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Successful digital technology development: A multilevel and spatial approach on organizations and their ecosystems

Ann Hipp [a,b,*], Enno Kohlisch [c]

[a] Johann Heinrich von Thünen Institute, Institute of Rural Economics, Bundesallee 64, 38116, Braunschweig, Germany
[b] University of Bremen, Faculty of Business Studies and Economics, Max-von-Laue-Str. 1, 28359 Bremen, Germany
[c] German Economic Institute, Konrad-Adenauer-Ufer 21, 50668, Köln, Germany

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ABSTRACT

The development of digital technologies in ecosystems became a key strategy for firms to achieve competitive advantages. However, despite the increasing importance of innovation ecosystems, only little is known about their spatial and multilevel structure. This study analyzes the impact of an organization's multilayer and spatial innovation ecosystem on the success of digital technology development. The authors estimate a multilevel model based on three levels by using data on 411,389 patents including 57,627 digitalization patents from the German and European Patent Office, which are nested within 25,017 organizations in Germany and a specific ecosystem, for the period from 2010 to 2021. The results show that the probability of developing a digitalization patent is higher for large firms than for small and medium-sized enterprises (SMEs). Furthermore, an ecosystem of applied research organizations and universities as well as technology subsidies increases patent success of large firms in this field compared to more established technologies. SMEs, in contrast, only play a minor role in the development of digital technology, and the impact of their ecosystems and subsidies is less obvious. In addition, this study provides recommendations for technology managers and policy makers to support the transformation towards digitalization.

1. Introduction

Digital technologies became important types of product innovation for organizations to achieve competitive advantages and to survive (Nambisan et al., 2017). Digital technologies are products with reprogrammable functionality and data homogenization that entail the process of converting information into a digital, computer-readable format; typical examples are road sign detection, drones, and sensors (Yoo et al., 2010). Such technologies entail high levels of uncertainty and ambiguity in their development because of their unpredictability regarding usage and future application, shorter life cycles, and a complex product architecture. Therefore, they significantly differ from more established technologies (Yoo et al., 2012).

While a wide range of studies examines the potential of digital technologies for society and the economy (e.g., Mansell, 2021; Appio et al., 2021; Ciarli et al., 2021), less is known about the spatial and multilayer determinants of their development processes. In particular, these studies mostly focus on how to adopt digital technologies within organizations (Endres et al., 2022), necessary skills for their generation and usage (Ciarli et al., 2021), formalization processes (Pesch et al., 2021), and internationalization structures (Andersson et al., 2023). In parallel, the research field of innovation ecosystems underlines the co-development of products with close organizations to access and exchange resources (Gawer and Cusumano, 2014). To date, we know much about the importance of ecosystems for innovation (e.g., Jiang and Stylos, 2021; Beltagui et al., 2020; Radziwon and Bogers, 2019; Adner and Kapoor, 2010) and entrepreneurship (Endres et al., 2022; Elia et al., 2020; Sussan and Acs, 2017), but their multilayer and spatial structure remains less understood (Baldwin et al., 2024; Prokop and Thompson, 2023).

However, the multilayer and spatial structure of innovation ecosystems is important to understand because organizations are nested and interconnected within a geographically constrained context in which they transfer knowledge. This is substantial for innovation and digital technology development (Oh et al., 2016). Spatial proximity between interconnected actors is thereby necessary for capturing value from innovation, for learning, and for the diffusion of tacit knowledge in an ecosystem (Audretsch et al., 2022; Liang and Li, 2023). Moreover, a

* Corresponding author at: Johann Heinrich von Thünen Institute, Institute of Rural Economics, Bundesallee 64, 38116, Braunschweig, Germany.
E-mail address: ann.hipp@thuenen.de (A. Hipp).

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better understanding of the intangible factors of innovation ecosystems, such as knowledge flows, is decisive to ensure cohesion among actors and ecosystem evolution, especially in digital environments (Neto et al., 2024). Similarly, we need to better understand the multilayer structure of innovation ecosystems to study the impact of nesting (Baldwin et al., 2024). So far, there have been only studies on multilevel innovation in technical or regime contexts (Walrave et al., 2018; Kuan and West, 2023; Reiter et al., 2024), while the simultaneous embeddedness of innovation in an organizational and geographical context is less clear. As a result, organizations may often undervalue ecosystems and refrain from participation due to unintended knowledge spillovers, transaction and operational costs (Cuvero et al., 2023), competitive dynamics (Gomes et al., 2021), or initiative, interdependence and integration risks (Adner, 2006).

Given these high uncertainties that might exacerbate the risks and ambiguities of digital innovation management (Pesch et al., 2021; Nambisan et al., 2017; Loebbecke and Picot, 2015), we need to know much more about the spatial and multilevel structure of innovation ecosystems to appropriate value from knowledge access and exchange with close partners. If these resources are used effectively in the digital economy, they will ensure competitive advantages and sustained economic growth (Liang and Li, 2023).

The authors apply resource-based and systemic concepts (Alam et al., 2022; Wang, 2021; Adner and Kapoor, 2010; Teece, 2006) to analyze the multilayer structural components of innovation ecosystems—i.e., the innovation capabilities of actors, which are nested in a particular spatial environment—on the success of an organization's digital technology development. The research question is as follows: *How does the multilayer and spatial structure of an organization's innovation ecosystem support the success of digital technology development?* The authors expect that certain structural components of an innovation ecosystem, such as the presence of universities, public research institutes, or a supportive regulatory environment, will provide complementary resources, interdependencies, and network effects that reduce an organization's uncertainties and ambiguity in digital technology development.

To account for the multilayer structure of innovation (Audretsch et al., 2022; Bischoff et al., 2023), the authors estimate a multilevel model based on three levels by using data on 411,389 patents from the German and European Patent Office (DPMA/EPO), which are nested within 25,017 organizations in Germany and a specific ecosystem, for the period from 2010 to 2021. They deploy a new measure to identify 57,627 digitalization patents based on International Patent Classification (IPC) classes and measure the spatial structure of an organization's ecosystem by retrieving region-specific data from the INKAR database and subsidy data from the Foerderkatalog.

This study contributes to the research field of digital innovation management and innovation ecosystems with regard to the multilayer and spatial dimension of the development of digital technologies. First, it goes beyond a focus on the firm-internal organizational processes and outcomes of digital innovation management (e.g., Ciarli et al., 2021; Pesch et al., 2021; Endres et al., 2022; Chouaibi et al., 2022) by adopting a spatial approach that includes the co-existence and interconnections of a diverse set of actors within a geographically constrained context. This helps to better understand the access and exchange of organizational resources for digital technology development. Second, in addition to traditional innovation ecosystem studies that focus on specific actors, organizational factors, or sectors (Gomes et al., 2021; Jiang and Stylos, 2021; Beltagui et al., 2020), the authors explore the multilevel structure of a digital technology ecosystem. Specifically, they investigate the hierarchical and nested structure of developing digital technologies by utilizing complementarities, interdependencies, and network effects, thereby extending recent studies (Baldwin et al., 2024; Neto et al., 2024; Walrave et al., 2018).

This study is structured as follows: Section 2 provides the theory and hypotheses on the actors and their resources for digital technology development, the structure of their innovation ecosystem, and the role of subsidies. Section 3 encompasses the empirical strategy including the sample selection, data, and method used. Section 4 describes the results of the analysis. These findings are discussed in Section 5. Section 6 concludes.

2. Theory development and hypotheses

2.1. Digital technologies, patents, and innovation

Digital technologies are significantly novel products or services characterized by reprogrammable functionality (through its "Von-Neumann" architecture) and data homogenization (through the inclusion of data in 0 and 1), resulting in malleable, editable, open, and transferrable solutions (Yoo et al., 2010). Digital technologies transfer capabilities into objects of physical materiality for private or business use, which are hard to change but can be seen and touched, e.g. medical sensors on clothing (Yoo et al., 2012). Many digital technologies are patentable and related to product innovation (Pesch et al., 2021). Further, firms need to protect their digital inventions formally and obtain intellectual property rights (Miric et al., 2019). Ardito et al. (2018) give an overview of the reasons for using patents as an indicator to capture digital technology developments. For instance, patenting is a common practice among innovative organizations, the requirements for a patent application are related to innovative activity, and they possess a vast longitudinal availability. Since all patents are classified into their respective technology (i.e., IPC classes), samples of specific technologies and information, like participating organizations or the location of the inventors, allow for comprehensive analyses. Most other indicators for innovation like survey or process innovation data do not offer such longitudinal or cross-sectional richness. However, not all inventions are patentable, some firms prefer secrecy or other techniques to protect their intellectual property, differences exist across countries and technologies, and the simple count of patents does not fully indicate a certain economic value (ibid.).

Digital technologies possess high degrees of uncertainty and ambiguity in their development processes for the following reasons: First, organizations cannot predict how digital technologies impact markets, customers, and competitors (Loebbecke and Picot, 2015). Because digital technologies can complement physical products, such as security cameras that connect to mobile phones in case of suspicious incidents, they often remain incomplete and fluid as they continue to evolve after launch and implementation, increasing the uncertainty and ambiguity regarding their usage and application (Nambisan et al., 2017). Second, managers might not fully understand the functionalities and effects of digital technologies (Nylén and Holmström, 2015), making the market responses hard to foresee (Pesch et al., 2021). Third, since digital technology development projects often include members from different business units, which possess diverse capabilities, motives, and goals, their actions can cause coordination ambiguities (Nambisan et al., 2017).

Nonetheless, digital technologies have an increasing and disruptive impact on society and economy (Bohnsack et al., 2021; Santoalha et al., 2021). They enable automation, data storage, and predictive analysis (Agrawal et al., 2019). Furthermore, their application offers incomparable opportunities for the development of new products (Verganti et al., 2020). Different actors, such as users, competitors, suppliers, or research organizations, can provide inputs for the development of digital technologies (Nambisan et al., 2017; Bohnsack et al., 2021). However, it remains an underexplored issue which actors and resources in a multilayer and spatial context affect the probability of organizations to develop digital technologies.

