technological search." *Strategic Management Journal* 25 (8-9): 909–928.

Forman, Chris, Anindya Ghose, and Avi Goldfarb. 2009. "Competition between local and electronic markets: How the benefit of buying online depends on where you live." *Management Science* 55 (1): 47–57.

Froumin, Isak, and Mikhail Lisyutkin. 2015. "Excellence-driven policies and initiatives in the context of Bologna process: Rationale, design, implementation and outcomes," 249–265. Springer International Publishing.

Fu, Yuan-Chih, David P Baker, and Liang Zhang. 2020. "Engineering a world class university? The impact of Taiwan's world class university project on scientific productivity." *Higher Education Policy* 33:555–570.

Fudickar, Roman, and Hanna Hottenrott. 2019. "Public research and the innovation performance of new technology based firms." *The Journal of Technology Transfer* 44 (2): 326–358.

Furman, Jeffrey L, and Scott Stern. 2011. "Climbing atop the shoulders of giants: The impact of institutions on cumulative research." *American Economic Review* 101 (5): 1933–1963.

Gawellek, Bastian, and Marco Sunder. 2016. *The German excellence initiative and efficiency change among universities, 2001-2011.* University of Leipzig, Faculty of Economics and Management Science No. 142, Working Paper.

Gebhardt, Andreas, and Jan-Steffen Hötter. 2016. *Additive manufacturing: 3D printing for prototyping and manufacturing.* Munich: Carl Hanser Verlag GmbH & Co. KG.

Geels, Frank W. 2002. “Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study.” *Research Policy* 31 (8-9): 1257–1274.

Gentzkow, Matthew. 2007. “Valuing new goods in a model with complementarity: Online newspapers.” *American Economic Review* 97 (3): 713–744.

Gershenfeld, Neil A. 2005. *Fab: The coming revolution on your desktop–from personal computers to personal fabrication.* Basic Books (AZ).

Ghobadian, Abby, Irene Talavera, Arijit Bhattacharya, Vikas Kumar, Jose Arturo Garza-Reyes, and Nicholas O’regan. 2020. “Examining legitimatisation of additive manufacturing in the interplay between innovation, lean manufacturing and sustainability.” *International Journal of Production Economics* 219:457–468.

Gibson, Ian, David Rosen, and Brent Stucker. 2014. *Additive manufacturing technologies: 3D printing, rapid Prototyping, and direct Digital Manufacturing.* Berlin: Springer.

Gittelman, Michelle, and Bruce Kogut. 2003. “Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns.” *Management Science* 49 (4): 366–382.

Gök, Abdullah, Alec Waterworth, and Philip Shapira. 2015. “Use of web mining in studying innovation.” *Scientometrics* 102 (1): 653–671.

Goldfarb, Avi, and Catherine Tucker. 2019. “Digital Economics.” *Journal of Economic Literature* 57 (1): 3–43.

Goldmanis, Maris, Ali Hortaçsu, Chad Syverson, and Önsel Emre. 2010. “E-commerce and the market structure of retail industries.” *The Economic Journal* 120 (545): 651–682.

Gottwald, Johannes F. 1971. Liquid metal recorder. US 3596285A, filed July 27, 1971.

Grossman, Gene M, and Elhanan Helpman. 1993. *Innovation and growth in the global economy.* MIT press.

Gschnaidtner, Christoph, Robert Dehghan, Hanna Hottenrott, and Julian Schwierzy. 2024. “Adoption and diffusion of blockchain technology.” *ZEW-Centre for European Economic Research Discussion Paper,* nos. 24-018.

Halbinger, Maria A. 2018. “The role of makerspaces in supporting consumer innovation and diffusion: An empirical analysis.” *Research Policy* 47 (10): 2028–2036.

———. 2020. “The relevance of makerspaces for university-based venture development organizations.” *Entrepreneurship Research Journal* 10 (2): 20200049.

Hall, Bronwyn H. 2006. “Innovation and diffusion.” Chap. 17 in *The Oxford Handbook of Innovation,* edited by Jan Fagerberg, David C. Mowery, and R.R. Nelson, 312–326. Oxford, UK: Oxford University Press.

———. 2020. “Patents, innovation, and development.” *Max Planck Institute for Innovation & Competition Research Paper* No. 20-07.

