Fueling the Fire? How Government Support Drives Technological Progress and Complexity

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Papers in Evolutionary Economic Geography

24.07

Utrecht University Human Geography and Planning

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Acknowledgements

We express our gratitude to Lars Mewes, whose initiation of this project and subsequent fruitful discussions were invaluable. Our thanks also extend to Ron Boschma for his insightful comments and suggestions on an earlier version of this paper. Special appreciation goes to the editor, Alex Coad, and three anonymous reviewers whose constructive comments and suggestions played a significant role in enhancing the quality of our paper.

Funding: This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 860887.

Declaration of interest: The authors declare that they have no conflict of interest that could have influenced this work.

Abstract

This study investigated two major trends shaping contemporary technological progress: the growing complexity of innovation and the increasing reliance on government support for private research and development (R&D). We analyzed United States patent data from 1981 to 2016 using structural vector autoregressions and uncovered an indirect interplay between these trends. Our findings showed that government incentives and support played a crucial role in spurring private-sector innovation. This government-fueled innovation, in turn, paved the way for advancements in more intricate and sophisticated technological areas.

Our study sheds light on the dual role of the United States' innovation policy over the past four decades; the policy has not only accelerated technological advancement but also steered it toward increasingly complex domains. While this trend presents opportunities for economic growth and technological breakthroughs, it also poses challenges, including the potential for further escalating R&D costs. This research has significant implications for policymakers and industry leaders, suggesting a need for a balanced approach to fostering innovation while considering the long-term economic and technological landscape.

Keywords: Innovation, patents, technological complexity, government R&D

JEL: O31, O33, O38

1 Introduction

Today's technological progress is characterized by two major trends. The first is the increasing complexity of technologies and their research and development (R&D) activities. Many of today's technologies can do more things, have more elements and connections, and need more R&D resources and development time than before (Broekel, 2019; Hidalgo, 2015; Prencipe, 2000; Strumsky et al., 2010). For example, keeping up with Moore's law—according to which computer chips get twice as dense every two years, implying massively growing computational power and a greater diversity of applications—requires eighteen times more R&D staff now than in the 1970s (Bloom et al., 2020). The second is the growing role of government intervention and support in innovation processes. The government can support innovation in different ways, for example by funding basic research that creates new opportunities for firms or by directly helping the development of specific technologies or solutions. After the Second World War, a small percentage of all US patents were associated with some form of government backing. Today, this share is between 25 and 30 percent (Fleming et al., 2019).

We argue that these two trends are likely to be related to each other due to two mechanisms. On the one hand, the rising complexity of technologies makes it harder and costlier for private actors to innovate on their own. Therefore, government resources and assistance are needed to keep up with technological progress. On the other hand, the government may encourage innovations that push complexity in order to generate economic and social benefits associated with such developments. For instance, Mewes and Broekel (2020) showed that regions with capabilities in more complex technologies grow economically faster than regions without such competencies.

In the empirical part of this study, we sought to identify the dominant direction of the influence: Does growing complexity lead to more government support, or vice versa? To answer this question, we used patent data on 630 technologies from the United States Patent and Trademark Office (USPTO) for the period 1981–2016. These data were matched with information on government support (Fleming et al., 2019) and technological complexity (Broekel, 2019). We used the VAR-LiNGAM (Vector Autoregressive Linear Non-Gaussian Acyclic Model) method, which can, arguably, detect causal relationships in non-normal data (Hyvärinen et al., 2010).

We found that government support was not uniformly distributed across technologies. On the contrary, it increasingly concentrated on complex technologies. In agreement with the literature, our study confirms that government support stimulates private innovation activities. In addition, we contribute to this literature by providing evidence for government support being indirectly responsible for the growth of technological complexity. That is, greater government support (government ownership and funding) tends to increase private investments that subsequently contribute to the growth of technological complexity. Similarly, innovations referring to previous government R&D may also facilitate the growth of complexity. In summary, we show that government support is not a reaction to increasing complexity. Rather, it acts as a driver of the growth of complexity and, given the positive effect of complexity on economic growth (Hidalgo & Hausmann, 2009; Mewes & Broekel, 2020), it may (indirectly) contribute to today's economic growth. However, by pushing the levels of technological complexity, government support is likely to increase the future resource requirements of R&D and thereby lower its productivity and contribution to economic growth.

The paper is structured as follows. Section 2 discusses the relationship between complexity and government support from a theoretical perspective. Section 3 presents the data and empirical approach of this study. The results are presented and discussed in Section 4. Section 5 concludes the paper by putting the findings into perspective and outlining their future research potential.

2 Is government support the answer to increasing complexity or its cause?

2.1 Government-supported research fuels innovation

Recent research suggests that private R&D activities are increasingly relying on government support. For example, Fleming et al. (2019) classified US patents that rely on some types of (federal) government support. According to these authors, the share of government-supported patents in overall patenting has constantly increased from 1926 onward. While it was 5% shortly after the end of the Second World War, it grew to over 30% in 2011. Hence, already by 2011, every third US patent relied on government R&D support, and there are few reasons to believe that this share has decreased over the last decade.

In general, such government interventions are justified by the belief that R&D activities are subject to market failure (Arrow, 1962; Nelson, 1959). Knowledge is frequently assumed to be a non-rivalrous and non-excludable good (although this is debatable; see, for example, Witt et al., 2012), as the use of knowledge by one actor does not prevent its use by others and it is impossible to exclude others from using the knowledge. Consequently, actors investing in knowledge cannot fully appropriate all its benefits and, therefore, underinvest in it. Another reason for market failures is argued to be the high uncertainty inherent in knowledge production (Nelson, 1959). Uncertainty describes a condition under which actors in an economy must decide on inputs when the output is difficult to predict or even completely unknown. In the case of technological innovations, the uncertainly inherent in basic research is related to the question of when and where the innovation is applied (Pavitt, 1991). In response to these market failures, private actors may invest in R&D investments below the socially desired optimum (Klette et al., 2000; Mazzucato, 2012; Weber & Rohracher, 2012). Basic research, often supported by the government, increases the stock of useful knowledge, thus expanding technological opportunities available to society by providing new ideas and technological knowledge (Klevorick et al., 1995; Narin et al., 1997; Salter & Martin, 2001).

There are multiple approaches to raising R&D investments to a socially desired optimum. One of the primary approaches is the patent system, which grants innovators a temporary monopoly on the commercialization of their inventions in exchange for publishing the corresponding knowledge and a small fee. In addition, the government provides public research capacity. Such government R&D activities are most visible in basic research activities, where uncertainty is highest and the goals are less tied to specific practical problems. This is evident in the US, where government spending on R&D for basic research accounts for 57% of the total spending on basic research. In comparison, government spending accounts for only 26% of the total R&D spending in the US (Mazzucato, 2012). In 2017, universities and colleges conducted the majority of basic research in the US (48%), while the business sector accounted for 27% and the federal government (being the main source of funding for basic research) for only 11%. However, even in applied research, where uncertainty is less pronounced and the research goals are more visible than in basic research, government agencies, non-profit organizations, universities, and colleges carried out 43% of the activities, with the business sector engaging in the remaining 57%.[1] Deficiencies in private R&D activities are problematic for many reasons, one of them being that the application of basic research, potentially enabled by government support, depends on investment in downstream activities by private firms (Pavitt, 1991).

The different approaches to R&D support are frequently interrelated. The original patent system has been amended multiple times to strengthen its supporting role and to better integrate other

[1] The numbers are drawn from the National Science Foundation (NSF) at https://ncses.nsf.gov/pubs/nsb20201/u-s-r-d-performance-and-funding, accessed on September 11, 2022.

government support measures. For instance, the Bayh–Dole Act (BDA) of 1980 encouraged US universities to patent their research outcomes by granting them full property rights, including commercial licensing. Although the BDA has stimulated university patenting, its overall effect is arguably overstated (Mowery et al., 2001; So et al., 2008). Consequently, and considering the rather monotonically growing shares of government-supported patents, the BDA is not enough to explain the strong increase in government-supported patenting, as shown by Fleming et al. (2019). The same is true for the second substantial change to the intellectual property rights system: the Federal Technology Transfer Act of 1986, which allowed federal research laboratories to enter into Cooperative Research and Development Agreements with private organizations (Mowery, 1998). These changes stimulated public actors' greater involvement in patented R&D activities as well as collaboration with private actors. Further measures involve programs that explicitly target research collaborations and grant R&D subsidies to private as well as public organizations (Hall & Lerner, 2010). One such program is the Advanced Technology Program, which aims to stimulate high-risk R&D conducted by private organizations (Mowery, 1998). These programs frequently require private–public cooperation, further expanding government involvement in and support for R&D.

There is an ongoing debate about the consequences of government investments in R&D with respect to the crowding-in or -out effects of private investments. However, there is increasing evidence substantiating the positive impact of government subsidies on commercial R&D activities (i.e., the economic return) at the micro-level (Becker, 2015; Carboni, 2011, 2017; Clausen, 2009; David et al., 2000; Trajtenberg, 2002) and in relation to military R&D crowding-in privately funded R&D (Pallante et al., 2023). However, the market failure–based justification of government intervention is not without criticism. Some argue that government support is unlikely to be successful on average and even less likely in the case of projects with a high social return that the private sector does not realize on its own (Klette et al., 2000). The reasons are that government officials lack ownership competence (in reference to “which resources to own, […], how to create value by owning these resources […], and when to own them,” Murtinu et al., 2022, p. 60). R&D projects become successful because of entrepreneurship and not because of government action (Murtinu et al., 2022). These authors argue that it is “merely” the law of large numbers that leads to economically and socially successful R&D projects, as the state simply supports many projects.

Based on these arguments, the first contribution of this paper is to investigate the relationship between government support and the extent of innovation activities, with the number of private patents as a proxy of the latter. We propose the following as our first hypothesis:

H1: Government support increases the number of innovations.

Our rationale for this positive relationship is mainly based on the assumption that government support enables private actors to develop innovations that would otherwise be too uncertain or risky.

2.2 Government support and complexity

Government support can lead to increased innovation, but this does not always translate to sheer quantity. While the innovations or new products might be fewer in number, they might explore more complex and advanced technologies. Therefore, an apparent decrease in innovative activities could merely be a result of measuring quantity without considering quality. To account for this, we introduce the concept of “complexity” as a measure to gauge the quality and depth of technological advancements.

Technological complexity grows over time because technology and knowledge are cumulative. Each technological advancement builds on the knowledge of previous innovations (Aunger, 2010;

Hidalgo, 2015; Jones, 2009). Moreover, technologies begin to deepen in complexity when they embark on serving more functions (like Microsoft's Windows) and need to be compatible with other innovations (Broekel, 2019; Fai & von Tunzelmann, 2001). Recent studies by Broekel (2019) and van der Wouden (2020) empirically confirm this increase in technological complexity over time. They show that the average complexity across all technologies is growing and that younger technologies tend to be characterized by higher levels of complexity. The creation of these new technological combinations involves the meticulous task of piecing together different knowledge fragments, often through guided trial-and-error methods (Dosi, 1988). The more complex a technology is, the more diverse its knowledge base. This means that its creation involves rarer knowledge components and demands more trial-and-error efforts (Carbonell & Rodriguez, 2006; Fleming & Sorenson, 2001; Broekel, 2019).