2.2. Actors and resources for digital technology development

A resource-based view (RBV) is used to identify the relevant actors and their resources for digital technology development. The RBV focuses on the resources of an organization to achieve a competitive advantage (Barney, 1991). These assets have certain characteristics (i.e., value, rarity, non-imitability, non-substitutability, and non-transferability), and need to be accumulated to retain this competitive advantage (ibid.). Interestingly, recent research shows that the resources of large firms and SMEs for digital technology development largely differ (Chaudhuri et al., 2022). The following section therefore explores the role of large firms and SMEs for the success of digital technology development.

Technology giants, such as Audi or General Motor, constitute important actors of digital technology development (Bohnsack et al., 2021) for three reasons. First, these technology giants usually have large internal research and development (R&D) departments and spend more resources on R&D than SMEs (Veugelers, 1997). Their advantages of scale and scope support the generation of those types of innovation that require large and specialized teams or particular equipment (Cohen and Klepper, 1992). Since digital technology development is highly unpredictable and ambiguous, firms with larger internal R&D might be better able to encounter these uncertainties by investing more resources and adapting more advanced technologies in comparison to SMEs. Second, digital technologies require skills to be developed and introduced in production processes and to support the new organization, including the division of labor and coordination with buyers and suppliers (Ciarli et al., 2021). These digital skills are shaped by, for example, competencies related to information and communication technology (ICT) (Bessen, 2019). Larger firms are capable to attract and retain such skilled workers and—together with a higher technology adaption rate—achieve higher productivity than SMEs (Idson and Oi, 1999). Third, since larger firms are more likely to engage in risky projects (Audretsch and Keilbach, 2008), and digitalization projects are highly risky (Chouaibi et al., 2022), we expect that they carry out such development projects more often.

However, there exist SMEs that also engage in digital technology development. For example, B-Horizon GmbH develops specialized integrated circuits, Commsolid GmbH focuses on ultra-low power Internet of Things devices, and KONUX GmbH advances digital solutions in the rail transport. In general, SMEs show higher agility, adaptation, and ambidexterity, for instance, in smart manufacturing (Del Giudice et al., 2021). SMEs are more flexible than large firms and absorb a disproportionate share of industrywide output fluctuation (Mills and Schumann, 1985). Moreover, SMEs are less bureaucratic and react more quickly to market and technological changes (Rothwell and Zegveld, 1982). Also, they devote more resources to external collaborations (White, 1988) and use them more effectively than large firms (Nooteboom, 1994) in order to exchange information, retrieve resources, transfer technologies, and manage risks (Nieto and Santamaría, 2010).

Nonetheless, even though SMEs might have an advantage over large firms to organize development processes, we posit that large firms have more resources to better achieve digital innovation success:

H1. The probability of developing a digitalization patent is higher for large firms than for small and medium-sized enterprises.

2.3. Ecosystem resources and digital technology development

An ecosystem is a complex system consisting of actors that are interdependent through their structural couplings, co-evolving, and in possession of agency (Choi et al., 2001). It can emerge for different purposes, such as the creation of innovation, business, or entrepreneurship, and can include intra- or inter-systemic interactions on diverse tasks (Wang, 2021). In innovation ecosystems, a multilateral set of independent actors relate to jointly materialize a focal value proposition and appropriate returns (Adner and Kapoor, 2010). Because they simultaneously face cooperation and competition, ecosystems can evolve in unforeseen ways and require orchestration (ibid.). Based on this co-evolutionary process, innovation ecosystems might follow a certain life cycle including birth, expansion, leadership, and self-renewal (Gomes et al., 2021).

Particular features of innovation ecosystems are its economic complementarities and technological interdependencies among the actors, which enable access and use of specialized complementary resources and/or capabilities (Teece, 2006), and network effects that allow for independent search and experimentation through the diversity of interconnected actors (Baldwin et al., 2024). These interdependence and network effects can increase over time due to social exchange and trust (Alam et al., 2022) and are particularly important for reducing uncertainties in technology development processes (Adner and Kapoor, 2010). Because of the larger uncertainties and ambiguities in developing digital technologies, firms often engage in ecosystems to create product innovation (Bohnsack et al., 2021). Current studies found large spatial disparities in the generation of digital technologies (Santoalha et al., 2021).

The spatial dimension of ecosystems is particularly important to enable knowledge transfer, interactive learning, and innovation (Balland et al., 2022). It further facilitates other forms of proximity, such as cognitive or social proximity (Balland et al., 2015). The unique advantage of spatial proximity is that tacit knowledge can be transferred within spatially concentrated communities though face-to-face communication and learning by doing-using-interacting, in contrast to codified knowledge (e.g., in blueprints or books) that can be reproduced or copied anywhere (Polanyi, 1967). These locational advantages cannot be easily reproduced elsewhere (Maskell and Malmberg, 1999). While current studies in the field of entrepreneurial ecosystems often incorporate a multilevel and spatial focus by acknowledging different layers of technological or system development (Baldwin et al., 2024; Cuvero et al., 2023; Prokop and Thompson, 2023), this remains underdeveloped in the context of innovation ecosystems.

Actors of a spatial innovation ecosystem are large firms, SMEs, and public research organizations including universities, but also supporting agencies, such as banks or regulators (Gomes et al., 2021). Firms are core actors of knowledge creation and exchange on digital technologies (Bohnsack et al., 2021; Alam et al., 2022). Especially large firms can take a leading role within an ecosystem by setting the goals and creating a common platform (Gawer and Cusumano, 2014). They often enter into collaborations with SMEs to retrieve their specialized knowledge (Bjerke and Johansson, 2015), even though they are usually less incentivized to share information with other actors (Röller et al., 2007). In contrast, SMEs have higher collaboration intensities than large firms to access resources, such as physical and human capital (Hottenrott and Lopes-Bento, 2016). They often participate in digital entrepreneurial ecosystems to support entrepreneurial activities (e.g., Elia et al., 2020; Endres et al., 2022; Sussan and Acs, 2017). Thus, both large firms and SMEs might provide complementary resources, interdependence, and network effects in an organization's digital ecosystem.

Public research organizations can either have a focus on basic or applied research. Basic research often does not aim to appropriate or commercialize products (Beise and Stahl, 1999), but it accounts for substantial spillovers (Funk, 2002) and breakthrough innovation (Perkmann et al., 2013). Applied research organizations rather focus on short-term technology management and technical assistance, but they are locally anchored to increase the competitiveness of firms (Giannopoulou et al., 2019). We expect that particularly applied research organizations in an innovation ecosystem reduce uncertainty and ambiguity in the development of digital technologies because of their technical assistance, application focus, and local impact.

Universities in an innovation ecosystem are low-risk partners with a focus on basic research and education that enable public funding (Tether, 2002), attract human capital (Faggian and McCann, 2008), produce spillovers for the industry (Drucker, 2016), and contribute to firm innovation (Moon et al., 2019). They received particular attention in the Triple Helix model, affecting knowledge and industrial production through a strong university–industry–government network (Etzkowitz and Leydesdorff, 1997). In the digital ecosystem, they deliver new scientific knowledge (Sussan and Acs, 2017), ideas and resources (Alam et al., 2022), and support the emergence of digital technologies (Mas and Gómez, 2021). SMEs might particularly profit from their spillovers, and large firms attract engineers with digital skills trained in universities (Casalet and Stezano, 2020). However, the long-term orientation of universities on basic research, knowledge creation, and training (Giannopoulou et al., 2019) might oppose the application-oriented focus required for the development of digital technologies and, therefore, might not necessarily reduce an organization's uncertainties and ambiguities in this process.

Two prominent examples underscore the importance of specific actors and their interdependencies in a spatial ecosystem for digital technology development. First, the ecosystem around Erlangen-Nuremberg hosts the largest public research institute of the Fraunhofer association, i.e., the Fraunhofer Institute for Integrated Circuits (IIS), that attained worldwide relevance by developing the mp3 standard around the 1990s. Today, the IIS employs about 1200 people and is mainly focused on digital audio, media, and cognitive sensor technologies. It also offers an integrated degree program together with the local University of Erlangen-Nuremberg to allow students insights into applied research. This university is very patent active and was ranked fifth of all universities in Germany and 49th in the world (Haag et al., 2024). Within this ecosystem, large firms like Siemens AG (electronics), Siemens Healthcare (medical engineering), or Continental and Schaeffler (automotive suppliers) are responsible for 90 % of all patent applications. Many SMEs—such as Kopernikus Automotive GmbH specialized in autonomous parking, Portabiles HealthCare Technologies GmbH developing therapies for Parkinson's disease, or JUMATECH GmbH focusing on high-current printed circuit boards—are located in this ecosystem to utilize complementary resources, interdependencies, and network effects for their digital technology development projects.

Second, the ecosystem in the region around Aachen is a well-known area for the joint development of information processing technologies, especially in the mobile network environment. It hosts the RWTH Aachen, which is ranked fourth of all universities in Germany (Haag et al., 2024), and basic research organizations of the Helmholtz Association, such as Forschungszentrum Jülich with 7500 employees. Its ecosystem encompasses a diverse array of Fraunhofer institutes and numerous SMEs that maintain strong collaborative relationships with the local university. A large firm in the area is LM Ericsson including its Ericsson Eurolab, which was founded in 1991 and has 600 employees who are currently working on 6G mobile network technologies. Other large firms in the ecosystem are Ford Motor (automotive), Luminleds (electric lamps and lights), the FEV Group (automotive), or the Saint-Gobain Group (multi-industry), which add interdependencies, knowledge transfer, and network learning for digital solutions.