Hall, Bronwyn. 2022. “Patents, innovation, and development.” *International Review of Applied Economics* 38 (1–2): 1–26.

Harhoff, Dietmar, Francis Narin, Frederic M Scherer, and Katrin Vopel. 1999. “Citation frequency and the value of patented inventions.” *Review of Economics and Statistics* 81 (3): 511–515.

Hartl, Richard F, and Peter M Kort. 2017. "Possible market entry of a firm with an additive manufacturing technology." *International Journal of Production Economics* 194:190–199.

Hausman, Naomi. 2022. "University innovation and local economic growth." *The Review of Economics and Statistics* 104 (4): 718–735.

Henderson, Rebecca, Adam B Jaffe, and Manuel Trajtenberg. 1998. "Universities as a source of commercial technology: A detailed analysis of university patenting, 1965–1988." *Review of Economics and Statistics* 80 (1): 119–127.

Heyard, Rachel, and Hanna Hottenrott. 2021. "The value of research funding for knowledge creation and dissemination: A study of SNSF research grants." *Humanities and Social Sciences Communications* 8 (1): 1–16.

Hicks, Diana, Anthony Breitzman Sr, Kimberly Hamilton, and Francis Narin. 2000. "Research excellence and patented innovation." *Science and Public Policy* 27 (5): 310–320.

Hotelling, Harold. 1929. "Stability in competition." *The Economic Journal* 39 (2): 41–57.

Hottenrott, Hanna. 2022. *52. Research and development subsidies.* 420. Edward Elgar Publishing.

Hottenrott, Hanna, and Cornelia Lawson. 2017. "Fishing for complementarities: Research grants and research productivity." *International Journal of Industrial Organization* 51:1–38.

Hottenrott, Hanna, and Cindy Lopes-Bento. 2014. "(International) R&D collaboration and SMEs: The effectiveness of targeted public R&D support schemes." *Research Policy* 43 (6): 1055–1066.

Hottenrott, Hanna, Cindy Lopes-Bento, and Reinhilde Veugelers. 2017. "Direct and cross scheme effects in a research and development subsidy program." *Research Policy* 46 (6): 1118–1132.

Hottenrott, Hanna, and Robert Richstein. 2020. "Start-up subsidies: Does the policy instrument matter?" *Research Policy* 49 (1): 103888.

Hottenrott, Hanna, Michael E Rose, and Cornelia Lawson. 2021. "The rise of multiple institutional affiliations in academia." *Journal of the Association for Information Science and Technology* 72 (8): 1039–1058.

Hu, Bin, and Zhankun Sun. 2022. "Managing self-replicating innovative goods." *Management Science* 68 (1): 399–419.

Hull, Charles W. 1884. Apparatus for production of three-dimensional objects by stereolithography. US 4575330A, filed August 8, 1884.

Humphrey, David B. 2004. "Replacement of cash by cards in US consumer payments." *Journal of Economics and Business* 56 (3): 211–225.

Iaria, Alessandro, Carlo Schwarz, and Fabian Waldinger. 2018. "Frontier knowledge and scientific production: Evidence from the collapse of international science." *The Quarterly Journal of Economics* 133 (2): 927–991.

Jacob, Brian A, and Lars Lefgren. 2011a. "The impact of NIH postdoctoral training grants on scientific productivity." *Research policy* 40 (6): 864–874.

———. 2011b. "The impact of research grant funding on scientific productivity." *Journal of Public Economics* 95 (9-10): 1168–1177.

Jaffe, Adam B. 1989. "Real effects of academic research." *The American Economic Review,* 957–970.

Jaffe, Adam B, Manuel Trajtenberg, and Rebecca Henderson. 1993. "Geographic localization of knowledge spillovers as evidenced by patent citations." *The Quarterly journal of Economics* 108 (3): 577–598.

Jin, Haifeng, Qingquan Song, and Xia Hu. 2019. "Auto-Keras: An efficient neural architecture search system." In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining,* 1946–1956. ACM.

Jones, Raymond F. 1950. "Things Pass By." *Thrilling Wonder Stories* 46 (3): 48–67.