Such complexity drives increased R&D efforts since developers need stronger absorptive capacities (Cohen & Levinthal, 1989). This can result in longer development periods (Griffin, 1997) and a heightened risk of setbacks (Singh, 1997). In this case, market failures may arise, which justify government support to provide the necessary security net for innovators. Given the increasing average complexity, such situations may become more frequent, implying continual extension of government support. Another observation supports this idea. Research teams have notably expanded in size over recent decades (Jones, 2009; 2010). This expansion is intrinsically tied to the escalating complexity of innovative endeavors (Broekel, 2019; van der Wouden, 2019). The quantum of global knowledge has surged exponentially. Unlike the Renaissance, marked by polymaths with proficiency across myriad disciplines, the present landscape is dominated by highly specialized experts (Jones, 2009). Balland et al. (2022, p. 2) articulated the view that augmentation of societal knowledge operates on an extensive margin: "The collective knowledge reservoir deepens not because individuals know more, but because they know differently. The proliferation of know-how is essentially a product of specialization."

At its core, innovation is the art of ingeniously reconfiguring pre-existing ideas (Fleming & Sorenson, 2001; Weitzman, 1998). The propagation of novel technologies necessitates the amalgamation of insights from these hyper-specialized individuals. Yet, the resultant fragmentation and stratification of knowledge amplify coordination exigencies (Becker & Murphy, 1992). To actualize multifaceted technological innovations, these individuals need to function within harmonized, cohesive teams (Neffke, 2019). However, the orchestration of such synergistic assemblies not only escalates resource demands, due to an increased workforce, but also poses the challenge of multiple iterative attempts to curate a team that perfectly coalesces.

State-sponsored interventions can foster and amplify social interconnectivity, knitting a denser web of relationships within technological communities. This, in turn, augments the reservoir of specialized talents accessible to enterprises (Callon, 1994; Lundvall, 1992; Salter & Martin, 2001). The empirically observed enlargement in R&D team dimensions provides tangible corroboration of the narrative of burgeoning complexity.

In sum, advancements across the (ever more) complex technological landscape have become more complicated and resource-intense (Bloom et al., 2020). Jones (2009) famously summarized this development as "the burden of knowledge," which triggers increasing government support. However, there are also arguments for the opposite to hold true. Government support may also be a driving force behind the growth of technological complexity.

Complex technologies provide a better basis for further technological advancement and diversification (Hidalgo & Hausmann, 2009). They often require a deep understanding of various scientific principles and engineering concepts and specialized skills. The engagement with such technologies necessitates a workforce with high levels of education and expertise. This accumulation of knowledge and skills creates a foundation for further technological advancement, amplified by spillover effects and the creation of opportunities for diversification. Consequently, the investment in complex technologies promises greater economic returns (Broekel, 2019; Kogut & Zander, 1992; Sorenson et al., 2006; Winter, 1987; Zander & Kogut, 1995), which attract support from the government seeking to benefit from these gains.

Another rationale behind the increased government support attracted by complex technologies is the recognition that certain highly desirable technologies, notably green technologies, are inherently complex (Barbieri et al., 2020). Despite the scarcity of empirical research on the linkages between ownership structures and sustainable technological change, recent findings by Steffen et al. (2022) reveal a conspicuous trend: state-owned utilities within the electricity industry outpace their private counterparts in investing significantly more in renewable energy, signaling responsiveness to climate policy objectives. This phenomenon also encompasses instances such as military technologies in the US, characterized by not only social benefits for specific groups but also substantial catalysis of technological progress, exemplified by the internet's development, as discussed by Abbate (2000).[2]

Typically, such societal advantages are not pivotal considerations in the investment calculus of private entities, although noteworthy exceptions exist (Mazzucato, 2012). However, from a political standpoint, they hold immense allure. Consequently, government backing is likely to be channeled toward technologies that are socially and economically desirable and often coincide with

[2] We acknowledge that military technologies are primarily developed and used for warfare, which brings harm to people in many ways.

technologies with heightened complexity. Given the challenge inherent in precisely quantifying the requisite resources or, conversely, a certain political impetus to showcase (over)investments in these domains, the scenario arises where government support may occasionally exceed optimal levels. This implies that the R&D ecosystem could be inundated with resources surpassing the balance for sustaining advancement in less and more complex technologies. In the case of military technologies, for example, international competition and the pursuit of security compel governments to endorse projects that are otherwise too complex and costly for private enterprises.

In such scenarios, government support could inadvertently push the frontiers of technology beyond pragmatic economic utility, resulting in involvement with exceedingly complex technologies whose progress is less efficient, for instance, because supportive technologies in related but simpler fields receive less support and do not keep up with their advancement. In this case, government support is an enabling force that actively pushes technological complexity.

An additional explanation supporting this direction of impact starts from the previously discussed idea that the greater resource requirements, higher potential for failure, and longer development times make market-failure situations more likely and (more) complex technologies relatively less attractive to private R&D. Consequently, assuming a constant distribution of R&D across technologies, growing complexity should lead to lower private investments and, if a constant rate of innovation is desired, an increased need for government intervention.

In this context, it becomes apparent that technological complexity adds another dimension to the traditional crowding-out debate (Guellec & Van Pottelsberghe De La Potterie, 2003; Marino et al., 2016). While higher levels of technological complexity imply the need for greater R&D investments, these technologies also promise greater economic returns (Broekel, 2019; Kogut & Zander, 1992; Sorenson et al., 2006; Winter, 1987; Zander & Kogut, 1995). If these returns sufficiently compensate for the necessary investments, complexity can be unrelated or even negatively related to the degree of market failure. However, as indicated above, this is unlikely precisely because of the long-term nature of economic returns associated with complex technologies and the expectation that private firms would struggle to mobilize R&D resources for technological advancements in complex domains. When the potential social and ecological benefits of (many) complex technologies that attract policy interest are also considered, crowding out is a less likely scenario for complex technologies. While clarifying the exact relationship between crowding out and complexity is beyond the scope of the current paper, we nevertheless seek to understand the link between government support and technological complexity, which is reflected in the following hypothesis:

H2: Government support increases technological complexity.

To conclude, the presence of compelling counterarguments to our hypothesis underscores the necessity of the empirical investigation detailed in the subsequent sections of this paper.

3 Methods and data

3.1 Overview of the methodological approach

In this study, we investigated the intricate relationship between government support and the complexity of technological innovations. Our analysis used a comprehensive dataset of patent records from the USPTO that reflected a wide range of technological innovations. These patents, categorized into various technology groups, allowed us to examine how complexity in technology evolves and the role government support plays in this process.

Complexity in this context is understood as the degree to which various components and ideas are interwoven within a technology. More complex technologies exhibit a denser, more intricate web of interconnected ideas and components. We assessed this complexity using the structural diversity measure designed for patent data, which reflects the varied and multifaceted nature of technological innovations. In addition, our dataset included information on whether patents were supported by the government and whether such support was through direct ownership, funding, or building on government R&D.

The application of VAR-LiNGAM, a structural vector autoregression (SVAR) model, in our study was particularly important for decoding the multifaceted ways government support influences technological complexity. By distinguishing between immediate and delayed effects, our analysis shed light on how various forms of government support—ranging from direct funding and ownership to indirect mechanisms such as building upon government R&D—exerted their influence on the evolution of technological complexity. This methodological approach enabled us to unravel not only the direct, apparent influences but also the subtler, indirect modalities through which government actions shaped the technological innovation landscape. The VAR-LiNGAM method stands out for its ability to completely identify linear relationships from data with non-Gaussian error terms and acyclic contemporaneous effects, which made it an invaluable tool in our investigation of the complex interplay between government support and technological complexity.

The rest of this chapter provides more detailed information on our methodological approach, including how we captured technological innovations, measured their complexity, identified government support, and applied the empirical model.

3.2 Measuring technological innovations and their complexity

We used patent data from the PatentsView Database, which covers all patent applications to the USPTO, to approximate technological activities (Cohen et al., 2000)[3]. The Cooperative Patent Classification (CPC) classifies patents into different technologies. The CPC is hierarchically organized into nine sections at the highest level and approximately 250,000 sub-groups at the lowest level. Each patent was assigned to one main technology class and multiple secondary classes. We focused on the four-digit CPC level, which allowed us to differentiate between 655 technologies. The four-digit level represents an appropriate trade-off between a good degree of differentiation between technologies and sufficiently large patent counts in each technology class (Balland & Boschma, 2021; Leydesdorff et al., 2017). Crucially, previous research has successfully estimated and analyzed technological complexity at this level (Broekel, 2019).

We calculated the measure of technological complexity ("structural diversity"), which has been shown to reflect commonly accepted characteristics of technological complexity (complexity increasing over time and requiring more R&D efforts and collaboration, as well as concentrating in space) more accurately than alternative measures (Broekel, 2019; Pintar & Essletzbichler, 2022). In addition, it has been used to empirically identify the positive impact of technological complexity on economic growth (Mewes & Broekel 2020). The measure quantifies the complexity of a technology by analyzing its structural diversity through network analysis. The foundational premise is that technologies are composites of various knowledge elements. These elements, akin to nodes in a network, are interconnected in multiple configurations, such as star-like or lattice structures. The assumption is that the complexity of a technology is correlated with the diversity

[3] The use of patent data has several well-discussed drawbacks (Cohen et al., 2000; Griliches, 1990). However, patent data provided essential information for our empirical analysis of technological innovations, their characteristics, and inventors.

of these configurations. Essentially, more intricate and varied network structures indicate a higher degree of technological complexity.

The network diversity score (NDS) was calculated for each technology (four-digit CPC code) using a binary co-occurrence network. This network included as nodes all CPC codes listed in patents that featured at least one CPC code belonging to the focal technology. Edges between nodes indicated the existence of co-occurrence. A technology-specific complexity metric, which reflected higher complexity as its value increased, was derived by applying the NDS to this network and making some transformations (for details, see the appendix under "Details on the empirical model").

To account for the inherent variability in patent data, particularly for niche technologies, the analysis incorporated a three-year moving window. This approach expanded the dataset for each year's analysis by including patents from the target year and the preceding two years. By doing so, the measure was stabilized, resulting in one individual complexity score for each of the 655 technologies per year, corresponding to the four-digit CPC classes.

3.3 Measuring government support for technological innovation

The information on the link between technological activities (patents) and government support was retrieved from a publicly available data set provided by Fleming et al. (2019).[4] They collected information on whether a patent's creation between 1926 and 2016 relied on government support. The reliance on support was defined in three ways. First, the government owned the patent; second, it funded the underlying research; or, third, the patent cited government R&D[5]. The three categories

[4] The data on government support for patents from Fleming et al. (2019) is freely downloadable from https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DKESRC

[5] The last category (government R&D cited) referred to whether the patent cited a patent or a scientific paper that met the first two criteria (government ownership or funding) or was affiliated with a government agency.

were not mutually exclusive, with the sources of government support overlapping in about 39 percent of the patents (Fleming et al., 2019).[6] Due to the relatively low reliability of the data before 1980[7], we restricted our empirical analysis to the years 1981 to 2016 (see Fleming et al., 2019, and supplementary material). While the three types of support were distinguishable from one another, none of them seemed to be particularly related to technological complexity. Consequently, we did not have a particular expectation concerning which type was more likely to capture the phenomenon of interest. Nevertheless, we treated them independently in the analyses for analytical clarity.

While the dataset represents a unique information source linking (patented) innovation outcomes to government support, it is important to consider its limitations. We did not have information on how much resources were invested or the specifics of the outcomes. Government support does not always lead to the development of a patentable innovation. However, it is only the latter that we observed in our data. In the case of patented innovations, we also did not have information on how much resources a patent had received; we only knew whether or not it had received any resources.

All patents were assigned to their main four-digit CPC class, and their numbers were aggregated at this level to obtain technology-level variables. For each technology c and time period t, we calculated the absolute number of patents that (1) were owned by the government, $Government\ Ownership_{c,t}$; (2) were funded by the government, $Government\ Funding_{c,t}$; or (3) cited government R&D, $Government\ R\&D\ Cited_{c,t}$. When aggregating patents to the level of four-digit CPC classes, their numbers tended to fluctuate strongly between years. Therefore, we

[6] The dataset provided by Fleming et al. (2019) was on the patent level and stated for each patent if it was owned or funded by the government or cited government research and development. Thus, the three original government support variables were binary variables.