Based on the importance of the actors and their interrelations in the ecosystem mentioned above, we derive the following hypotheses:

H2. The probability of developing a digitalization patent increases with the presence of a) large firms, b) small and medium-sized enterprises, c) applied research organizations, d) basic research organizations, and e) universities in the innovation ecosystem.

2.4. Financial support to develop digital technologies

Since negative externalities in form of costs and uncertainties in the process of technology development and a low appropriability of patents can arise, the state often provides financial incentives for innovation in form of, for example, technology subsidies, tax reductions, or public procurement (Arrow, 1962). In particular, technology subsidies are a frequently used policy instrument to reduce market failures and to offer financial support for R&D and innovation (for a recent overview, see Jugend et al., 2020). Technology subsidies are effective financial incentives for developing new or improved products and technologies without crowding out internal R&D expenses (Dimons and Pugh, 2016). Recent studies provide empirical evidence on the importance of technology subsidies for innovation and economic growth of regions (Cantner et al., 2019).

Technology subsidies are also used to incentivize the development of digital technologies (Mansell, 2021; Liang and Li, 2023). Related to the empirical examples above, the ecosystems of Aachen and Erlangen-Nuremberg received comparatively high project funding in recent years through several regional and national funds. However, even though policy makers focused on supporting digital development projects, especially of SMEs (EFI, 2023), their effectiveness was recently called into question when it comes to future venture capital investments, sales, or initial public stock offerings (Fini et al., 2023). Nonetheless, since technology subsidies might be particularly important for organizations in an innovation ecosystem to reduce the high uncertainties and costs related to digital technology development, we argue that they increase the probability of generating a digitalization patent.

Thus, we hypothesize the following:

H3. The probability of developing a digitalization patent increases with the amount of technology subsidies in the innovation ecosystem.

3. Empirical approach

3.1. Sample selection

The hypotheses are tested in the context of patent applications for digital technologies in Germany between 2010 and 2021 when the government established first concepts of digitalization and respective support schemes, such as the "digital agenda" (BMWK, 2015). Germany is a good example to study the determinants of digital technology development due to its growing international relevance, the emergence of digital ecosystems, and supportive policy measures in recent years.

First, Germany has the largest number of world-class patents in the field of digital technologies among all European states and it ranks 6th in international comparison after the US, Japan, Korea, China, and Canada in 2015 (Gramke and Glauser, 2017).

Second, German regions have prominent digital ecosystems that are covered by studies from artificial intelligence (Kinne and Axenbeck, 2020), to microelectronics and photonics (Schroth and Häußermann, 2018), to telecommunications (Rohrbeck et al., 2009). In these ecosystems, a diverse set of actors is located in close proximity to each other which opens up various channels of resource transfer, interdependencies, and network effects. However, there are differences in the configuration of ecosystems, and some can be found in more peripheral areas, such as the germanium electronics ecosystem in Frankfurt/Oder, which creates a distinct specialization pattern in the patenting landscape (Hornych and Schwartz, 2009). These differences also exist in the deployment of the digital technologies (Hölscher et al., 2021).

Third, the German government allocates generous subsidies to support digital technology development in the realm of ICT research programs since the 2000s (BMWK, 2011). The shift towards digitalization only occurred during the 2010s when the digital transformation was assessed a main driver of economic growth and societal welfare (BMWK, 2015). Especially SMEs received political attention because they lack financial resources and engineers with ICT-related skills to engage in digital technology development (EFI, 2023).

3.2. Data

The authors collected a set of data by using different sources: Patent and organizational data is retrieved from the patent database created at the German Economic Institute, subsidy data is composed from the Foerderkatalog, and regional data is obtained from the INKAR database provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). The operationalization of the variables is explained in the following section.

3.2.1. Digitalization patent data

The patent database of the German Economic Institute contains all patent applications with an application year after 1994 and an intended protection in Germany obtained from different patent offices[1] and adjusted by families to prevent double counts. This analysis examines four distinct dimensions of a patent application: time, inventors, technology, and applicants. First, the observation period is from 2010 to 2021. The year 2021 represents the most recent fully analyzable year because a) post-filing, applicants have the option to maintain the confidentiality of their submission for 18 months, and b) applicants have a one-year window to file a follow-up application at another patent office with the same application year, which influences family adjustments and, therefore, patent analysis. Second, each patent application is geographically categorized based on the inventor's residence. Prior research indicates that the inventor's residence is the most accurate geographic indicator for identifying where the innovative work behind a patent was conducted (Fritsch and Wyrwich, 2021; OECD, 2009). Third, to classify patents as related to digital technology, we utilize the lowest hierarchy of the IPC, specifically the main and subgroups. Following the methodology of Ardito et al. (2018) and Ceipek et al. (2021) for Internet of Things solutions, we define a set of IPCs that align with the following definition of digital technology:

We understand digital technology as the conversion of analog signals into digital values and formats, the collection or generation of digital data, processing or storage in a digital technical system, or the creation of primarily digital representations. A comparison with Inaba and Squicciarini (2017) provides insights into how we differentiate between ICT and digitalization. We excluded all components that do not meet our definition of digital technologies, such as hardware components (except semiconductors) and their manufacturing, for example, light-emitting diodes (LEDs), sensors in general, or electronic circuits and cables.[2] Overall, we include 3474 of the 51,691 IPCs in our sample as related to digital technology. Our dependent variable DIGITAL is 1 if at least one digitalization affine IPC-class is included in a patent, and 0 otherwise. Table 1 shows the Top−20 IPC subgroups with the most digitalization patents. These subclasses account for 95.5 % of all digitalization affine patents in our analysis.

Fourth, we consider applicants of digitalization patents, which are juristic persons, and categorize these organizations into five types (ACTOR). Firms are distinguished by their size between large firms and SMEs. Following the definition of the EU commission, SMEs are firms with less than 250 employees and less than 50 million Euro in turnover. In addition, we consider the group context of each firm. For instance, a start-up that is controlled by a large corporation is not counted as SME, because firms inside a group have more financial opportunities as opposed to independent SMEs (EU Commission, 2020). The same holds true for SMEs that are controlled by other entities in case together they have more than 250 employees or 50 million Euro in turnover.

Furthermore, the variable UNI represents universities as well as firms that are direct subsidiaries of universities, closely connected to a university context, and operate without any profit goals. The latter are organizations like NaMLab gGmbH, a company of the Technical University Dresden, or NEXT Energy that is part of the University of Oldenburg. However, this variable mainly relates to the 186 patent-active universities in our dataset. BASIC are all organizations with ties to the Leibniz (~21,000 employees), Helmholtz (~45,000 employees), or Max-Planck institutions (~24,000 employees). These institutions are the largest associations for basic research in Germany. APPLIED represents all organizations of the Fraunhofer association, which is the largest organization for applied research in Europe with 32,000 employees and thus an important part of the German research landscape. These three types of research organizations might have legal forms like "GmbHs" but are not classified as firms when they are subsidiaries of the respective institutions and, therefore, publicly funded. Each organization is assigned to one of eleven aggregated sectors (SECTOR) based on the more detailed 3-digit level defined by the "Klassifikation der Wirtschaftszweige" (Statistisches Bundesamt, 2008).

3.2.2. Ecosystem data

We use the ecosystem level of 96 German planning regions. Planning regions are non-administrative entities arranged based on commuting patterns and the aggregation of NUTS-3-level administrative regions. NUTS-3 regions are amalgamated into a single planning region when they exhibit substantial commuting interactions indicating significant interconnections. Each planning region is designed to maximize internal connectivity while minimizing external linkages, thereby forming a self-contained ecosystem.[3] The configuration of the ecosystem is measured by the presence and geographical proximity between different kinds of ACTORs in a region in each year.[4] Our baseline specifications for ECO_APPLIED, ECO_BASIC, and ECO_UNI are equal to 1 if at least one respective actor applied for one patent in the region and year, and 0 otherwise. Since this measurement for the variables ECO_SME and ECO_LARGE would be equal to 1 for almost each region and year, we used their specific number instead of their presence.[5]

Furthermore, we included subsidy data from the Foerderkatalog,[6] which entails over 110,000 running and completed projects to financially support the development of new or improved products and technologies by six federal ministries since 1960.[7] The subsidies are measured by the organization that performed a project and thus measure the place where the research for a project is conducted. Subsidies usually take some time to unfold in a region and, therefore, a lag structure of four years is applied (Cantner et al., 2019). Our variable SUBSIDIES includes the natural logarithm of the amount of subsidies divided by the total population in each region and year.

Last, we include several region-specific variables from the INKAR database. We control for the economic structure of a region by using GDP as the natural log of a region's per capita income. UNEMP is the unemployment rate. Regional human capital is captured by STUDENT that accounts for the number of students as percent of the total population between 18 and 25 years (Bischoff et al., 2023). The agglomeration structure (AS) is measured by the types of planning regions URBAN, SUBURBAN, and RURAL assigned by the BBSR to each planning region.

[1] Due to the home bias (Bacchiocchi and Montobbio, 2010) and an over-representation of applicants with a German origin, this approach would be counterproductive for an international comparison, but it is necessary for a detailed contemplation of digitalization patents in Germany, which requires comprehensive information from different patent offices.

[2] It is important to note that, at the German Patent and Trade Mark Office (DPMA) and other patent offices, pure software codes are excluded from patent protection and are instead protected under copyright law.

[3] Kropp and Schwengler (2016) give an overview of how functional regions are built in general and the performance of planning regions in specific.

[4] We refrain from measuring direct visible links between the organizations because this would neglect the diversity of knowledge flows, interdependencies, and network effects. Only 3 % of the observed patent applications between 2010 and 2021 represent cooperations between applicants.