Jones, Rhys, Patrick Haufe, Edward Sells, Pejman Iravani, Vik Olliver, Chris Palmer, and Adrian Bowyer. 2011. "RepRap–the replicating rapid prototyper." *Robotica* 29 (1): 177–191.

Kemp, Adam. 2013. *The makerspace workbench: Tools, technologies, and techniques for making.* Maker Media, Inc.

Keune, Anna, and Kylie Peppler. 2019. "Materials-to-develop-with: The making of a makerspace." *British Journal of Educational Technology* 50 (1): 280–293.

Kinne, Jan, and Janna Axenbeck. 2020. "Web mining for innovation ecosystem mapping: A framework and a large-scale pilot study." *Scientometrics* 125.

Kinne, Jan, and David Lenz. 2021. "Predicting innovative firms using web mining and deep learning." *PLoS ONE* 16 (4): e0249071.

Kleer, Robin, and Frank T Piller. 2019. "Local manufacturing and structural shifts in competition: Market dynamics of additive manufacturing." *International Journal of Production Economics* 216 (C): 23–34.

Kodama, Hideo. 1981. Stereoscopic figure drawing device. JPS 56144478A, filed November 10, 1981.

Kota, Sridhar, Kannan Sethuraman, and Raymond Miller. 2000. "A metric for evaluating design commonality in product families." *Journal of Mechanical Design* 122 (4): 403–410.

Kreyer, Ann-Christin. 2025. "Essays on the economics of digitalization and innovation." Forthcoming. PhD diss., Ludwig Maximilian University of Munich.

Krieger, Bastian. 2024. "Heterogeneous university funding programs and regional firm innovation: An empirical analysis of the German Excellence initiative." *Research Policy* 53 (5): 104995.

Krieger, Joshua L, Monika Schnitzer, and Martin Watzinger. 2024. "Standing on the shoulders of science." *Strategic Management Journal* 45 (9): 1670–1695.

Krücken, Georg, Guido Bünstorf, Uwe Cantner, Jetta Frost, Thomas Grebel, Julian Hamann, Hanna Hottenrott, Anna Kosmützky, Frank Meier, Uwe Schimank, et al. 2021. "Multipler Wettbewerb im Hochschulsystem–Interdisziplinäre Perspektiven und wissenschaftspolitische Implikationen." *Das Hochschulwesen* 69 (3): 4.

Leinster, Murray. 1945. "Things Pass By." *Thrilling Wonder Stories* 27 (2): 11–35.

Lukeš, Martin, Maria Cristina Longo, and Jan Zouhar. 2019. "Do business incubators really enhance entrepreneurial growth? Evidence from a large sample of innovative Italian start-ups." *Technovation* 82:25–34.

Malte, Aditya, and Pratik Ratadiya. 2019. "Evolution of transfer learning in natural language processing." *arXiv preprint arXiv:1910.07370.*

Mansfield, Edwin. 1995. "Academic research underlying industrial innovations: Sources, characteristics, and financing." *The review of Economics and Statistics,* 55–65.

Marx, Matt, and Aaron Fuegi. 2020. "Reliance on science: Worldwide front-page patent citations to scientific articles." *Strategic Management Journal* 41 (9): 1572–1594.

Mersand, Shannon. 2021. "The state of makerspace research: A review of the literature." *TechTrends* 65 (2): 174–186.

Meulen, Barend Van der. 1998. "Science policies as principal–agent games: Institutionalization and path dependency in the relation between government and science." *Research policy* 27 (4): 397–414.

Meyer-Krahmer, Frieder, and Ulrich Schmoch. 1998. "Science-based technologies: University–industry interactions in four fields." *Research policy* 27 (8): 835–851.

Milgrom, Paul, and John Roberts. 1990. "The economics of modern manufacturing: Technology, strategy, and organization." *The American Economic Review* 80 (3): 511–528.

Moilanen, Jarkko. 2012. "Emerging hackerspaces–peer-production generation." In *Open Source Systems: Long-Term Sustainability: 8th IFIP WG 2.13 International Conference, OSS 2012, Hammamet, Tunisia, September 10-13, 2012. Proceedings 8,* 94–111. Springer.