[7] Data inaccuracies were due to changes in reporting, acknowledgment of behavior, requirements of references, and funding in patent applications (for further information, see Fleming et al., 2019).

opted for three-year intervals as periods of observation to reduce the potential distortion of such fluctuations.

We assessed the stationarity of our data by means of a panel unit root test (Im et al., 2003; Pesaran, 2007), log-transformed all our variables, and subsequently performed a first-difference transformation to ensure stationarity.[8] In other words, we took log-differences of the variables that corresponded to their expression as growth rates (Törnqvist et al., 1985). Based on this, we created a final panel dataset for 561 four-digit CPC technologies and three-year periods between 1981 and 2016, including information on the respective growth rates of government support (ownership, funding, or government R&D cited), complexity, and the number of private patents[9] in each technology class. Crucially, for all variables, we used the mean of a period's annual values.

In total, we obtained 6,164 individual observations that were the basis of the subsequent empirical analysis.[10] Table 1 presents the summary statistics of all variables used in this study (Table A2 in the appendix provides additional definitions of the variables used in the empirical model. Table A3 in the appendix provides additional descriptive statistics).

[8] We report the unit root tests in the appendix (Table A7).

[9] The number of private patents in a technology class was calculated for the final panel dataset (for 561 four-digit CPC technologies) by subtracting patents with government support from the total number of patents.

[10] Of the 655 different technology classes, 561 were present in our patent data. Thus, initially, we had 12 distinct periods (between 1981 and 2016) and 561 distinct technology classes. We took the first differences and finally performed the analysis with 11 periods (between 1984 and 2016). The panel was not balanced. A balanced panel would have needed 6171 observations (561 technologies * 11 periods); however, we had only 6,164 observations (a difference of 7 observations). We had all 11 observations for 557 technologies; however, for 4 technologies some observations were missing (namely 7 in total) because the technologies did not have any patents in certain periods.

Variable	Statistic	1986	1989	1992	1995	1998	2001	2004	2007	2010	2013	2016
Complexity	Mean	0	0.3	0.46	0.48	0.48	0.45	0.21	0.08	-0.07	0.32	0.36
	Median	0.05	0.29	0.44	0.43	0.48	0.40	0.21	0.09	-0.04	0.22	0.29
	SD	0.99	1.08	1.07	1.07	1.11	0.99	1.01	1.08	0.89	0.96	1.01
Government funded	Mean	0.08	-0.03	0.09	0.05	0.04	0.12	-0.01	-0.04	0.09	0.26	0.02
	Median	0	0	0	0	0	0	0	0	0	0.14	0
	SD	0.54	0.6	0.55	0.57	0.56	0.6	0.57	0.57	0.54	0.56	0.57
Government ownership	Mean	0	-0.13	0.13	0	-0.13	0	-0.05	-0.11	-0.02	0.13	-0.04
	Median	0	0	0	0	0	0	0	0	0	0	0
	SD	0.53	0.58	0.6	0.56	0.56	0.55	0.54	0.54	0.49	0.49	0.54
Government R&D cited	Mean	0.15	0.18	0.11	0.12	0.17	0.22	0.04	-0.04	0.1	0.27	0.08
	Median	0.15	0.2	0.09	0.11	0.16	0.22	0.05	-0.01	0.1	0.29	0.1
	SD	0.53	0.57	0.55	0.54	0.54	0.5	0.49	0.49	0.47	0.51	0.48
Number of private patents	Mean	0.05	0.08	0.09	0.03	0.09	0.15	-0.11	-0.22	-0.06	0.23	0.12
	Median	0.05	0.10	0.08	0.01	0.09	0.16	-0.09	-0.21	-0.06	0.22	0.15
	SD	0.33	0.37	0.32	0.3	0.33	0.31	0.31	0.34	0.36	0.38	0.39

Table 1: Descriptive summary statistics.

Note: These summary statistics are based on the final variables we used in our empirical model. The variables are described in Table A2 in the appendix. We provide further summary statistics using less cleaned data in the appendix (see Table A3).

3.4 Empirical model

To effectively analyze the interplay between government support and technological complexity, we implemented the VAR-LiNGAM method, a particular form of a SVAR model (Hamilton, 1994; Hyvärinen et al., 2010; Moneta et al., 2013). This sophisticated statistical tool was particularly effective in disentangling the dynamic and intricate interactions present in our dataset. In contrast to conventional models, VAR-LiNGAM is specifically tailored to address data with linear relationships and non-Gaussian error terms, allowing full identification of the potential causal dynamics in the data without further background knowledge.

The VAR-LiNGAM methodology operates on the fundamental premise of distinguishing between instantaneous and time-lagged effects within the data. This approach was instrumental for dissecting the temporal relationships in our dataset, particularly how government support and technological complexity interacted contemporaneously and over time. A critical assumption underpinning this method is the acyclic nature of these contemporaneous relationships. This assumption enabled us to delineate a directional flow of influence without the entanglement of feedback loops within a single time interval. It was key to controlling for potential immediate influences that might otherwise have confounded our analysis.

The practical application of VAR-LiNGAM involved several distinct steps (for details see "Details of the empirical model" in the appendix). Initially, we estimated the coefficients of the reduced-form VAR model. This step established the foundational relationships between observed variables across different periods. We then applied the LiNGAM approach (Shimizu et al., 2006) to estimate the instantaneous causal effects. By assuming non-Gaussian distribution of the structural residuals and employing independent component analysis (ICA; Hyvärinen et al., 2001), we identified the matrix of instantaneous effects and statistically independent residuals. This phase was critical for identifying the immediate causal relationships between the variables. Finally, we calculated the lagged causal effects matrices by excluding the instantaneous effects from the lagged coefficients of the reduced-form VAR. These lagged causal effects revealed how past values of variables influenced their current states, thereby capturing the dynamic interplay over time.

We used the code package in R from Moneta et al. (2013), adapting it slightly to suit the specific research needs of this study. We evaluated the model fit using different estimators (ordinary least squares [OLS] and least absolute deviations [LAD]) and lags. Several assumptions of the model were assessed: (1) different information criteria for lag selection[11]; (2) auto-correlation of the residuals; (3) non-Gaussianity of the residuals; and (4) acyclicity of the instantaneous effects. Based on these characteristics, the model fit proved to be good for OLS and two lags, also confirming the applicability of the VAR-LiNGAM approach (for details see "Details on the empirical model" in the appendix). Furthermore, we used a block-bootstrap approach with 500

[11] Akaike Information Criterion, Hannan–Quinn Information Criterion, and Schwarz Information Criterion; see Tables A7 and A8 in the appendix.

bootstrap samples not only to evaluate the robustness of the model but also to infer statistical significance of the coefficients estimated using a t-test. A further robustness analysis was performed using different pre-processing steps of the data (see section 4.3).

4 Results and discussion

4.1 A descriptive look at government support and technological complexity

Figure 1 illustrates the increase since 1981 in patents whose inventions relied on government support, with a certain level of stagnation observable from 2010 onward. However, this trend is not equal across all types of government support. While the number of patents citing government R&D steadily increased, those that received funding from the government increased only minimally. The number of patents owned by the government even stagnated. The heterogeneity in these three indices clearly suggests their treatment as independent indicators.

Similar heterogeneities were evident in the development of individual technologies (Figure 2). During the period of observation, the field of physics and electricity benefited the most from government support, with more than 400 patents relying on this support. Chemistry was in third place until 2010, and after 2010, human necessities had more patents relying on government support than chemistry. This result illustrates that there are also substantial dynamics in the ranking of technologies in terms of the support received.

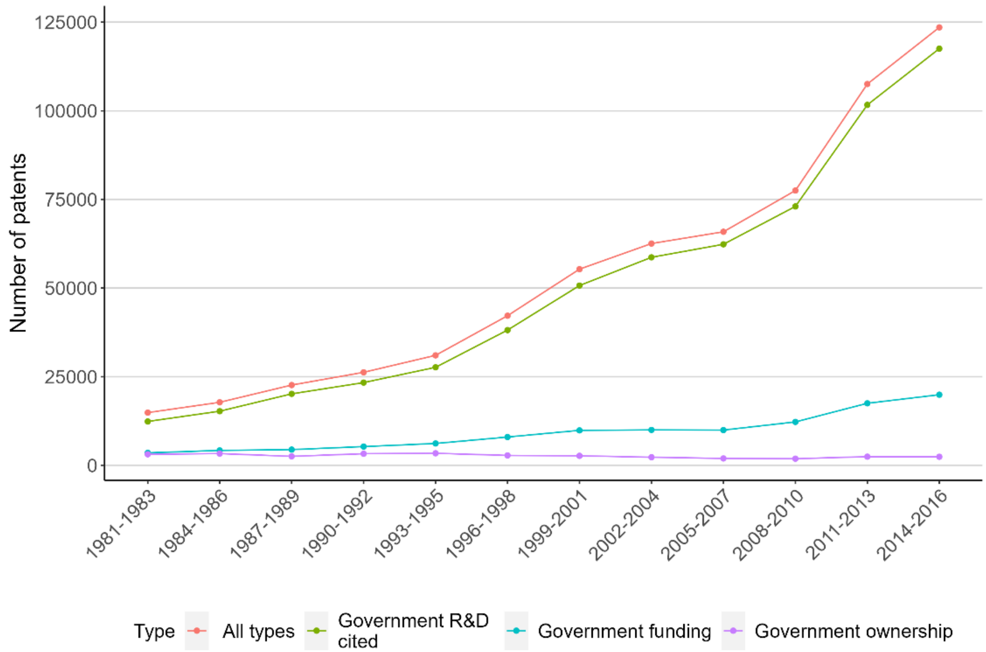

Figure 1: The growth in different types of government support.

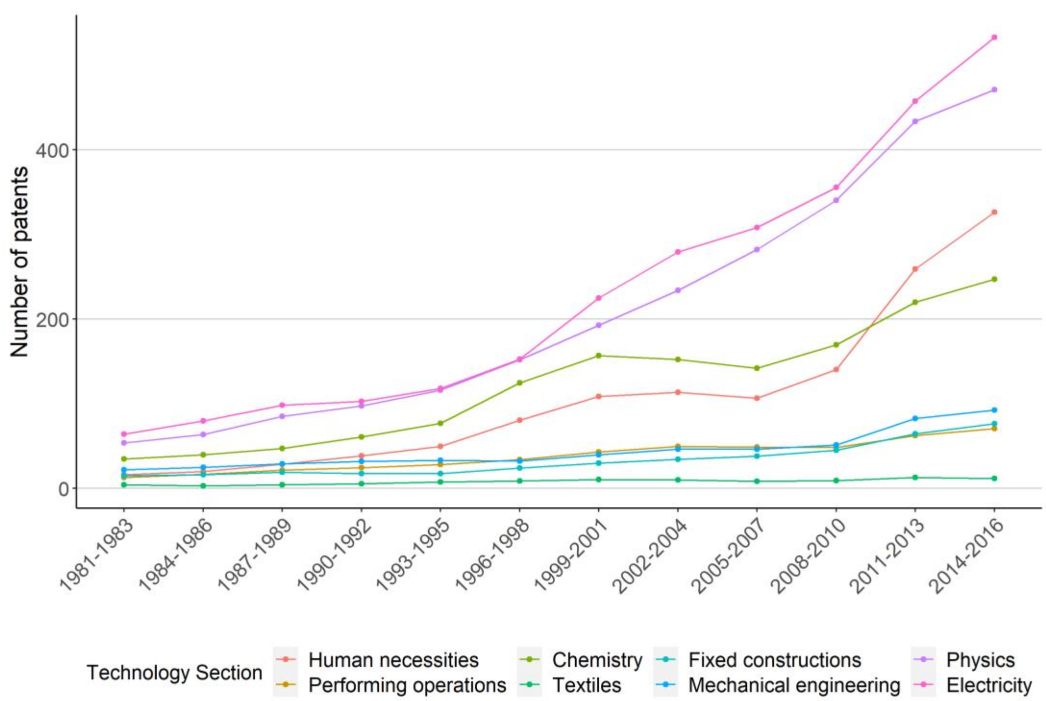

Figure 2: Government support across different technologies.