[5] An important limitation with this approach is that it excludes organizations within the ecosystem that do not engage in patent applications.

[6] See: https://foerderportal.bund.de/foekat/jsp/StartAction.do?actionMode=list

[7] However, the database excludes policy measures for which one of the six ministries is not involved. Moreover, projects that are solely funded by the federal state or European projects are excluded.

Table 1
Top-20 IPC subclasses with the overall most digitalization patents.

Subclass	Description	All IPC (Main- or Subgroup)	All Patents	Digital IPC	Digital Patents	Percent Digital/ Patent	Percent Digital overall
H01L	Semiconductor devices not covered by class H10	535	10,228	535	10,228	100.0	17.7
G06F	Electric digital data processing	544	9105	544	9105	100.0	15.8
H04L	Transmission of digital information, e.g., telegraphic communication	523	6085	523	6085	100.0	10.6
B60W	Conjoint control of vehicle sub-units of different type or different function	105	7753	26	4866	62.8	8.4
H04W	Wireless communication networks	320	3643	314	3616	99.3	6.3
G06Q	Information and communication technology [ict]	82	3009	82	3009	100.0	5.2
G08G	Traffic control systems	47	2879	17	2206	76.6	3.8
G06T	Image data processing or generation in general	106	2149	106	2149	100.0	3.7
G05B	Control or regulating systems in general	89	2889	26	1933	66.9	3.4
H05K	Printed circuits	57	3224	32	1765	54.7	3.1
G06K	Graphical data reading	73	1874	49	1614	86.2	2.8
A61B	Diagnosis; surgery; identification	374	6051	8	1486	24.6	2.6
H04N	Pictorial communication	535	1848	350	1290	69.8	2.2
G01C	Measuring distances, levels or bearings	110	1856	6	1236	66.6	2.1
G06N	Computing arrangements based on specific computational models	48	1094	48	1094	100.0	1.9
G06V	Image or video recognition or understanding	105	1091	105	1091	100.0	1.9
G10L	Speech analysis techniques or speech synthesis	123	924	123	924	100.0	1.6
H03M	Coding, decoding or code conversion, in general	89	562	89	562	100.0	1.0
H02J	Circuit arrangements or systems for supplying or distributing electric power	73	2589	5	381	14.7	0.7
G01S	Radio direction-finding	306	4235	33	366	8.7	0.6

Notes: The table displays the 20 different IPC subclasses that have the most digital patents in the analyzed timeframe. A patent is characterized as affine to digital technology if at least one of the named IPCs is digital. The weight of a patent is only allocated to the digital IPCs. Consequently, a patent with, for example, three IPCs containing one digital affine IPC is considered a digital affine patent and the weight of one is added to the digital affine IPC. The descriptions are shortened to improve readability.

3.3. Multilevel method

The data structure indicates that patents in year t (level 1) are nested within organizations (level 2) and organizations are embedded in innovation ecosystems (level 3). We expect that observations are not independent of each other, consequently, a patent from an organization and/or a region might not be independent from other patents of the same organization and/or region. A multilevel model (MLM) should be an appropriate choice to analyze data with such a nested structure (Hox, 2010; Srholec, 2010). We first describe the general analytical structure of the MLM model and then how our sample fits into this structure.

This analysis adheres to the methodological framework established by Bischoff et al. (2023), which conduct a 3-level analysis of firms (level 2) that exhibit innovation (level 1) across different years within regions (level 3), albeit with slightly different indicators. At level 1, DIGITAL depends on the dummy variable *Year* representing the application year and the corresponding coefficient vector δ, γ_{0ij} represents the random intercept that varies between organizations and regions, and e_{tij} is the normally distributed random residual at the patent level. For level 2, X_{tij} is the matrix of firm-level variables and β_1 represents the corresponding coefficient vector, γ_{00j} introduces the random intercept that varies between regions, and u_{0ij} denotes the normally distributed residuals at the organizational level. At level 3, γ_{000} represents the overall intercept, u_{00j} indicates the normally distributed residual for the regional level, $C_{t,j}$ is the matrix of the ecosystem variables, and β_2 represents the corresponding coefficient vector. Substituting all equations yields the full model with the fixed part $\gamma_{000} + \delta Year + \beta_1 X_{tij} + \beta_2 C_{t,j}$ and the random part $u_{00j} + u_{0ij} + e_{tij}$ to test our hypotheses. Consequently, our overall model deviates from standard regression analysis primarily by incorporating not only one but three normally distributed residuals and therefore allows for variation at different levels of analysis.

Level 1:

$$DIGITAL_{tij} = \gamma_{0ij} + \delta Year + e_{tij}$$

Introducing Level 2:

$$\gamma_{0ij} = \gamma_{00j} + \beta_1 X_{tij} + u_{0ij}$$

Introducing Level 3:

$$\gamma_{00j} = \gamma_{000} + \beta_2 C_{t,j} + u_{00j}$$

Resulting in the overall model:

$$DIGITAL_{tij} = \gamma_{000} + \delta Year + \beta_1 X_{tij} + \beta_2 C_{t,j} + u_{00j} + u_{0ij} + e_{tij}$$

Binary response MLMs can be estimated through quasi-likelihood estimation or Markov-Chain-Monte-Carlo (MCMC) methods that are based on Bayesian statistics. Following Bischoff et al. (2023), we decided to estimate our models by MCMC.[8] MCMC requires starting values that are obtained by the iterative generalized least squares (IGLS) method (Browne, 2009). The MCMC convergence diagnostics suggest a burn-in period of 15,000 and a monitoring period of 150,000 iterations.

A common example of other multilevel structures is students attending schools within districts, where each student can only be enrolled in one school at a time within a single district. However, the patent data in this analysis may deviate from this pattern because multiple organizations can be listed as applicants for a single patent and different inventors of the same patent may be georeferenced to multiple regions. In the following, we describe how modifications to our sample prevent these cases to apply the previously described MLM.

First, we reduce our initial sample of 569,205 patents between 2010 and 2021 to those patents that are nested within only one organization, resulting in 549,936 patents (97 %). Second, we must restrict patents to a single planning region to ensure a direct link between patents and the organizations within their respective ecosystems. All patents are regionalized on a fractional basis, i.e., each inventor residence is divided by the total number of inventors in a patent. We then aggregate this number by each planning region named in a patent and consider all

[8] In order to estimate our models, we use the MLwiN Software developed by the Centre for Multilevel Modeling at the University of Bristol (https://www.bristol.ac.uk/cmm/software/mlwin/).

patents where more than half of the weights are allocated to one planning region. 60 % of all 549,936 patents are naming just one planning region, 16 % of the patents have more than half of the inventors residing in one planning region, and 24 % of all patents do not have a planning region where more than half of the named inventors are residing. This reduces the sample to 415,956 patents. Furthermore, for some patents, important organizational data is missing, further reducing the sample to 411,389 patents. Overall, the different restrictions reduce the initial sample of 569,205 patents to 411,389 patents (72 %) including 57,627 digitalization patents. The percentage reduction is consistent across application years and comparable between DIGITAL and non-DIGITAL patents and thus should ensure that the described model can be deployed for our analysis.

4. Results

4.1. Descriptive results

Table A1 and A2 in the appendix contain the summary statistics and correlation matrix. Fig. 1 depicts the share of digitalization patents of all patents per year from 2010 to 2021 in German planning regions. There are strong regional disparities and an uneven distribution of digitalization patents in Germany, with only a few regions having a high or moderate share. However, regarding the number of digitalization patents per 100,000 residents in Fig. A1, we observe that a few regions have a high share of digitalization patents accompanied by a larger total amount of patents. Munich, Ingolstadt, Regensburg, Nuremberg, Friedrichshafen, and Stuttgart in the South, followed by Wolfsburg and Aachen in the West, as well as Berlin and Dresden in the East are the most important regions for digitalization patents.

Table A3 displays the Top-20 ecosystems in Germany with the most digitalization patents. These ecosystems are responsible for 79 % of all digitalization patents in Germany. Furthermore, there is large variation between these ecosystems with regard to the types of actors, subsidies per population, and main IPC subclasses. Also, ecosystems with a low percentage share of their main subclass have a diverse technology structure. For example, in Aachen the main subclass H01L (semiconductor devices) has a share of 14 %, followed by 13 % in H04W (wireless communication), and 11 % in H04L (telegraphic communication), which all underline the relevance of mobile network technologies.

Table A4 includes the descriptive statistics by types of actors and sectors. Digitalization patents are in 94 % applied for by firms, that is 6 % by SMEs and 88 % by large firms. The highest number of digitalization patents is produced by large firms from the automotive and electrical sector like Robert Bosch GmbH and Siemens AG; each alone produces substantially more digitalization patents than the other actors combined (UNI, BASIC, APPLIED). These firms are followed by large German automotive manufacturers (e.g., Mercedes-Benz, BMW, Audi, Volkswagen). The automotive and electrical sector are responsible for 69 % of all digitalization patents. The share of digitalization patents out of all patents is the highest in the ICT sector (69 %); however, it is only responsible for 9 % of all digitalization patents.

4.2. Regression results

Table 2 shows the multilevel regression results on the probability of developing a digitalization patent by the specific actors and their ecosystem including technology subsidies. Fig. 2 depicts these findings. The empty MLM results from Specification 1 can be used to estimate the interclass correlations coefficient (ICC). The ICC shows that 67.8 % of the variability of digitalization patents exists between organizations and 4.2 % of the variability occurs across regions. Specification 2 and 3 encompass the probability of generating a digitalization patent by the types of actors (LARGE, APPLIED, BASIC, and UNI compared to the reference group of SMEs). Not only large firms but also applied and basic research organizations and universities have larger odds than SMEs for developing a digitalization patent, which supports Hypothesis 1. The odds for large firms increase by 2 compared to SMEs. The not reported indicator variable YEAR is implying that the probability of developing a digitalization patent increases in more recent years. Also, not reported but expected, the odds are the highest for organizations in the ICT sector, followed by the electrical sector. Organizations in the chemical and pharma sector have the lowest probability. The coefficients of SUBURBAN and RURAL become slightly significant in some specifications. The positive coefficient of GDP is as expected. The positive coefficient of UNEMP is puzzling but not significant in all specifications.