Möller, Torger, Marion Schmidt, and Stefan Hornbostel. 2016. "Assessing the effects of the German Excellence Initiative with bibliometric methods." *Scientometrics* 109 (3): 2217–2239.

Moster, Petra. 2013. "Patents and innovation: Evidence from economic history." *Journal of Economic Perspectives* 27:23–44.

Myers, Kyle. 2020. "The elasticity of science." *American Economic Journal: Applied Economics* 12 (4): 103–134.

Narin, Francis, Kimberly S Hamilton, and Dominic Olivastro. 1997. "The increasing linkage between US technology and public science." *Research Policy* 26 (3): 317–330.

Nelson, Richard R. 1959. "The simple economics of basic scientific research." *Journal of Political Economy* 67 (3): 297–306.

Nielsen, Rasmus Kleis, and Richard Fletcher. 2020. "Democratic creative destruction? The effect of a changing media landscape on democracy." *Social media and democracy: The state of the field, prospects for reform,* 139–162.

Norman, George, and Jacques-François Thisse. 1999. "Technology choice and market structure: Strategic aspects of flexible manufacturing." *The Journal of Industrial Economics* 47 (3): 345–372.

Oancea, Alis. 2019. "Research governance and the future (s) of research assessment." *Palgrave Communications* 5 (1).

Palomeras, Neus, and Eduardo Melero. 2010. "Markets for inventors: Learning-by-hiring as a driver of mobility." *Management Science* 56 (5): 881–895.

Panda, Sunil Kumar, Kali Charan Rath, Sujit Mishra, and Alex Khang. 2023. "Revolutionizing product development: The growing importance of 3D printing technology." *Materials Today: Proceedings.*

Pattabhiramaiah, Adithya, Eric Overby, and Lizhen Xu. 2022. "Spillovers from online engagement: How a newspaper subscriber's activation of digital paywall access affects her retention and subscription revenue." *Management Science* 68 (5): 3528–3548.

Petrescu, Marius Gabriel, Costin Ilincă, and Maria Tănase. 2023. "Reliability of manufacturing technologies." In *Innovation and Sustainable Manufacturing,* 29–65. Elsevier.

Petrovic, Vojislav, Juan Vicente Haro Gonzalez, Olga Jordá Ferrando, Javier Delgado Gordillo, Jose Ramón Blasco Puchades, and Luis Portolés Griñan. 2011. "Additive layered manufacturing: Sectors of industrial application shown through case studies." *International Journal of Production Research* 49 (4): 1061–1079.

Pezzoni, Michele, Reinhilde Veugelers, and Fabiana Visentin. 2022. "How fast is this novel technology going to be a hit? Antecedents predicting follow-on inventions." *Research Policy* 51 (3): 104454.

Poege, Felix, Dietmar Harhoff, Fabian Gaessler, and Stefano Baruffaldi. 2019. "Science quality and the value of inventions." *Science Advances* 5 (12): eaay7323.

Pose-Rodriguez, Javier, Judy Ceulemans, Yann Ménière, Aliki Nichogiannopoulou, and Ilja Rudyk. 2020. *Patents and additive manufacturing: Trends in 3D printing technologies.* European Patent Office.

Pradel, Patrick, Zicheng Zhu, Richard Bibb, and James Moultrie. 2017. "Complexity is not for free: The impact of component complexity on additive manufacturing build time."

Reimers, Nils, and Iryna Gurevych. 2019. "Sentence-BERT: Sentence embeddings using siamese BERT-networks." In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP),* 3982–3992. Hong Kong, China: Association for Computational Linguistics, November.

Roach, Michael, and Wesley M Cohen. 2013. "Lens or prism? Patent citations as a measure of knowledge flows from public research." *Management Science* 59 (2): 504–525.

Roche, Maria P, Alexander Oettl, and Christian Catalini. 2024. "Proximate (Co-) working: Knowledge spillovers and social interactions." *Management Science* 70 (12): 8217–9119.

Röller, Lars-Hendrik, and Mihkel M Tombak. 1990. "Strategic Choice of flexible production technologies and welfare implications." *The Journal of Industrial Economics* 38 (4): 417–431.

Romer, Paul M. 1990. "Endogenous technological change." *Journal of Political Economy* 98 (5): 71–102.