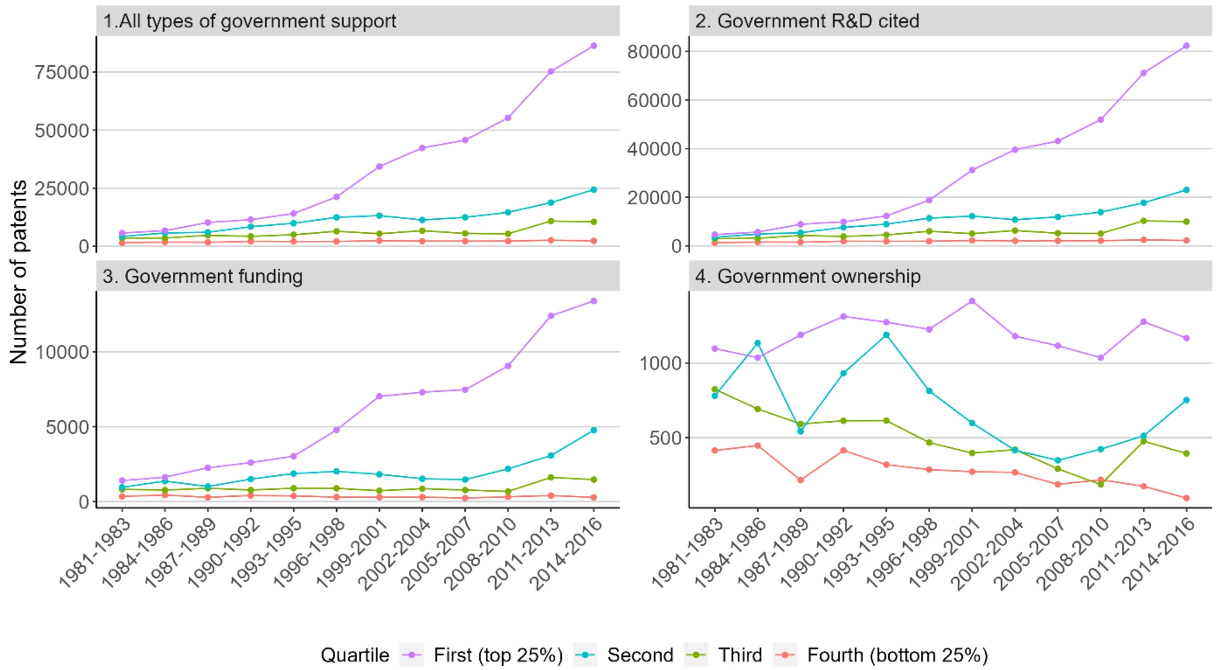

Figure 3: Differences in government support by complexity.

Note: The y-axes have different scales.

What explains these differences in government support between technologies? The first indication that complexity was a relevant factor in this context is apparent in the distribution of government support across the complexity quartiles. Panel 1 in Figure 3 provides an insight into this distribution across all types of government support, Panel 2 into patents citing government R&D, Panel 3 into government-funded patents, and Panel 4 into government-owned patents.

The most complex technologies were characterized by the highest number of supported patents (Figure 3, panel 1). When differentiating between types of support, the most complex technologies were also the ones that cited government R&D to the largest degree (Figure 3, panel 2) and that generally had higher numbers of patents funded by the government (Figure 3, panel 3). The dimension of government ownership showed similar patterns after 1986: the most complex technologies had the highest number of supported patents (Figure 3, panel 4). Figure 3 clearly shows that the ranking of "technologies" by complexity corresponds quite well to their ranking by government support. A rank-correlation analysis supported this observation and revealed a positive correlation between government R&D cited and complexity (significant rho of 0.56, $p < 0.001$) and between government funding and complexity (significant rho of 0.52, $p < 0.001$), as well as a weakly positive correlation between government ownership and complexity (significant rho of 0.42, $p < 0.001$). Consequently, the bivariate correlation analysis suggested a positive relationship between government support and technological complexity.[12]

[12] Additional correlation analyses are provided in Tables A3, A4, and A5 in the appendix.

4.2 Disentangling the relationship between government support and complexity.

		BO					B1					B2				
		Complexity	Gov. funding	Gov. R&D cited	Gov. ownership	No. of private patents	Complexity	Gov. funding	Gov. R&D cited	Gov. ownership	No. of private patents	Complexity	Gov. funding	Gov. R&D cited	Gov. ownership	No of private patents
Complexity	coeff	0	-0.0259	**0.2199**	-0.0308	**0.4819**	**-0.2347**	-0.0461	**0.174**	-0.0301	**0.5312**	**-0.1687**	**-0.0728**	**0.1434**	0.0053	**0.2255**
	SD	0	0.0264	0.0414	0.0264	0.0616	0.0216	0.0327	0.0434	0.0297	0.0567	0.0223	0.0282	0.0349	0.0276	0.0552
Gov. funding	coeff	0	0	0	**0.3987**	0	0.005	**-0.4854**	**0.0588**	**0.2186**	**0.0813**	0.0019	**-0.2191**	**0.0361**	**0.0961**	0.0358
	SD	0	0	0	0.0165	0	0.0063	0.0161	0.0157	0.018	0.0207	0.006	0.0162	0.0138	0.0161	0.0223
Gov. R&D cited	coeff	0	**0.1874**	0	**0.0385**	**0.4187**	0.0153	**0.1711**	**-0.4892**	0.0227	**0.2983**	0.0067	**0.1023**	**-0.2226**	0.0158	**0.1141**
	SD	0	0.0134	0	0.0112	0.0184	0.0071	0.0134	0.017	0.0126	0.022	0.0069	0.0119	0.0163	0.0106	0.0229
Gov. ownership	coeff	0	0	0	0	0	0.0023	0.0295	0.0317	**-0.5133**	**0.072**	-0.0134	0.0411	0.0205	**-0.2198**	0.0375
	SD	0	0	0	0	0	0.0057	0.0152	0.0128	0.0176	0.0191	0.0062	0.0168	0.0138	0.0169	0.0217
No. of private Patents	coeff	0	**0.1164**	0	**0.0356**	0	0.0103	**0.0829**	**0.0712**	0.0095	**-0.1144**	0.005	0.0265	0.0117	0.0087	**-0.0679**
	SD	0	0.0097	0	0.0104	0	0.0066	0.011	0.0127	0.0123	0.0238	0.0067	0.0111	0.0129	0.0115	0.0242

Table 2: Structural vector autoregression model results with ordinary least squares estimator and two lags.

Note: Coefficients in bold are statistically significant at the $p < 0.01$ level.

The results of the SVAR model for identifying the relationships between complexity and government support are presented in Table 2. To improve readability and in line with the literature (Coad & Binder, 2014; Coad & Grassano, 2019; Hyvärinen et al., 2010; Lanne et al., 2017; Moneta et al., 2013; Pearl, 2009; Spirtes et al., 2000), we present its results in a causal manner. However, since we relied on observational data without external intervention, such an interpretation can be debated.

The table shows the estimated coefficients of the SVAR model.[13] For the instantaneous effects matrix $\boldsymbol{B}_0$ (relations between variables at the same moment in time; in our case, relations within a three-year period), the following causal order was inferred: starting from government ownership, followed by government funding, number of private patents, government R&D cited, and, lastly, complexity. The lagged effects (relations between variables across periods; in our case, relations over periods of three years) were estimated for one and two lags and reported for the matrices $\boldsymbol{B}_1$ and $\boldsymbol{B}_2$, respectively. The standard deviations of the coefficients were calculated using 500 bootstrap samples by applying a block-bootstrap approach. Figure 4 provides a graphical representation of the SVAR results listed in Table 2 (showing results for the two-lag SVAR). To evaluate the robustness of these results, the SVAR was estimated for other lags with both OLS and LAD analyses and always yielded the same causal order.[14] Furthermore, about 65% of the 500 bootstrap samples resulted in the exact same causal order in the OLS analysis, rising to about 80% with the LAD model. In the case of the variables' positions in the inferred causal orders, in over

[13] In the case of coefficient interpretation, note that we focused on growth and interpreted the relative size of the coefficients. Given our aggregated data structure, we refrained from interpreting the absolute magnitude of the coefficient. However, given that we analyzed growth rates, even small coefficients could have had a relevant effect.
[14] We calculated and assessed the model with one and three lags for robustness without finding significant differences from the OLS model with two lags. We also compared the coefficients of the OLS model with two lags with those of the LAD model with two lags for robustness without finding significant differences.

90% of the bootstrap samples, government ownership was first, and complexity was last in both the OLS and LAD analyses. Thus, the overall order was very robustly inferred, considering that there were, in total, 120 different possible orders with five variables (Figures A3 and A4 in the appendix provide a further explanation).

The crucial observation is that complexity did not have any effect on any of the other variables. In the case of instantaneous effects, complexity was placed at the end of the causal order, suggesting that complexity was not a driver of other variables but rather an outcome of them. This held true for effects within the same period (i.e., within a three-year period) and supported our hypothesis **H2**, according to which increasing government support pushes the levels of complexity of technologies. Moreover, government ownership had a large effect on government funding and a very small effect on the number of private patents and government R&D cited. Government funding had a small effect on the number of private patents and government R&D cited. The number of private patents had a strong effect on complexity and government R&D cited, while government R&D cited had a medium effect on complexity. This causal ordering and the instantaneous effects suggest that government support (ownership and funding) increases private innovations (supporting our hypothesis **H1**), as well as those private innovations relying on government support driving complexity. However, complexity growth is a slow process (Broekel, 2019), and from a theoretical perspective, it is difficult to achieve within three years (we aggregated the data into three-year periods). Consequently, the lagged effects are of greater relevance and will be our focus.

In the case of effects lagged by one period (B1/t-1), we found that government ownership had a positive effect on subsequent growth in government funding. This means that the government owned crucial research capacities in specific technologies of interest to it. Over time, this shifted toward more funding-based support schemes. However, this sequence of providing support became less frequent over time. A possible explanation for the shift from state ownership to funding might be linked to productivity challenges associated with state ownership of firms and innovation processes (Steffen et al., 2022).

Government funding had a small effect on the subsequent growth in the number of private patents and in the number citing government R&D. Thus, through its impact on government funding, government ownership also contributed to a growing number of private patents. This suggests that the government support for basic research provides the groundwork for further technological developments. Alternatively, through its support, the government sends a strong signal of the future viability of a technology.

An increase in private patenting had a medium-sized effect on the growth of patents citing government R&D. It also strongly contributed to complexity growth. We also observed a small effect of the number of private patents on government ownership and government funding. This suggests that the government does follow private investments and supports technologies after private innovation activities have increased. It is likely that private innovation activities signal to the government which technologies are relevant and promising or the private sector is successful in lobbying for government support. Lastly, patents that cited government R&D had a small positive effect on government funding, the number of private patents, and complexity growth.