Specification 4 includes the impact of the innovation ecosystem on the probability of developing a digitalization patent by SMEs and Specification 5 relates to that of large firms. The variance between SMEs (9.929) is almost double the variance between large firms (5.106), indicating a more heterogeneous group of SMEs. ECO_UNI has a larger effect on SMEs compared to large firms by increasing the odds with their presence by 1.5 and 1.11, respectively, supporting Hypothesis H2e. STUDENT has a small positive impact on the probability of developing a digitalization patent by SMEs, which underlines the importance of universities for SMEs in this context. The coefficient of ECO_APPLIED is also positive for both by increasing the likelihood of developing a digitalization patent by 1.4 for SMEs and 1.15 for large firms, supporting H2c. ECO_SME, ECO_LARGE, and ECO_BASIC have non-significant or lower-effect coefficients, which leads us to reject Hypothesis 2a, b, and d.

Specification 6 to 8 relate to the impact of technology subsidies on digital technology development by all organizations, SMEs, and large firms, respectively. The variable SUBSIDIES has a positive and significant impact on the probability of developing a digitalization patent in the ecosystem, supporting Hypothesis 3. Subsidies increase the odds mostly for SMEs with 1.55, which is 19 % more than for large firms.

4.3. Robustness check

We apply several robustness tests to ensure the reliability of the study. First, we run the models on another regional level. Second, we check for alternative specifications to measure the innovation ecosystem. Third, we investigate the effects of subsidies by only considering firm subsidies and implementing interaction effects.

First, we rerun the analysis of Table 2 on the level of 223 labor market regions instead of 96 planning regions in Table A5 in the Appendix. The larger number of regions combined with the restriction that a patent is only considered when more than half of the inventors are residing in a single region leads to 3 % less observations. The overall conclusions are still the same except for the difference in the effect of technology subsidies.

Second, we use alternative specifications of the innovation ecosystem in Table A6. Three alternative specifications extend Model 4 and 5 in Table 2. First, the ECO variables solely measure digitalization patents. ECO_LARGE_DIGITAL and ECO_SME_DIGITAL are the number of firms producing digitalization patents in the respective region and year. For APPLIED_DIGITAL, BASIC_DIGITAL, and UNI_DIGITAL, the dummies are 1 if at least one digitalization patent is developed. Second, we control for the size of an innovation ecosystem by the number of all patents per 10,000 population as well as the logarithm of this number. Large firms, applied research organizations, and universities in the ecosystem still have a positive impact on the probability of developing a digitalization patent. Regarding SMEs, the results are not very robust over all models. Last, we account for the digital-technology-enhancing effect from each partner by including the ecosystem variables separately in Table A7. The results remain robust for each partner.

Third, we focus on firm subsidies and their interaction effects with the actors in the innovation ecosystem in Table A8. The interaction effects in specification 6.1 indicate that SUBSIDIES have the highest impact on SMEs, which supports the results in Table 2. However, when

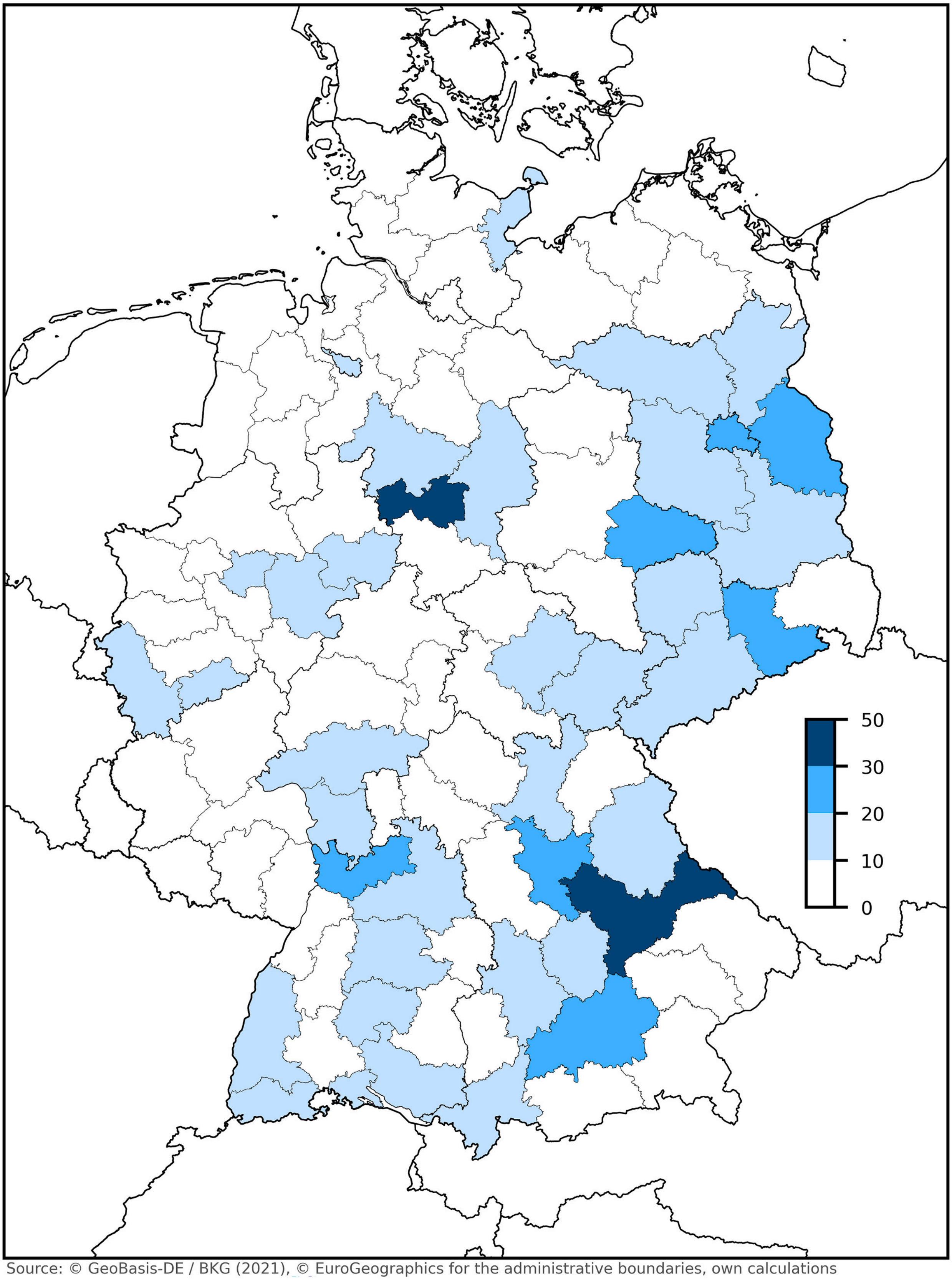

Fig. 1. Mean share of digitalization patents on all patents per year from 2010 to 2021 in German planning regions.

Table 2
Multilevel regression (3-MLM, binary dep. var.: DIGITAL).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dataset	All	All	All	SME	LARGE	All	SME	LARGE
YEAR		Yes	Yes	Yes	Yes	Yes	Yes	Yes
SECTOR		Yes	Yes	Yes	Yes	Yes	Yes	Yes
LARGE		0.675***	0.670***			0.663***		
APPLIED		2.328***	2.303***			2.334***		
BASIC		0.969***	0.966***			0.948***		
UNI		1.863***	1.774***			1.791***		
SUBURBAN			−0.293**	−0.116	−0.274*	−0.244**	−0.142	−0.295**
RURAL			−0.264*	0.062	−0.127	0.005	0.246	−0.006
GDP			0.558***	0.848*	0.985***	0.202*	0.767***	0.287**
UNEMP			0.046***	0.054	0.036**	0.033***	0.046	0.014
STUDENT			−0.003*	0.006*	−0.004**	−0.003**	0.002	−0.006
SUBSIDIES						0.271***	0.442***	0.264***
ECO_SME				−0.003	−0.003***			
ECO_LARGE				0.002	0.000			
ECO_APPLIED				0.337***	0.144***			
ECO_BASIC				−0.082	−0.028			
ECO_UNI				0.406***	0.111***			
Constant	−4.553***	−5.512***	−7.298***	−10.582***	−8.114***	−6.743***	−10.672***	−6.144***
Var(constant level 2)	7.951***	5.490***	5.464***	9.929***	5.106***	5.474***	9.882***	5.107***
Var(constant level 3)	0.489***	0.218***	0.190***	0.190***	0.176***	0.130***	0.144***	0.135***
Observations	411,389	411,389	411,389	37,973	357,947	411,389	37,973	357,947
ICC (level 2)	0.678							
ICC (level 3)	0.042							

Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01, respectively. The ACTOR variables LARGE, APPLIED, BASIC, and UNI are referenced to SME. The AS variables SUBURBAN and RURAL are referenced to URBAN. The regional level (level 3) are the 96 German planning regions.