Rotolo, Daniele, Diana Hicks, and Ben R Martin. 2015. "What is an emerging technology?" *Research Policy* 44 (10): 1827–1843.

Salazar, Mónica, and Adam Holbrook. 2004. "A debate on innovation surveys." *Science and Public Policy* 31 (4): 254–266.

Salmi, Jamil. 2016. "Excellence strategies and the creation of world-class universities." In *Matching visibility and Performance,* 13–48. Brill.

Salop, Steven C. 1979. "Monopolistic competition with outside goods." *The Bell Journal of Economics* 10 (1): 141–156.

Sandvik, Jason J, Richard E Saouma, Nathan T Seegert, and Christopher T Stanton. 2020. "Workplace knowledge flows." *The Quarterly Journal of Economics* 135 (3): 1635–1680.

Sauerwein, Marita, Eugeni Doubrovski, Ruud Balkenende, and Conny Bakker. 2019. "Exploring the potential of additive manufacturing for product design in a circular economy." *Journal of Cleaner Production* 226:1138–1149.

Savvides, Leandros. 2021. "3D printing in hackerspaces, makerspaces, and fab Labs." In *3D Printing Cultures, Politics and Hackerspaces,* 109–168. Emerald Publishing Limited.

Saxenian, AnnaLee. 1996. *Regional advantage: Culture and competition in silicon valley and route 128, with a new preface by the author.* Harvard University Press.

Schaper, Thomas, Sam Arts, and Reinhilde Veugelers. 2023. *Not like the others: Frontier scientists for high-impact inventions.* MSI Discussion Paper No. 2302, Working Paper.

Scherer, Frederic M, and Dietmar Harhoff. 2000. "Technology policy for a world of skew-distributed outcomes." *Research Policy* 29 (4-5): 559–566.

Schiermeier, Quirin. 2017. "Academic excellence: Golden Germany." *Nature* 549 (7670): 119–121.

Schmidt, Sebastian, Jan Kinne, Sven Lautenbach, Thomas Blaschke, David Lenz, and Bernd Resch. 2022. "Greenwashing in the US metal industry? A novel approach combining SO2 concentrations from satellite data, a plant-level firm database and web text mining." *Science of The Total Environment* 835:155512.

Schubert, Torben. 2009. "Empirical observations on new public management to increase efficiency in public research—boon or bane?" *Research Policy* 38 (8): 1225–1234.

Schubert, Torben, Rainer Frietsch, and Oliver Rothengatter. 2017. *An analysis of the Excellence initiative and its effects on the funded universities.* Fraunhofer Institute for Systems and Innnovation Research, ISI No.11, Working Paper.

Schumpeter, Joseph Alois Julius. 1934. *The Theory of Economic Development.* Cambridge, MA: Harvard University Press.

———. 1942. *Capitalism, socialism and democracy.* New York and London: Harper & Brothers.

Sethuraman, Nagarajan, Ali K Parlaktürk, and Jayashankar M Swaminathan. 2023. "Personal fabrication as an operational strategy: Value of delegating production to customer using 3D printing." *Production and Operations Management* 32 (7): 2362–2375.

Simmel, Georg. 1908. *Soziologie.: Untersuchungen über die Formen der Vergesellschaftung.* Duncker & Humblot.

Sinha, Arnab, Zhihong Shen, Yang Song, Hao Ma, Darrin Eide, Bo-June Hsu, and Kuansan Wang. 2015. "An overview of microsoft academic service (mas) and applications." In *Proceedings of the 24th international conference on world wide web,* 243–246.

Smuha, Nathalie A. 2021. "From a 'race to AI'to a 'race to AI regulation': Regulatory competition for artificial intelligence." *Law, Innovation and Technology* 13 (1): 57–84.

Song, Jing-Sheng, and Yue Zhang. 2020. "Stock or print? Impact of 3-D printing on spare parts logistics." *Management Science* 66 (9): 3860–3878.

Stephan, Paula E. 1996. "The economics of science." *Journal of Economic Literature* 34 (3): 1199–1235.

Stephan, Paula. 2012. *How economics shapes science.* Harvard University Press.

Sun, Luoyi, Guowei Hua, TCE Cheng, and Yixiao Wang. 2020. "How to price 3D-printed products? Pricing strategy for 3D printing platforms." *International Journal of Production Economics* 226:107600.