With respect to lagged effects over two periods (B2/t-2), we want to highlight several interesting observations. Government ownership still had an effect on government funding and government funding on government R&D cited. Interestingly, government funding had a small but negative direct effect on complexity growth over this six-year period. Government support overall did not positively influence the number of private patents over such a long period. An increase in private patenting still had an effect on the growth of patents citing government R&D; however, this effect was small. The effect of private patenting on complexity growth was weak. Patents citing government R&D maintained a small positive effect on complexity growth.

In addition, the negative autocorrelation found for all variables (see B1 and B2) suggests a cyclical pattern of growth rates, where a period of heightened increase was often succeeded by a period of diminished increase. In their study of Germany, Buerger et al. (2012) observed similar patterns and suggested that they were related to the inherently stochastic nature of human creativity underlying the patented innovation. However, this aspect should be further investigated in future research, as it does not directly concern our research questions. Therefore, it is not included in the graphical representation of the results in Figure 4.

In summary, our main model provided evidence for a link between government support and increasing numbers of private patents, thereby supporting our first hypothesis (**H1**), which states that government support increases the number of innovations. Note the effect of government support (more precisely funding and ownership) on the number of private patents, and simultaneously, the effect of the number of private patents on government support over time. However, the causal ordering placed the number of private patents after government ownership and funding, which suggests that the first effect was stronger, further confirming our first hypothesis. The results also suggested a link between government support and complexity, thereby confirming our second hypothesis (**H2**). However, this link was not direct. Government support (funding and ownership) fueled complexity growth by increasing the number of patented innovations. A direct boost to complexity comes from innovation activities that cites government

R&D.[15] However, as in many cases, this research is not under the direct control of the government and represents an indirect mechanism. In addition, the relationship (the indirect link between government support and complexity growth through the number of private patents) only existed over a shorter period (with a lag by one period [B1/t-1]), not over a longer period (with a lag by two periods [B2/t-2]).

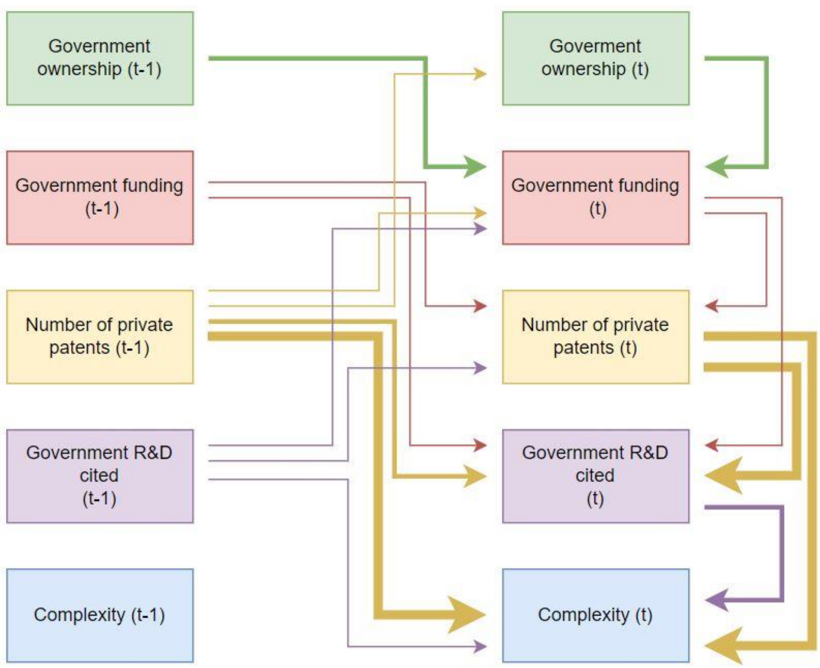

Figure 4a: Graphical representation of structural vector autoregression model results from Table 2 (one time lag).

Notes: The solid arrows indicate positive effects. The size of the arrow reflects the magnitude of each effect (thin: 0.05–0.19; medium: 0.2–0.39; thick: ≥0.4). For simplicity and to maximize visibility, this figure does not show coefficients smaller than 0.05 and autocorrelations. We provide a graph with all effects in the appendix (Figure A2a). Instantaneous effects are shown on the right side of the figure, lagged effects with one time lag (B1) on the left side. The row order corresponds to the empirically inferred causal ordering: government ownership first, followed by government funding, number of private patents, government citing, and, lastly, complexity.

[15] We inferred the indirect link between government support and complexity from the chain of positive effects from government ownership to government funding, government funding to the number of private patents, and the number of private patents to complexity (shown in Figure 4a). The more direct link between government support and complexity is shown in Figure 4b, which indicates the positive effect of government citing on complexity.

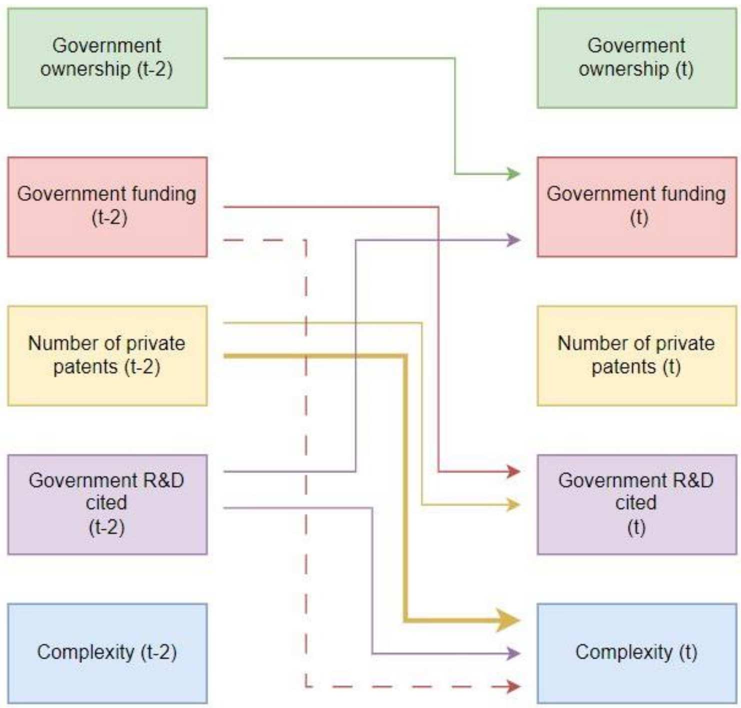

Figure 4b: Graphical representation of structural vector autoregression model results from Table 2 (two time lags).

Notes: The solid arrows indicate positive effects and the dashed arrows negative effects. The size of the arrow reflects the magnitude of each effect (thin: 0.03–0.19; medium: 0.2–0.39; thick: ≥0.4; the negative scale is equivalent [thin: -0.03 to -0.19, etc.]). For simplicity and to maximize visibility, this figure does not show coefficients smaller than 0.05 and autocorrelations. We provide a graph with all effects in the appendix (Figure A2b). For simplicity, instantaneous effects are not shown again on the right side of the figure, but only lagged effects with two lags (B2) are shown on the left side. The row order corresponds to the empirically inferred causal ordering: government ownership first, followed by government funding, number of private patents, government citing, and, lastly, complexity.

4.3 Robustness of the results

To test the validity and reliability of our main results, we performed several robustness checks using different model specifications and data subsets. The details of these robustness models and their specifications are provided in Table A12 in the appendix.[16]

First, we used two- and four-year periods (models 2 and 3 in Table A12) instead of the three-year periods in our main model (model 1 in Table A12). The main results remained consistent across

[16] All robustness models fulfilled the model fit characteristics of triangularity of the instantaneous effects matrix $\boldsymbol{B}_0$ and lack of autocorrelation of the residuals.

different periods. Government support was positively associated with the number of private patents, which in turn was positively associated with increased technological complexity. These effects were significant both within time and over time.

Second, we accounted for potential effects specific to a technological field by including fixed effects at the level of the technological field in model 5 (Table A12). We also followed the approach of Coad and Grassano (2018) and developed a model 6 using standardized growth rates and technological-field fixed effects (Table A12). The inclusion of the technological-field effects did not alter the main results. Government support continued to have a positive effect on the number of private patents, which was the main driver of the increase in technological complexity. The coefficients for government support and private patents changed in size due to standardization, but they were similar in relative magnitude to those in our main model.

Third, we tested the stationarity assumption by focusing on technologies for which this assumption was successfully tested in model 4 (Table A12).[17] The main results were robust to this restriction. Government support remained a significant predictor of private patents, which in turn predicted technological complexity.

In summary, all our robustness models substantiated our main results. They confirmed that government support drove the number of private patents, which was the main driver of increased technological complexity over a rather short period. Our robustness models did not confirm the negative effect of government funding on complexity growth over a longer period (i.e., with a lag of more than one period); rather, they indicated that there was no relationship between government

[17] We applied a strict approach to stationarity testing of panel data by performing an augmented Dickey–Fuller test for every variable of each technology. In this robustness model, we only included the technologies for which at least one variable per technology was confirmed to be stationary. This led to the inclusion of 326 technologies.

funding and complexity growth over a longer period. We also found that these effects were robust to different periods, technological field effects, and assumption of stationarity.

5 Conclusion

One of the long-standing features of technological progress is the increasing complexity of technologies (Aunger, 2010; Broekel, 2019; Hidalgo, 2015; Jones, 2009; Strumsky et al., 2010; van der Wouden, 2020). This trend reflects the cumulative nature of knowledge and its growing specialization and diversification (Hidalgo, 2015). However, it has only gained more attention from scientists in recent times. Concurrently, a contemporary trend is spotlighting the rising reliance of innovation processes on government support. This shift is manifested as the expanding presence of patents owned by the government, those funded by government sources, and those citing government research and development (Fleming et al., 2019).

This study proposed a relationship between the two trends. More precisely, we argued that complex domains and higher levels of technological complexity may go hand in hand with economic and social benefits that the public sector seeks to harness. Thus, the public sector, in turn, pushes the levels of complexity of technologies by providing extra resources. Alternatively, we posited that escalating government support is crucial for maintaining a consistent pace of technological progress due to growing complexity, which amplifies resource demands.

We tested these two arguments using US patent data disaggregated into 561 individual technologies for the period between 1981 and 2016. We distinguished three categories of government support as outlined by Fleming et al. (2019). Technological complexity was calculated using the structural diversity index proposed by Broekel (2019) and the VAR-LiNGAM method was applied to analyze the empirical relationships. The VAR-LiNGAM method supports a causal interpretation conditional on its reliance on observational data (Coad and Grassano, 2018; Hyvärinen et al., 2010; Moneta et al., 2010).

Our analysis identified government support as a driving force behind the advancement of technological complexity. Government ownership and funding of innovation activities increased private interest in a technology (evident in the growth in the number of private patents). The subsequent increase in innovation activities in these domains (as indicated by growing patent numbers) contributed to the growth of a technology's complexity. In addition, innovations citing government R&D facilitated further complexity advancements.

While complexity is not a dimension informing the allocation of government support (Aschhoff, 2008; Yin et al., 2022), our study showed support to be skewed toward more complex technologies. Accordingly, complexity seems to be correlated with other dimensions considered in the design of innovation policy. For example, many of the technologies needed for the sustainability transition are complex (Barbieri et al., 2020). In the USA, the massive support for military technologies is likely to play a similar role, as military considerations shape significant portions of the government resource allocation across technologies (as mentioned by Zhang et al., 2022, for the Cold War period). In addition, our study suggests that it is because of pursuing such goals that policy (involuntarily) advances technological complexity.

By identifying such an impact of innovation policy, this study advances the growing literature on (technological) complexity by addressing a neglected question: What factors drive the evolution of complexity over time? Previous studies have often assumed that complexity grows as a "natural process" resulting from the cumulative nature of knowledge (Balland et al., 2022; Hidalgo, 2015). However, this does not account for the temporal variation in the rate of complexity increase (Broekel, 2019; van der Wouden, 2020). Our findings suggest that societal conditions, such as the level of government support for innovation in complex technologies, influence the pace of this process. This invites further research to explore other factors that shape the direction and speed of complexity's development and assess their relative importance.