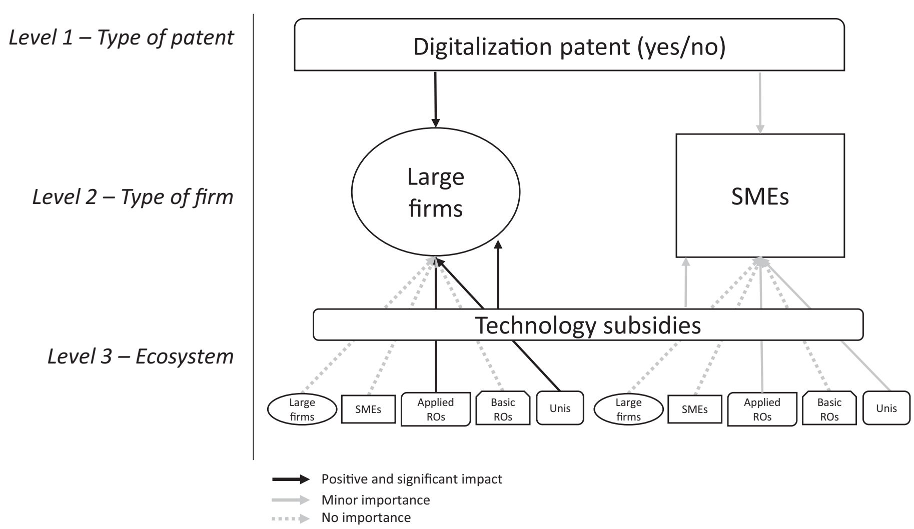

Fig. 2. Summary of findings.

only subsidies for firms are considered, the effects only remain positive for large firms.[9] Moreover, we test if digital technology development of SMEs is particularly driven by subsidies for research organizations in the ecosystem via collaborations and spillovers in Table A8. We observe positive effects from subsidies for research organizations, which further challenge the digital-technology-enhancing impact of SME subsidies.

5. Discussion

The results have important implications for the literature on digital innovation management and innovation ecosystems to support the development of digital technologies.

First, the authors could show that large firms have a higher probability of generating a digitalization patent than SMEs (Hypothesis 1). Large firms are responsible for 88 % of all applications for digitalization patents. This finding underlines the importance of technology giants (Bohnsack et al., 2021) and hints to their respective resources to engage in R&D, retain skilled workers (Ciarli et al., 2021), and participate in risky projects (Chouaibi et al., 2022) to encounter the unpredictable and ambiguous nature of digital technology development. A possible explanation for the lesser importance of SMEs in this field relates to their barriers to innovation, such as financial and resource constraints (Cecere et al., 2020), employee barriers (Castillo-Vergara et al., 2021), markets and institutions (Arza and López, 2021), or information deficits (Love and Roper, 2015), which might be particularly high in light of the uncertainties of digital technology development. In particular, SMEs often lack access to equity and loan financing as well as to funding from banks and private institutions (Athreye et al., 2021). Thus, when applying for patents, SMEs seem to prefer the development

[9] Specified in the same way as all subsidies described in the data section.

of established technologies over digital technologies to better predict their future application with regard to functionalities, longer life cycles, and usage, which creates more certainty and less ambiguities. The findings contribute to the literature on the management of digital innovation (Chouaibi et al., 2022; Endres et al., 2022; Pesch et al., 2021; Appio et al., 2021) by identifying the crucial actors and their resources within a spatial structure for such development processes. As a result, the innovation-related capabilities of firms, their processes and routines, as well as the understanding of contextual factors, need to evolve in response to the digital transformation (Appio et al., 2021). Therefore, a firm's strategy implementation—from defining the scope of transformation to the identification of customers for whom to create value—should be in line with its formulation (Correani et al., 2020).

Second, for large firms, the existence of an innovation ecosystem has a positive impact on digital technology development. Applied research organizations and universities in the ecosystem have the greatest influence on a large firm's probability to achieve digitalization patents (Hypothesis H2c and e). Applied research organizations assist large firms in managing digitalization-related patenting activities and predicting future application and usage. Universities, as trustworthy partners in an ecosystem, provide cutting-edge scientific knowledge on more complex products with shorter life cycles. In contrast, profit and basic research organizations in the ecosystem do not enhance the development of digital technologies by large firms and SMEs (Hypothesis H2a, b, and d). Profit organizations entail high risks of opportunistic behavior, resource misappropriation, and involuntary spillovers (Vanhaverbeke et al., 2015). Basic research organizations may have a too strong focus on fundamental research themes that neglect the need for application of digital technologies. The results extend previous studies that connect the importance of innovation ecosystems (e.g., Baldwin et al., 2024; Neto et al., 2024; Alam et al., 2022; Gomes et al., 2021) to its distinct multilayer configuration for achieving digitalization patents. In particular, the ecosystems of applied research organizations and universities seem to provide necessary complementary resources, interdependencies, and network effects, and support the development of digital innovation.

Regarding SMEs, no robust positive influence of the innovation ecosystem on digitalization patents can be observed. The inconsistent link between digital SME innovation and actors of an ecosystem, especially universities and applied research organizations, challenge previous studies that underline the benefits of such connections, like, for example, knowledge and cost sharing (Audretsch et al., 2022). This finding might be explained by the various barriers to innovation mentioned above (e.g., Love and Roper, 2015). The high uncertainties and ambiguities of digital technology development regarding usage and future application, shorter life cycles, and a complex product architecture might exacerbate these barriers.

Third, the development of digital technologies is positively influenced by the availability of technology subsidies in an organization's innovation ecosystem. Similar to recent findings that challenge the effectiveness of such subsidies for digital-affine SMEs (Fini et al., 2023), the authors could not find a robust effect that their availability in the ecosystem increases a SME's probability of generating a digitalization patent more than established technologies (Hypothesis H3). However, subsidies help to incentivize digital technology development of large firms by reducing its higher uncertainties and ambiguities of usage and future application compared to established technologies. This finding underlines that technology subsidies could not only support innovation and structural change of regions (e.g., Cantner et al., 2019) but also help the transformation towards digitalization in large organizations.

6. Conclusion

This paper aims at investigating the impact of an organization's ecosystem on the success of digital technology development. By combining knowledge from digital innovation management and innovation ecosystems, the authors derived hypotheses on the multilevel and spatial determinants of digital technology development. They empirically test the hypotheses using a multilevel model based on three levels for the case of patent applications for digital technologies in Germany between 2010 and 2021. The results show that large firms and their innovation ecosystem of applied research organizations and universities including technology subsidies increase the development of digital technologies more than of established technologies. SMEs only play a minor role in digital technology development, and their ecosystem and technology subsidies do not result in increased patent success in this field.

These findings have important implications for technology managers and policy makers. While large firms take on an important role as enablers of digital technology development by relying on their larger R&D departments, highly skilled workers, and their possibility to realize risky projects, SMEs are only of minor significance in digitalization-related patenting activities. Even though SMEs are often called the "pacemaker of digitalization" (e.g., BMBF, 2023), highlighting their importance for developing and deploying digitalization technologies, their probability to achieve patents in this field is much lower compared to large firms. However, SMEs are not per se less likely to patent than large firms, despite of the "portfolio effect", which enables large firms to obtain a larger number of patents (Athreye et al., 2021). Thus, in order to take part in the digital transformation, the authors recommend SMEs to take the following steps:

First, SMEs should become aware of their greater resource and financial constraints compared to large firms. These barriers to innovation should not prevent SMEs from engaging in patenting activities of digitalization technologies, given their positive effects on innovation and financial performance in general (Andries and Faems, 2013). Instead, based on these internal barriers to innovation, SMEs can align their capabilities, processes and routines, as well as their strategy formulation and implementation in accordance with the requirements of digital transformation (Appio et al., 2021; Correani et al., 2020).

Second, SMEs should consider their external barriers to innovation (Arza and López, 2021) and actively participate in local innovation ecosystems to enhance access to frontier knowledge, learning, and applicability of digital technologies. They might not only align their business models with the ecosystem (Radziwon and Bogers, 2019), but also actively shape their innovation ecosystem by leveraging knowledge transfer with applied research organizations and universities for digital technology development.

Third, SMEs can participate in local public research not only to finance the costs of digital development projects (Athreye et al., 2021), but also to enter into strategic cooperations with universities and application-oriented research partners that allow for resource sharing, assistance in patenting activities, and forecasting of digital product applications. As SMEs often resist opening up to other firms ("tribe syndrome") (Dubouloz et al., 2021), networks with public actors, especially applied research organizations and universities, can be effective means to diminish their barriers to innovation (Castillo-Vergara et al., 2021). However, as noted by Cecere et al. (2020), public funding should be complemented by access to fiscal incentives for private innovative activity in order to be effective.

At the same time, policy makers could support digital-affine firms with technology subsidies that encourage local knowledge transfer, learning, and digital technology development in innovation ecosystems involving universities and applied research organizations. In designing such programs, policy makers should particularly take into account SME's financial constraints and reduce the administrative burden to increase their participation, which is in line with Cecere et al. (2020).

Future research can extend these findings by focusing on particular types of digital technologies and observe the distinct influence of an organization's ecosystem. This study uses a multilevel approach based on patent data, which delivers comprehensive insights into spatial and multilayer structures of digital innovation ecosystems over a long-time horizon. However, different approaches, such as web scraping or insights from cross-sectional survey data, could help to focus on other types of digitalization technologies, such as process innovation, which can be particularly relevant for SMEs. Making digitalization patents available to the market, enabling a digital infrastructure, or investing in the digital upskilling of the workforce are further important areas to understand the benefits of new technology adoption. Lastly, even though Germany as the European frontrunner of patenting in the field of digital technologies is a case in point for exploring the multilayer structure of its ecosystems, the findings need to be tested in other spatial contexts.