The White House. 2022. "Using additive manufacturing to improve supply chain resilience and bolster small and mid-size firms." Accessed January 5, 2025. https://www.whitehouse.gov/cea/written-materials/2022/05/09/using-additive-manufacturing-to-improve-supply-chain-resilience-and-bolster-small-and-mid-size-firms/.

Tijssen, Robert JW. 2001. "Global and domestic utilization of industrial relevant science: Patent citation analysis of science–technology interactions and knowledge flows." *Research policy* 30 (1): 35–54.

Tirole, J. 1988. *The theory of industrial organization.* MIT Press.

Trajtenberg, Manuel. 1990. "A penny for your quotes: Patent citations and the value of innovations." *The Rand Journal of Economics* 21:172–187.

Turko, Tamara, Gennady Bakhturin, Vitaly Bagan, Stanislav Poloskov, and Dmitry Gudym. 2016. "Influence of the program "5–top 100" on the publication activity of Russian universities." *Scientometrics* 109:769–782.

Ungern-Sternberg, Thomas von. 1988. "Monopolistic competition and general purpose products." *The Review of Economic Studies* 55 (2): 231–246.

Van Holm, Eric Joseph. 2014. "What are makerspaces, hackerspaces, and fab labs?" *Hackerspaces, and Fab Labs.*

———. 2015. "Makerspaces and contributions to entrepreneurship." *Procedia-Social and Behavioral Sciences* 195:24–31.

———. 2017. "Makerspaces and local economic development." *Economic Development Quarterly* 31 (2): 164–173.

Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. "Attention is all you need." In *Advances in Neural Information Processing Systems,* 5998–6008.

Veugelers, Reinhilde, Jian Wang, and Paula Stephan. 2022. *Do funding agencies select and enable risky research: Evidence from ERC using novelty as a proxy of risk taking.* Working Paper, Working Paper Series 30320. National Bureau of Economic Research.

Wang, Dashun, Chaoming Song, and Albert-László Barabási. 2013. "Quantifying long-term scientific impact." *Science* 342 (6154): 127–132.

Wang, Jian, Reinhilde Veugelers, and Paula Stephan. 2017. "Bias against novelty in science: A cautionary tale for users of bibliometric indicators." *Research Policy* 46 (8): 1416–1436.

Wang, Lucy Xiaolu, and Thomas Schaper. 2024. *Tracking and mapping intellectual property scholarship in Economics and Management.* UMass Amherst, MA, U.S. and ZEW–Leibniz Centre for European Econmic Research, Mannheim, Germany, Working Paper.

Weller, Christian, Robin Kleer, and Frank T Piller. 2015. "Economic implications of 3D printing: Market structure models in light of additive manufacturing revisited." *International Journal of Production Economics* 164 (C): 43–56.

West, Joel, and George Kuk. 2016. "The complementarity of openness: How MakerBot leveraged Thingiverse in 3D printing." *Technological Forecasting and Social Change* 102:169–181.

Yang, Tiantian, Jiayi Bao, and Howard Aldrich. 2020. "The paradox of resource provision in entrepreneurial teams: Between self-interest and the collective enterprise." *Organization Science* 31 (6): 1336–1358.

Yu, Sandy. 2020. "How do accelerators impact the performance of high-technology ventures?" *Management Science* 66 (2): 530–552.

Zhang, Han, Donald Patton, and Martin Kenney. 2013. "Building global-class universities: Assessing the impact of the 985 Project." *Research Policy* 42 (3): 765–775.

Zhang, Zhiming, Da Ren, Yanfei Lan, and Shanxue Yang. 2022. "Price competition and blockchain adoption in retailing markets." *European Journal of Operational Research* 300 (2): 647–660.

Zong, Xiaohua, and Wei Zhang. 2019. "Establishing world-class universities in China: Deploying a quasi-experimental design to evaluate the net effects of Project 985." *Studies in Higher Education* 44 (3): 417–431.

Zucker, Lynne G, Michael R Darby, and Jeff Armstrong. 1998. "Geographically localized knowledge: Spillovers or markets?" *Economic Inquiry* 36 (1): 65–86.