Our study has several policy implications. Complex technologies tend to be spatially concentrated and diffuse slowly across regions (Balland & Rigby, 2019; Broekel et al., 2023), which implies that the support of complex technologies may exacerbate spatial inequalities in R&D. Moreover, complex technologies have high economic growth potential (Hidalgo & Hausman, 2009; Mewes & Broekel, 2022), which may further widen the economic gap between regions. Importantly, this occurs even without policy explicitly targeting complex technologies, e.g., Germany's former HighTech strategy (BMBF, 2006), as many complex technologies are related to and benefit from policy pursuing other socially or economically desirable goals, such as achieving the sustainability transition. Therefore, policy faces a trade-off between fostering (directly or indirectly) technological progress in complex domains and promoting spatial economic cohesion.

This trade-off also needs to be considered in the debate about using complexity and relatedness in regional smart-specialization policies (Balland et al., 2019). Here, (technological) complexity is argued to indicate the attractiveness of domains for regional diversification. This makes complexity an explicit policy dimension. Our results raise the question of whether such a policy position is necessary or desirable.

In the case of necessity, we showed that government R&D support in the USA is already skewed toward more complex technologies. It can be argued that by focusing on other dimensions, such as sustainability and digitalization, policy ensures indirect support for complex technologies. However, we also observed that a large part of policy influence stems from stimulating private R&D activities. This suggests that private investments in these domains are limited until policy ensures government support or helps overcome bottlenecks. Therefore, further research is needed to clearly identify differences in the role played by government support between simple and complex technologies.

In the case of desirability, our study casts some doubts on government R&D supporting complex technologies. Despite potential positive effects such as larger growth potentials and increased diversification opportunities, government support pushes the levels of technological complexity further than the levels achieved without government intervention. Higher complexity makes progress harder and more expensive. Hence, today's benefits may come at the price of more difficult and resource-intensive research in the future. This is not just a theoretical notion, as the results of Strumsky et al. (2010) and Bloom et al. (2017) suggest. Research has become more costly, and R&D productivity has been falling. It may not be too far-fetched to hypothesize, although evidence is lacking, that declining R&D productivity is related to growing complexity. If so, the support of complex technologies may have a negative side effect: to advance these technologies, more resources need to be mobilized. This implies that, if qualitative dimensions of research output are disregarded, government support for complex technologies may reduce research productivity in the future.

Due to government intervention or other factors, humankind may have created and widened the gap between the capabilities and requirements of R&D. This might be driven by the diminishing returns of the last scientific revolution and the need for a new technological paradigm that boosts innovation and reduces resource requirements of R&D. Artificial intelligence may have the potential to turn these developments around. We currently lack the evidence to support these arguments and call for more research. Whether research productivity can be adapted by taking output quality into account may be debated, for instance, by looking at the levels of complexity achieved. Our study confirms that political decisions are associated with not only the direction of technological advancement but also the speed at which future R&D becomes increasingly expensive.

Another implication of this study is concerned with the use of different types of government support. We observed variations in their impact, which depended on the levels of complexity of the technologies. Hence, when designing and evaluating R&D support policies, attention needs to be paid to the level of technological complexity. However, we lacked information about the actual costs of the types of government support and, therefore, could not assess their effectiveness at varying levels of technological complexity. Nevertheless, our study may encourage further research on this issue.

Crucially, these implications are derived from an empirical study with several limitations that may affect the findings. Most importantly, we did not observe the true investments in R&D, nor the exact share of the government's contribution to it. The empirical insights were also restricted to patented innovation activities. Since such innovations usually have market potential and are rather application-oriented, market failures are less likely or are already reduced by the patent system. That is, our empirical analysis focused on the part of the R&D system for which the relevance of (other) government support is potentially the least likely. Moreover, because of our use of patent data, we could not observe service and process innovations, which constitute a large proportion of the innovation output. Other shortcomings of our empirical study are the lack of information on the importance of military technologies and the specific aims of policy schemes that are important factors for the distribution of R&D support. In addition, the category "Government R&D cited" is rather broad. It captures patents that refer to patents and publications funded or owned by the government or affiliated with a government agency. It would be interesting to subdivide this category in future research. Hence, further studies and better data are needed to disentangle the interplay between technological complexity, research productivity, and government support for R&D.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Appendix

Details of the empirical model

Measuring structural diversity

The structural diversity measure starts from the idea that technologies are developed through (re-) combinatorial processes and that they can be expressed as (combinatorial) networks of their (knowledge) components. These networks are characterized by different (sub)topologies, i.e., ways in which the knowledge components are combined. For instance, some components are combined in a star-like fashion, while others are in the form of a lattice. Both topologies require very little information for their individual description; however, the information required to describe the entire combinatorial network will generally increase with the number of distinct topologies that characterize its structure. Broekel (2019) argued that the increasing information content of networks with greater diversities of (sub)topologies reflects the levels of complexity of technologies, as the information content is correlated with the difficulty of inventing, learning, and mastering it.

In practice, this diversity can be approximated with the network diversity score (NDS) (Emmert-Streib & Dehmer, 2012) applied to the binarized co-occurrence network of 10-digit CPC codes (G_c) for all patents that are associated with technology c (four-digit CPC code). Network nodes (V) are the 10-digit CPC codes, and links (E) are established whenever these co-occur on a patent that features the four-digit CPC code representing the focal technology (Broekel, 2019).[18] Following Emmert-Streib and Dehmer (2012), from the empirically observed network G_c, a series of G_c^s subnetworks were randomly drawn from G_c by means of a Walktrap algorithm with $w = 200$ steps and an initial random sample of $S = 125$ nodes. For each subnetwork, an individual network diversity (iNDS) score was calculated:

$$\mathrm{iNDS}(G_c^s) = \frac{\alpha_{module} * r_{graphlet}}{v_{module} * v_{lamda})},$$

where $\alpha_{module} = \frac{M}{n}$ represented the share of modules in the network, M was their number, and V was the number of nodes. Modules were identified with a random walk approach, as suggested by Pons and Latapy (2006). α_{module} was multiplied by the ratio of graphlets of sizes three and four. The product obtained was set in relation to the product of the variability of the network's Laplacian (L) matrix ($\nu_\lambda = \frac{\mathrm{var}(\Lambda(L)}{\mathrm{mean}(\Lambda(L))}$) and the variance of the module sizes m ($v_{module} = \frac{\mathrm{var}(m}{\mathrm{mean}(m)}$). The subsampling of networks yields S distinct values of $\mathrm{iNDS}(G_c)$, for which we calculated the average to obtain the final value of the NDS:

$$\mathrm{NDS}(\{G_c^s|G_c\}) = \frac{1}{S}\sum \mathrm{iNDS}(G_c^s).$$

The measure represents the structural diversity of a technology's combinatorial network. It was converted to the final measure of technological complexity structural diversity (cpx_c) with the following equation:

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[18] The complexity values are freely downloadable from www.tombroekel.de.

$$\mathrm{cpx_c} = \log \frac{1}{\mathrm{NDS}(\{G_c^s | G_c\})}.$$

The conversion ensured that the empirical values were in an application-friendly range and that large values corresponded to higher levels of complexity.

Patent numbers fluctuate strongly for smaller technologies, which may introduce substantial distortions to the measure. To reduce this effect, we used a three-year moving window approach. That is, the combinatorial network of a technology in the year t included all patents in the years t to $t-2$ that featured its four-digit CPC code. Finally, we had one individual complexity score for each of the 655 technologies per year (corresponding to the four-digit CPC classes).

The estimation procedure of VAR-LiNGAM

Structural vector autoregression (SVAR) models are commonly used to explore the causal relationships between a set of variables (Coad & Binder, 2014; Coad & Grassano, 2019; Lanne et al., 2017; Moneta et al., 2013; Pearl, 2009; Spirtes et al., 2000). In this study, a Vector Autoregressive Linear Non-Gaussian Acyclic model (VAR-LiNGAM) (Hyvärinen et al., 2010; Moneta et al., 2013) was estimated to infer the relationship between government support and technological complexity. The SVAR model with q lags was defined as

$$\boldsymbol{y}_t = \boldsymbol{B}_0 \boldsymbol{y}_t + \sum_{i=1}^{q} \boldsymbol{B}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t \text{ (6)},$$

where $\boldsymbol{y}_t$ was the vector of variables at time t, $\boldsymbol{B}_0$ was the matrix of instantaneous effects, $\boldsymbol{B}_i$, with $i = 1, \ldots, q$, were the matrices of lagged effects, and $\boldsymbol{\varepsilon}_t$ was the vector of residuals. For the VAR-LiNGAM approach, the structural residuals $\boldsymbol{\varepsilon}_t$ were assumed to be independent of each other and over time and to have non-Gaussian distributions. Furthermore, VAR-LiNGAM assumed that $\boldsymbol{B}_0$ could be permuted to be lower triangularity, implying that the instantaneous (causal) effects were acyclic. Note that inferring causality from data using probability distribution information is a well-established concept (Pearl, 2009; Spirtes et al., 2000).

For the estimation of SVAR models, and in particular the VAR-LiNGAM model, three steps are necessary (Hamilton, 1994; Hyvärinen et al., 2010):

1. Estimation of the coefficients of the reduced-form VAR model:

   $$\boldsymbol{y}_t = \sum_{i=1}^{q} \boldsymbol{A}_i \boldsymbol{y}_{t-i} + \boldsymbol{e}_t \text{ (7)}.$$

   As stated above, in our case, the variables $\boldsymbol{y}_t$ were stationary such that ordinary least squares (OLS) or least absolute deviations (LAD) could be used to estimate the coefficients of the lagged effects. Note that the reduced-form VAR model does not include instantaneous effects. Several information criteria exist (Akaike Information Criterion, Hannan–Quinn Information Criterion, and Schwarz Information Criterion) for selecting the number of lags q.

2. Estimation of the instantaneous causal effects matrix using the LiNGAM approach (Shimizu et al., 2006):

   $$\boldsymbol{e}_t = \boldsymbol{B}_0 \boldsymbol{e}_t + \boldsymbol{\varepsilon}_t \text{ (8)}.$$

Re-writing this equation yields $\boldsymbol{e}_t = (\boldsymbol{I} - \boldsymbol{B}_0)^{-1}\boldsymbol{\varepsilon}_t$, where $\boldsymbol{I}$ denotes the identity matrix. With the non-Gaussianity assumption of the structural residuals $\boldsymbol{\varepsilon_t}$ and by applying independent component analysis (ICA; Hyvärinen et al., 2001) to the reduced-form residuals $\boldsymbol{e}_t$, the matrix $(\boldsymbol{I} - \boldsymbol{B_0})^{-1}$ and the statistically independent residuals $\boldsymbol{\varepsilon}_t$ can be identified up to the scaling and permutation indeterminacy inherent in ICA. These indeterminacies can be resolved using the lower triangularity assumption of $\boldsymbol{B_0}$. For the algorithmic details see Shimizu et al. (2006); the intermediate results of this step of the algorithm are shown in the appendix. Finally, the matrix $\boldsymbol{B_0}$ can be straightforwardly inferred.