CRediT authorship contribution statement

Ann Hipp: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Funding acquisition, Conceptualization. **Enno Kohlisch:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Ann Hipp reports financial support was provided by the State of Bremen. Ann Hipp reports financial support was provided by Deutsche Forschungsgemeinschaft. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

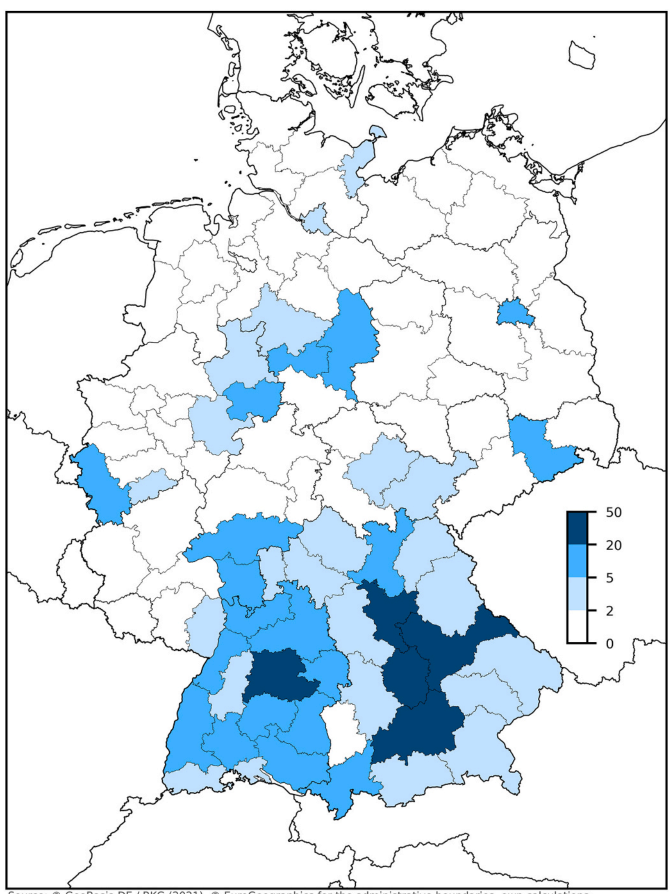

Fig. A1. Mean of digitalization patents per 100,000 population per year from 2010 to 2021 in German planning regions.

Table A1
Descriptive statistics.

Variable	Obs.	Mean	Std. dev.	Min	Max
Patent level					
DIGITAL	411,389	0.14	0.35	0	1
YEAR	411,389	2015.55	3.40	2010	2021
Organization level					
ACTOR	63,630	1.67	0.74	1	5
SECTOR	63,630	5.75	2.69	1	11
Regional level					
GDP	1152	3.51	0.24	3	4
UNEMP	1152	6.11	2.62	2	15
AS	1152	2.13	0.78	1	3
STUDENT	1152	36.47	22.93	0	214
SUBSIDIES	1152	2.61	1.15	−2	5
ECO_SME	1152	24.05	25.75	0	218
ECO_LARGE	1152	48.82	44.35	1	284
ECO_APPLIED	1152	0.42	0.49	0	1
ECO_BASIC	1152	0.41	0.49	0	1
ECO_UNI	1152	0.70	0.46	0	1

Sources: IW Patentdatabase; INKAR, Foerderkatalog. The organizational level is an unbalanced panel of 25,017 unique organizations that are observed over the period 2010–2021. The number of organizations per year varies between 5062 and 5644. Regional variables are collected yearly on the level of 96 German planning regions.

Table A2
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
DIGITAL	1													
YEAR	0.05	1												
ACTOR	0.04	0.01	1											
SECTOR	0.03	0.03	0.25	1										
GDP	0.12	0.39	−0.01	0.02	1									
UNEMP	−0.04	−0.23	0.05	0.04	−0.45	1								
AS	−0.08	−0.02	−0.04	−0.03	−0.47	−0.24	1							
STUDENT	0.09	0.20	0.06	0.05	0.21	0.27	−0.45	1						
SUBSIDIES	0.12	0.24	0.10	0.07	0.46	−0.03	−0.58	0.57	1					
ECO_SME	0.11	0.04	0.00	0.03	0.65	−0.16	−0.57	0.24	0.48	1				
ECO_LARGE	0.09	0.00	0.00	0.01	0.66	−0.20	−0.63	0.17	0.45	0.95	1			
ECO_APPLIED	0.09	0.00	0.08	0.05	0.30	0.05	−0.46	0.30	0.57	0.44	0.44	1		
ECO_BASIC	0.06	0.01	0.06	0.06	0.35	0.18	−0.51	0.30	0.47	0.50	0.52	0.43	1	
ECO_UNI	0.06	0.02	0.06	0.02	0.20	0.21	−0.47	0.48	0.49	0.30	0.33	0.42	0.39	1

Table A3
Top-20 ecosystems with the overall most digitalization patents.

Region	Name	Digital Patents	Percent DIGITAL/ PATENT	Percent DIGITAL_SME/ DIGITAL	Percent DIGITAL_LARGE/ DIGITAL	Percent DIGITAL_APPLIED/ DIGITAL	Percent DIGITAL_BASIC/ DIGITAL	Percent DIGITAL_UNI/ DIGITAL	SUBSIDIES/ POP	Main IPC-SC	Percent main IPC-SC/ DIGITAL
910	Munich	11,180	27.6	5.0	91.6	0.6	2.3	0.5	8,560,025	G06F	16.50
810	Stuttgart	8456	13.8	1.3	97.8	0.2	0.3	0.4	5,554,016	B60W	18.20
906	Middle Franconia	4293	22.4	2.4	80.4	16.5	0.0	0.7	4,047,024	A61B	14.10
915	Regensburg	3213	30.8	2.2	97.7	0.0	0.0	0.0	2,749,052	H01L	65.97
1101	Berlin	2313	23.8	11.9	67.0	15.4	3.6	2.1	7,151,723	G06F	14.05
604	Rhine-Main	1794	16.8	10.8	88.2	0.2	0.1	0.6	1,420,324	H04W	14.30
301	Braunschweig	1765	17.0	1.2	94.2	0.4	2.9	1.3	6,010,890	B60W	15.01
812	Lower Neckar	1588	22.1	4.1	94.8	0.1	0.5	0.6	6,758,416	G06F	42.75
907	Ingolstadt	1574	19.5	0.8	98.9	0.1	0.0	0.3	1,493,248	B60W	16.73
1401	Upper Elbe Valley	1303	23.5	11.2	70.2	7.6	2.9	8.1	11,725,302	H01L	45.74
805	Middle Upper Rhine	1127	9.5	17.6	75.0	2.3	0.1	5.1	12,317,055	G06F	13.33
801	Lake Constance-Upper Swabia	1017	10.1	1.4	98.6	0.0	0.0	0.0	2,677,234	B60W	26.45
501	Aachen	859	14.2	7.3	80.7	1.7	5.8	4.4	12,320,563	H01L	14.87

(*continued on next page*)

Table A3 (*continued*)

Region	Name	Digital Patents	Percent DIGITAL/ PATENT	Percent DIGITAL_SME/ DIGITAL	Percent DIGITAL_LARGE/ DIGITAL	Percent DIGITAL_APPLIED/ DIGITAL	Percent DIGITAL_BASIC/ DIGITAL	Percent DIGITAL_UNI/ DIGITAL	SUBSIDIES/ POP	Main IPC-SC	Percent main IPC-SC/ DIGITAL
811	Southern Upper Rhine	775	10.8	9.4	63.6	24.0	0.0	3.0	7,777,873	H01L	28.20
605	Starkenburg	769	13.5	14.0	76.3	2.7	0.4	6.5	4,256,987	H01L	13.95
307	Hanover	760	11.8	7.0	87.9	0.1	0.1	4.9	3,975,429	G06T	10.06
806	Neckar-Alb	743	11.9	3.5	94.1	0.0	0.8	1.6	5,400,468	H01L	28.05
912	Upper Franconia-West	736	15.8	2.9	96.3	0.8	0.0	0.0	594,691	A61B	21.43
803	Franconia	651	10.4	3.4	96.6	0.0	0.0	0.0	1,535,575	B60W	20.32
508	Düsseldorf	584	5.5	12.3	86.0	0.5	0.0	1.2	1,185,448	H04L	13.97

Notes: The table displays the 20 different innovation ecosystems that have the most digital patents in the analyzed timeframe. The shares for the different actors refer to their number of digitalization patents compared to all digitalization patents in the region. SUBSIDIES/POP are the total SUBSIDIES in Euro over the total timespan divided by the mean population over the total timespan. Main IPC-SC refers to the subclass that has the highest number of digital patents in a region. A description of each subclass can be found in Table 1. Percent main IPC-SC/DIGITAL displays this share within a region.

Table A4
Descriptive statistics by types of actors and sectors.

	Number of Juristic Persons	All Patents	Digital Patents	Percent DIGITAL/ PATENT	Percent PATENT overall	Percent DIGITAL overall
ACTOR						
SME	15,756	37,973	3579	9.4	9.2	6.2
LARGE	8921	357,947	50,767	14.2	87.0	88.1
APPLIED	4	4698	1716	36.5	1.1	3.0
BASIC	61	3855	665	17.3	0.9	1.2
UNI	275	6916	900	13.0	1.7	1.6
SECTOR						
Other Non-Service Sectors (KLDW: 01–03;35–43)	1040	2690	137	5.1	0.7	0.2
Other Industry Sectors (KLDW: 05–19;22–23)	2885	18,679	466	2.5	4.5	0.8
Chemical/Pharma Industry (KLDW: 20–21)	1177	19,668	538	2.7	4.8	0.9
Electrical Industry (KLDW: 26–27)	3597	79,524	20,940	26.3	19.3	36.3
Mechanical Engineering Industry (KLDW: 28)	4110	57,639	2322	4.0	14.0	4.0
Automotive Industry (KLDW: 29)	499	141,202	18,623	13.2	34.3	32.3
Other Metalworking and Electrical Industries (KLDW: 24–25; 30–33)	4436	34,904	1795	5.1	8.5	3.1
ICT Service Sector (KLDW: 60–63)	1303	7673	5309	69.2	1.9	9.2
Technical Services (KLDW: 71–72)	2831	25,058	4955	19.8	6.1	8.6
Universities (KLDW: 85.4)	186	6301	842	13.4	1.5	1.5
Other Service Sectors (KLDW: 45–59;64–70;73–85.3;85.5–99)	2953	18,051	1700	9.4	4.4	3.0
All	25,017	411,389	57,627	14.0	100.0	100.0

The aggregated sectors (SECTOR) are based on the more detailed 3-digit level of 258 different sectors defined by the "Klassifikation der Wirtschaftszweige" (KLDW) (Statistisches Bundesamt, 2008).