3. Calculation of the lagged causal effects matrices of the SVAR model:

$$\boldsymbol{B}_i = (\boldsymbol{I} - \boldsymbol{B}_0)\boldsymbol{A}_i, i = 1, \ldots, q \text{ (9).}$$

The code package with an implementation of VAR-LiNGAM in R released by Moneta et al. (2013) was used in this study with minor adaptations to estimate the models. The estimates were calculated and compared based on the OLS and LAD methods with several lags. The information criteria for selecting the number of lags to be considered (Akaike Information Criterion, Hannan–Quinn Information Criterion, and Schwarz Information Criterion; see Tables A7 and A8 in the appendix) delivered rather similar numbers for both estimation techniques (OLS and LAD). Thus, a specific model was not clearly indicated based on these information criteria. Further characteristics of a well-fitting model are the triangularity of the instantaneous effects matrix $\boldsymbol{B}_0$ (see Tables A7 and A8 in the appendix) and the lack of autocorrelation of the residuals. The triangularity, i.e., acyclicity of the instantaneous effects, was nicely given in the OLS models with two and three lags and the LAD models with one to five lags. The lower triangularity of the matrix $\boldsymbol{B_0}$, i.e., that there were no feedback loops within one time period, was also backed up by theoretical considerations: government support influencing technological complexity or vice versa is a slow process. Since the residual autocorrelations were not significant in the OLS models but significant (though small) in the LAD models, we proceeded with OLS and two lags.[19] After estimating the reduced-form VAR model (results are reported in Table A10 in the appendix), we investigated the distribution of the residuals. Histograms and QQ plots of the residuals (Figure A1 in the appendix), as well as the normality tests (Table A11 in the appendix), implied that all residuals were non-Gaussian. This confirmed the applicability of the VAR-LiNGAM approach. Furthermore, a block-bootstrap approach, following the implementation of the code package of Moneta et al. (2013), using 500 bootstrap samples was adopted not only to evaluate the robustness of the model but also to infer statistical significance of the estimated coefficients using a t-test. A further robustness analysis was carried out using different pre-processing steps of the data (see section 4.3).

LiNGAM and ICA: Estimation of the instantaneous effects matrix

Above the estimation procedure of VAR-LiNGAM is explained. In Step 2, the LiNGAM method was used to infer the instantaneous effects matrix B_0. LiNGAM is based on ICA, which is

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[19] Due to our data structure and theoretical considerations, we decided to proceed with a time lag of two instead of three. Given our data structure (aggregation into three-year periods), a lag of two already led to an observational period of six years. We saw this as a good compromise between reliably observing an effect of government support and the generally slow phenomenon of complexity growth.

accompanied by scaling and permutation indeterminacy, both of which can be resolved due to the lower triangularity assumption. Here, we show the single steps of how matrix B_0 was calculated.

Following Shimizu et al. (2006), the ICA model is given by $e_t = (I - B_0)^{-1}\varepsilon_t$, with $A \coloneqq (I - B_0)^{-1}$ being the mixing matrix and $W \coloneqq A^{-1} = (I - B_0)$ being the un-mixing matrix. The ICA model was estimated using the R package FastICA (Hyvärinen et al., 2001). [20]

A column-permutation indeterminacy of the mixing matrix was inherent in the ICA, with row-permutation indeterminacy of the un-mixing matrix and scaling indeterminacy. The latter was solved by permuting the rows of W such that the sum of the inverted, absolute value of the diagonal entries of W was minimized (if there were no estimation errors, there was only one permutation of the rows such that all entries along the diagonal were non-zero). With the small dimensionality of five variables, the permutation was performed using a brute force approach, i.e., by calculating the sum for each row permutation. The matrices are shown in Table A1 below. In the first row, the un-mixing matrix W is listed, showing that each row of W has exactly one entry which is larger than all other entries of that row (highlighted in bold). This is a sign that the ICA model fits the data well. The rows were permuted in such a way that these large entries were shown in the diagonal results in the matrix (shown in the second row of Table A1). Then, each row was divided by its diagonal element resulting in $\widetilde{W}$ with all ones on the diagonal (the third row in the table).

A first estimate of the instantaneous effects $\hat{B}$ is then given by $\widehat{B_0} = I - \widetilde{W}$, shown in the fourth row of Table A1. Again, since there were small estimation errors when estimating matrix $\widetilde{W}$, this matrix could not be permuted to strictly lower triangularity. Therefore, by simultaneous row and column permutations, a matrix that minimized the entries in the upper triangle was sought. In addition, a brute force approach was used since it was feasible with the small number of only five variables. The simultaneous row and column permutation yielding the best lower triangular matrix was $(4,\ 2,\ 5,\ 3,\ 1)$. The resulting matrix is shown in the fifth row of Table A1, which indicates that all entries are very small, except for the one in the third row and fourth column (in italics, 0.1041), although compared to the largest values, it is still rather small (e.g., 0.4434 or 0.1659).

The final matrix B_0 was then calculated with the Cholesky decomposition using the inferred order of the LiNGAM model. This is a common approach for estimating the instantaneous effects matrix when the causal order is known and follows the VAR-LiNGAM code package of Moneta et al. (2013). These matrices are shown in rows 6 and 7 of Table A1. There are some minor differences compared to the instantaneous effects matrix calculated using LiNGAM; however, the signs and rough magnitude of the values agree.

Un-mixing matrix W	**1.0348** 0.0195 -0.1879 -0.0051 -0.3880
	-0.0238 -0.3858 **2.3258** -0.1302 -0.5835
	0.0440 0.2025 0.3076 0.1136 **-2.9561**
	0.0056 **-2.1120** 0.0923 0.9365 0.0634
	-0.0124 -0.1191 0.0192 **-2.0091** 0.0070

[20] The R-package is available at https://www.rdocumentation.org/packages/fastICA/versions/1.2-3/topics/fastICA.

Row-permuted version of W minimizing the inverse, absolute value of the diagonal element	**1.0348** 0.0195 -0.1879 -0.0051 -0.3880 0.0056 **-2.1120** 0.0923 0.9365 0.0634 -0.0238 -0.3858 **2.3258** -0.1302 -0.5835 -0.0124 -0.1191 0.0192 **-2.0091** 0.0070 0.0440 0.2025 0.3076 0.1136 **-2.9561**
Row-permuted and with unit diagonal matrix $\widetilde{W}$	1.0000 0.0188 -0.1816 -0.0049 -0.3749 -0.0027 1.0000 -0.0437 -0.4434 -0.0300 -0.0103 -0.1659 1.0000 -0.0560 -0.2509 0.0062 0.0593 -0.0096 1.0000 -0.0035 -0.0149 -0.0685 -0.1041 -0.0384 1.0000
Estimated instantaneous effects matrix $\widehat{B_0}$ before permuting it in causal order	0.0000 **-0.0188 0.1816 0.0049 0.3749** 0.0027 0.0000 0.0437 **0.4434** 0.0300 0.0103 **0.1659** 0.0000 **0.0560 0.2509** -0.0062 -0.0593 0.0096 0.0000 0.0035 0.0149 **0.0685** 0.1041 **0.0384** 0.0000
Estimated instantaneous effects matrix $\widehat{B_0}$ in causal order	0.0000 -0.0593 0.0035 0.0096 -0.0062 **0.4434** 0.0000 0.0300 0.0437 0.0027 **0.0384 0.0685** 0.0000 *0.1041* 0.0149 **0.0560 0.1659 0.2509** 0.0000 0.0103 **0.0049 -0.0188 0.3749 0.1816** 0.0000
B_0 calculated using the Cholesky decomposition with the inferred causal order from LiNGAM, arranged in the original order of the data	0 **-0.0259 0.2199 -0.0308 0.4819** 0 0.0000 0.0000 **0.3987** 0.0000 0 **0.1874** 0.0000 **0.0385 0.4187** 0 0.0000 0.0000 0.0000 0.0000 0 **0.1164** 0.0000 **0.0356** 0.0000
B_0 calculated using the Cholesky decomposition with the inferred causal order from LiNGAM, arranged in the causal order of the data	0.0000 0.0000 0.0000 0.0000 0 **0.3987** 0.0000 0.0000 0.0000 0 **0.0356 0.1164** 0.0000 0.0000 0 **0.0385 0.1874 0.4187** 0.0000 0 **-0.0308 -0.0259 0.4819 0.2199** 0

Table A1. Matrices in the estimation of the instantaneous effects matrix B_0.

Variable	Definition
Government ownership	This variable represents the number of patents for each technology in each period owned by the government. It was calculated by taking the mean value of the yearly number within each period, taking the first difference, and performing a log-transformation.
Government funding	This variable represents the number of patents for each technology in each period funded by the government. It was calculated by taking the mean value of the yearly number within each period, taking the first difference, and performing a log-transformation.
Government R&D cited	This variable represents the number of patents for each technology in each period that cited government research. It was calculated by taking the mean value of the yearly number within each period, taking the first difference, and performing a log-transformation.
Complexity	This variable represents the technological complexity of each technology in each period. It was calculated using the measure of structural diversity (Broekel, 2019) and was log-transformed. For each period, we took the mean complexity value and the first difference.
Number of private patents	This variable represents the number of private patents for each technology in each period. It was calculated by subtracting the number of government-supported patents from the total number of patents, taking the first difference, and performing a log-transformation.

Table A2. Definitions of variables in the main model.

Note: This table shows the five variables used in the main empirical model.

Variable	Complexity			Number of private patents			Government R&D cited			Government funding			Government ownership		
Period	mean	min	max	mean	min	max	mean	min	max	mean	min	max	mean	min	max
1981–1983	5.99	0	13.32	161.29	0	2715	22.21	0	474	6.32	0	146	5.59	0	137
1984–1986	5.97	0	13.47	174.67	0	2538	27.31	0	602	7.51	0	214	5.92	0	189
1987–1989	6.27	0	11.82	198.59	0	2753	36	0	857	7.91	0	232	4.53	0	145
1990–1992	6.74	0	12.46	221.84	0	2820	41.59	0	1021	9.42	0	301	5.83	0	182
1993–1995	7.23	0	12.26	239.65	1	4358	49.28	0	1248	10.98	0	358	6.05	0	206
1996–1998	7.71	0	13.6	290.02	0	9420	68	0	1721	14.23	0	885	4.98	0	161
1999–2001	8.16	0	13.42	364.18	1	13687	90.39	0	2797	17.59	0	1087	4.78	0	162
2002–2004	8.37	0	13.25	358.4	0	15104	104.59	0	3814	17.8	0	852	4.07	0	134
2005–2007	8.45	0	14.82	326.04	0	17834	111.13	0	3860	17.72	0	807	3.46	0	140
2008–2010	8.39	0	12.91	351.41	0	23647	130.18	0	5125	21.82	0	1001	3.32	0	123
2011–2013	8.71	0.53	13.29	475.35	0	32516	181.22	0	7548	31.18	0	1381	4.35	0	157
2014–2016	9.07	1.17	13.24	573.39	0	44882	209.5	0	9868	35.5	0	2102	4.29	0	144
1981–1982	6.01	0	13.2	112.04	0	2026	15.04	0	329	4.12	0	91	3.77	0	94
1983–1984	5.94	0	13.5	107.56	0	1474	15.77	0	331	4.79	0	111	3.98	0	101
1985–1986	6	0	13.48	116.78	0	1753	18.76	0	416	4.94	0	152	3.78	0	131
1987–1988	6.19	0	11.87	124.81	0	1775	22.16	0	503	4.96	0	128	3	0	96
1989–1990	6.52	0	11.84	144.63	0	1921	26.48	0	655	5.67	0	193	3.27	0	107
1991–1992	6.81	0	13.41	151.6	0	2067	29.05	0	720	6.72	0	212	4.11	0	124
1993–1994	7.15	0	12.2	158.93	0	2629	32.21	0	792	7.43	0	231	4.26	0	143
1995–1996	7.46	0	13.64	168.99	0	4116	36.41	0	968	7.45	0	311	3.42	0	125
1997–1998	7.79	0	13.62	201.75	0	7033	48.66	0	1342	10.32	0	706	3.35	0	111
1999–2000	8.1	0	13.63	240.87	0	9059	57.97	0	1652	11.5	0	755	3.28	0	113
2001–2002	8.3	0	13.61	245.25	0	9351	65.65	0	2380	12.19	0	627	2.81	0	94
2003–2004	8.4	0	13.12	236.88	0	10381	71.49	0	2579	11.72	0	557	2.76	0	89
2005–2006	8.49	0	14.79	220.88	0	11815	74.13	0	2583	11.88	0	516	2.33	0	103
2007–2008	8.42	0	14.78	209.22	0	12706	74.38	0	2520	11.75	0	538	2.14	0	75
2009–2010	8.37	0	12.82	248.86	0	16960	93.32	0	3810	15.98	0	752	2.33	0	85
2011–2012	8.65	0	13.2	300.59	0	20123	115.48	0	4634	19.96	0	835	2.82	0	96
2013–2014	8.89	0	13.19	369.3	0	27049	136.28	0	6084	23.05	0	1181	3.05	0	117
2015–2016	9.14	0	13.41	381.94	0	30226	140.13	0	6698	23.87	0	1472	2.8	0	88
1981–1984	5.95	0	13.35	218.6	0	3500	30.68	0	660	8.87	0	202	7.72	0	195