Table A5
Robustness check - alternative regional level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dataset	All	All	All	SME	LARGE	All	SME	LARGE
YEAR		Yes	Yes	Yes	Yes	Yes	Yes	Yes
SECTOR		Yes	Yes	Yes	Yes	Yes	Yes	Yes
LARGE		0.668***	0.675***			0.673***		
APPLIED		2.336***	2.343***			2.270***		
BASIC		1.019***	1.019***			0.979***		
UNI		1.809***	1.769***			1.744***		
SUBURBAN			−0.001	0.091	0.025	0.069	0.097	0.103
RURAL			−0.191	−0.069	−0.128	0.027	0.082	0.070
GDP			0.353***	0.120	0.352**	0.165	0.808**	0.345**
UNEMP			0.039***	0.023	0.013	0.027**	0.049	0.011
STUDENT			0.001	0.008***	0.000	−0.000	0.006**	−0.002*
SUBSIDIES						0.223***	0.288***	0.227***
ECO_SME				−0.001	−0.003***			
ECO_LARGE				0.003	0.001			
ECO_APPLIED				0.418***	0.132***			
ECO_BASIC				0.050	0.004			
ECO_UNI				0.050	0.129***			
Constant	−4.774***	−5.592***	−6.968***	−7.693***	−6.167***	−6.650***	−10.484***	−6.599***

(*continued on next page*)

Table A5 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dataset	All	All	All	SME	LARGE	All	SME	LARGE
Var(constant level 2)	7.996***	5.531***	5.514***	9.605***	5.139***	5.523***	9.724***	5.145***
Var(constant level 3)	0.630***	0.296***	0.264***	0.185***	0.241***	0.171***	0.168***	0.174***
Observations	399,992	399,992	399,992	37,358	347,224	399,611	37,296	346,906
ICC (level 2)	0.671							
ICC (level 3)	0.053							

Notes: * / ** / *** denote *p*-values of 0.1. / 0.05 / 0.01 respectively. The ACTOR variables LARGE, APPLIED, BASIC, and UNI are referenced to SME. The AS variables SUBURBAN and RURAL are referenced to URBAN. The regional level (level 3) are the 223 German labor market regions in the BBSR allocation of 2021.

Table A6
Robustness check ecosystem – alternative measures.

	(4.1)	(5.1)	(4.2)	(5.2)	(4.3)	(5.3)
Dataset	SME	LARGE	SME	LARGE	SME	LARGE
YEAR	Yes	Yes	Yes	Yes	Yes	Yes
SECTOR	Yes	Yes	Yes	Yes	Yes	Yes
SUBURBAN	−0.371*	−0.305**	−0.434	−0.453**	−0.098	−0.463***
RURAL	−0.407	−0.208	0.275	−0.618*	0.017	−0.363**
GDP	−0.185	0.771***	0.483	−0.177*	1.007*	−0.432***
UNEMP	−0.023	0.018	0.060	−0.015	0.074*	−0.014
STUDENT	0.004	−0.007***	0.009	−0.010***	0.007**	−0.003
ECO_SME_DIGITAL	0.153***	−0.012***				
ECO_LARGE_DIGITAL	−0.047***	0.008***				
ECO_APPLIED_DIGITAL	0.125	−0.017				
ECO_BASIC_DIGITAL	0.016	0.072***				
ECO_UNI_DIGITAL	0.108	0.024				
ECO_SME_PATPOP					−0.297	−0.477***
ECO_LARGE_PATPOP					0.023	0.063***
ECO_APPLIED_PATPOP					0.939*	−0.114
ECO_BASIC_PATPOP					0.805	0.620***
ECO_UNI_PATPOP					0.582	0.442**
ECO_SME_LOGPATPOP			−0.372	−0.265***		
ECO_LARGE_LOGPATPOP			0.162	0.043		
ECO_APPLIED_LOGPATPOP			0.219***	0.037		
ECO_BASIC_LOGPATPOP			0.024	0.016		
ECO_UNI_LOGPATPOP			−0.039	0.064**		
Constant	−5.855***	−7.217***	−7.893***	−3.239*	−10.903***	−2.953***
Var(constant level 2)	9.854***	5.107***	10.618***	5.473***	9.961***	5.105***
Var(constant level 3)	0.187***	0.188***	0.171	0.285***	0.222***	0.194***
Observations	37,973	357,947	15,290	173,430	37,973	357,947

Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01, respectively. The ACTOR variables LARGE, APPLIED, BASIC, and UNI are referenced to SME. The AS variables SUBURBAN and RURAL are referenced to URBAN. The regional level (level 3) are the 96 German planning regions.

Table A7
Robustness check ecosystem – model specification.

	(4.4)	(4.5)	(4.6)	(4.7)	(4.8)	(5.4)	(5.5)	(5.6)	(5.7)	(5.8)
Dataset	SME	SME	SME	SME	SME	LARGE	LARGE	LARGE	LARGE	LARGE
YEAR	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SECTOR	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SUBURBAN	−0.338	−0.274	−0.232	−0.304	−0.306	−0.374***	−0.448***	−0.296**	−0.370**	−0.405***
RURAL	−0.293	−0.213	−0.137	−0.249	−0.188	−0.274*	−0.411**	−0.198	−0.296*	−0.338**
GDP	0.704	0.527	0.679**	0.817**	0.603	0.830***	0.555***	0.619***	0.578***	0.287***
UNEMP	0.050	0.051	0.040	0.056	0.035	0.027*	0.019	0.025	0.021	0.012
STUDENT	0.008**	0.008**	0.007**	0.008**	0.006*	−0.004**	−0.005***	−0.006***	−0.006***	−0.006***
ECO_SME	−0.001					−0.003***				
ECO_LARGE		0.001					−0.002***			
ECO_APPLIED			0.359***					0.140***		
ECO_BASIC				−0.043					−0.016	
ECO_UNI					0.441***					0.123***
Constant	−9.494***	−8.994***	−9.468***	−9.921***	−9.295***	−7.328***	−6.252***	−6.710***	−6.543***	−5.536***
Var(constant level 2)	9.966***	9.898***	9.823***	9.884***	9.919***	5.105***	5.103***	5.102***	5.119***	5.114***
Var(constant level 3)	0.262***	0.263***	0.175***	0.252***	0.225***	0.198***	0.198***	0.175***	0.197***	0.189***
Observations	37,973	37,973	37,973	37,973	37,973	357,947	357,947	357,947	357,947	357,947

Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01, respectively. The ACTOR variables LARGE, APPLIED, BASIC, and UNI are referenced to SME. The AS variables SUBURBAN and RURAL are referenced to URBAN. The regional level (level 3) are the 96 German planning regions.

Table A8
Robustness check – subsidies.

	(6.1)	(7.1)	(8.1)	(7.2)	(8.2)
Dataset	All	SME	LARGE	SME	LARGE
YEAR	Yes	Yes	Yes	Yes	Yes
SECTOR	Yes	Yes	Yes	Yes	Yes
LARGE	0.472***				
APPLIED	3.222***				
BASIC	2.677***				
UNI	3.035***				
SUBURBAN	−0.313***	−0.303	−0.357***	−0.220	−0.350**
RURAL	−0.090	−0.158	−0.170	0.092	−0.270
GDP	0.079	0.422	0.057	0.792*	0.393***
UNEMP	0.016	0.046	0.016	0.027	0.010
STUDENT	−0.003**	0.007**	−0.004**	0.001	−0.006***
SUBSIDIES	0.224***				
SUBSIDIES_FIRM		0.169**	0.181***		
SUBSIDIES_ABU				0.260***	0.047**
LARGExSUBSIDIES	0.061				
APPLIEDxSUBSIDIES	−0.295**				
BASICxSUBSIDIES	−0.518***				
UNIxSUBSIDIES	−0.391***				
Constant	−5.997***	−8.693***	−4.971***	−9.896***	−5.851***
Var(constant level 2)	5.461***	9.833***	5.105***	9.992***	5.132***
Var(constant level 3)	0.134***	0.207***	0.152***	0.155**	0.182***
Observations	411,389	37,949	357,849	37,247	353,563

Notes: * / ** / *** denote p-values of 0.1. / 0.05 / 0.01, respectively. The ACTOR variables LARGE, APPLIED, BASIC, and UNI are referenced to SME. The AS variables SUBURBAN and RURAL are referenced to URBAN. The interaction effect of ACTOR x SUBSIDIES is referenced to SME x SUBSIDIES. The regional level (level 3) are the 96 German planning regions. SUBSIDIES_ABU only include subsidies for universities and applied or basic research organizations.

Data availability

Data will be made available on request.

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Ann Hipp is a senior researcher at Thünen Institute of Rural Economics and a postdoctoral researcher at the University of Bremen, Chair of Economics of Innovation and Structural Change, Germany. Her research interests include the economics of innovation, system transformation, innovation policy, and technology transfer.

Enno Kohlisch is an economist at the German Economic Institute (IW) and a doctoral student at the University of Bremen, Chair of Economics of Innovation and Structural Change, Germany. His research interests comprise patent analysis, digital technologies, and innovation.