1985–1988	6.09	0	11.86	241.16	0	3528	40.85	0	919	9.88	0	280	6.76	0	227
1989–1992	6.67	0	11.8	295.71	1	3780	55.44	0	1375	12.37	0	405	7.37	0	231
1993–1996	7.3	0	12.29	327.92	1	6745	68.62	0	1760	14.89	0	524	7.68	0	268
1997–2000	7.95	0	13.57	442.62	1	16092	106.63	0	2741	21.83	0	1461	6.63	0	212
2001–2004	8.35	0.54	13.37	481.71	1	19732	137.01	0	4959	23.89	0	1184	5.57	0	183
2005–2008	8.44	0	14.78	428.58	0	24521	147.98	0	4949	23.55	0	1054	4.46	0	178
2009–2012	8.5	0.4	12.95	548.38	0	37083	208.39	0	8444	35.88	0	1587	5.13	0	181
2013–2016	9.01	0.88	13.3	749.22	1	57275	275.66	0	12782	46.79	0	2653	5.83	0	205

Table A3. Extensive descriptive statistics.

Note: The table shows the mean value across all technology classes and the minimum and maximum values of a technology class within a (three-year, two-year, and four-year) period. The government support variables and the number of private patents are total numbers (no first-difference transformation and no log-transformation), and the complexity value is log-transformed (but no first-difference transformation).

Variable	Government R&D cited (sum)	Government funding (sum)	Government ownership (sum)	Number of private patents (sum)	Complexity (log)
Government R&D cited (sum)	1				
Government funding (sum)	0.920	1			
Government ownership (sum)	0.879	0.942	1		
Number of private patents (sum)	0.779	0.576	0.527	1	
Complexity (log)	0.546	0.512	0.411	0.452	1

Table A4. Full rank correlation analysis.

Note: This table shows the results of the rank correlation analysis performed for variables different than those in our final model dataset as described in Table A2. The data used for this correlation analysis are cross-sectional. The government support variables and the number of private patents are total numbers (no first-difference transformation and log-transformation) and the complexity value is log-transformed (but no first-difference transformation).

Variable	Government R&D cited	Government funding	Government ownership	Number of private patents	Complexity
Government R&D cited	1				
Government funding	0.21	1			
Government ownership	0.13	0.39	1		
Number of private patents	0.29	0.14	0.08	1	
Complexity	0.14	0.05	0.03	0.20	1

Table A5. Correlation analysis.

Note: This table shows the results of the correlation analysis performed with the final model dataset with the variables explained in Table A2.

Variable	Complexity last value	Complexity first value	Complexity mean value
Complexity last value	1		
Complexity first value	0.88	1	
Complexity mean value	0.97	0.96	1

Table A6. Correlation analysis of the complexity measure.

Note: This table shows the results of the correlation analysis performed for two alternative operationalizations of our structural diversity measure of technological complexity. We computed the correlation between the first value within a period of three years, the last value, and the mean value. The values are log-transformed, but no first-difference transformation has been performed.

Variable	Technologies	AWB	DWB	SWB
Complexity	384	0.0015	0.0040	0.0000
Government funding	384	0.0000	0.0010	0.0000
Government ownership	384	0.0005	0.0010	0.0000
Government R&D cited	384	0.0000	0.0005	0.0005
Number of private patents	384	0.0015	0.0040	0.0005

Table A7. Unit root test for all variables in the first differences (p-value).

Note: The table shows the p-values of the unit root test for all five variables in the first differences. The null hypothesis is that all series have a unit root. The alternative hypothesis is that some series are stationary. All p-values are significant at the 0.05 level. This means that we can reject the null hypothesis. Thus, we conclude that our variables sufficiently fulfil the stationarity assumption (in first differences).[21]

Lags	Akaike	Hannan–Quinn	Schwarz	Triangularity of LiNGAM matrix
1	*-6.0174*	*-6.0079*	*-5.9901*	*Causal B only somewhat triangular*
2	*-6.2234*	*-6.2028*	*-6.1642*	*Causal B nicely triangular*
3	*-6.3481*	*-6.3141*	***-6.2510***	*Causal B nicely triangular*
4	*-6.3663*	*-6.3158*	*-6.2231*	*Causal B only somewhat triangular*
5	*-6.3783*	*-6.3073*	*-6.1780*	*Causal B only somewhat triangular*
6	*-6.4739*	***-6.3761***	*-6.2003*	*Causal B only somewhat triangular*
7	***-6.5094***	*-6.3751*	*-6.1374*	*Causal B only somewhat triangular*

Table A8. Lag selection in the ordinary least squares analysis.

Note: For the lag selection, three information criteria (Akaike, Hannan–Quinn, and Schwarz) were used. The maximum number of lags possible was 7, so they were calculated with all values. The triangularity of the instantaneous effects matrix was judged heuristically based on the percentage of the added values in the upper triangle compared to the total sum of all matrix entries. If less than 5% were in the upper triangle, the matrix was judged as "nicely triangular"; if between 5% and 20%, it was judged as "somewhat triangular"; and if otherwise, as "not triangular at all," following the initial implementation of the VAR-LiNGAM code package (Moneta et al., 2013).

[21] The unit root test required a balanced panel and a certain level of variability in the values of the variables; these requirements were not fulfilled for all the technologies. At the level of each technology and variable, the same value could not occur eight or more times. This occurred if a technology had too often received no government support. Thus, to perform the unit root test, we had to restrict the data to technologies (cpcs) with sufficient variability (i.e., occurrences of government support). This restricted the data for the unit root test to 384 of the 561 technologies.

Lags	Akaike	Hannan–Quinn	Schwarz	Triangularity of LiNGAM matrix
1	*-5.9166*	*-5.9071*	*-5.8893*	*Causal B nicely triangular*
2	*-6.0987*	*-6.0780*	*-6.0394*	*Causal B nicely triangular*
3	*-6.1658*	*-6.1317*	***-6.0686***	*Causal B nicely triangular*
4	*-6.1882*	*-6.1378*	*-6.0451*	*Causal B nicely triangular*
5	*-6.2126*	*-6.1415*	*-6.0122*	*Causal B nicely triangular*
6	*-6.2770*	***-6.1791***	*-6.0033*	*Causal B only somewhat triangular*
7	***-6.3109***	*-6.1766*	*-5.9389*	*Causal B only somewhat triangular*

Table A9. Lag selection in the least absolute deviations (LAD) analysis.

Note: For the lag selection, three information criteria (Akaike, Hannan–Quinn, and Schwarz) were used. The maximum number of lags possible was 7; therefore, they were calculated with all the values. The triangularity of the instantaneous effects matrix was judged heuristically based on the percentage of the added values in the upper triangle compared to the total sum of all matrix entries. If less than 5% were in the upper triangle, the matrix was judged as "nicely triangular"; if between 5% and 20%, it was judged as "somewhat triangular"; if otherwise, as "not triangular at all," following the initial implementation of the VAR-LiNGAM code package (Moneta et al., 2013).

		A1					A2				
		Complexity (cpx)	Gov. funding	Gov. R&D cited	Gov. ownership	No. of private patents	Complexity (cpx)	Gov. funding	Gov. R&D cited	Gov. ownership	No. of private patents
Complexity (cpx)	coeff	**-0.4107**	-0.0029	0.0508	0.0152	**0.5434**	**-0.1818**	0.0096	0.0453	-0.0204	0.0629
	SD	0.0188	0.0364	0.0447	0.0367	0.0636	0.0177	0.0353	0.0406	0.0344	0.052
Gov. funding	coeff	0.0043	**-0.4825**	**0.071**	0.0028	**0.1271**	-0.0037	**-0.2024**	**0.0371**	0.0023	0.0191
	SD	0.0047	0.0168	0.0148	0.0183	0.0202	0.0047	0.0159	0.0134	0.0153	0.0167
Gov. R&D cited	coeff	**0.0172**	**0.0943**	**-0.4448**	0.0098	**0.2907**	0.0029	**0.0718**	**-0.1946**	0.0193	**0.1243**
	SD	0.0053	0.0134	0.0175	0.012	0.0235	0.0054	0.0133	0.0156	0.0116	0.0185
Gov. ownership	coeff	0.0051	0.0292	0.0301	**-0.5276**	**0.0779**	-0.0056	0.0349	0.0173	**-0.2346**	0.0039
	SD	0.005	0.0132	0.0122	0.0184	0.0204	0.0049	0.0165	0.0124	0.0192	0.0171
N. of priv. patents	coeff	**0.0151**	0.0224	**0.0752**	0.0002	**-0.0989**	0.0021	0.0059	0.022	0.0061	-0.0293
	SD	0.0042	0.0089	0.0107	0.0094	0.0235	0.0042	0.0099	0.0112	0.0116	0.0148

Table A10. Results of the vector autoregression model.

Measure	Technological complexity	Government funding	Government R&D cited	Government ownership	Number of private patents
Shapiro–Wilk	2.5517e-39	2.2965e-19	1.8902e-48	3.8140e-31	1.7508e-26
Shapiro–Francia	5.1790e-38	5.0228e-19	4.7964e-20	3.0972e-30	7.9308e-26
Jarque–Bera	0	0	0	0	0

Table A11. P-values of the normality tests to confirm non-Gaussianity.

Note: The normality tests (Shapiro–Wilk, Shapiro–Francia, and Jarque–Bera) all resulted in very small p-values, indicating that the null hypothesis that the residuals were normally distributed should be rejected.

Model	Specifications	Causal ordering	Bootstrap	Result compared to the main model (Model 1) result	Interpretation
1 (main model)	3-year periods (561 technologies), 2 lags	Gov. ownership, Gov. funding, No. of private patents, Gov. R&D cited, Complexity	500 samples, 324 with same order (65%)		Government support is driving the number of private patents, which is the main driver of an increase in technological complexity. We observed this effect within time (B0) and over time (B1, corresponding to a period of 3 years). The effect did not hold over a longer period, when the number of private patents was still driving complexity, but government support was not driving the number of private patents anymore (B2, corresponding to a period of 6 years). Instead, over a longer period, government funding negatively influenced complexity.
2	2-year periods (561 technologies), 2 lags	Gov. ownership, Gov. funding, No. of private patents, Gov. R&D cited, Complexity	500 samples, 320 with same order (64%)	B0: Equal significance of coefficients and effect direction B1: Nearly equal significance of coefficients (equal effect direction of significant coefficients) One additional significantly positive effect from - Gov. funding → Gov. ownership B2: Differences in the significance of coefficients (equal effect direction of significant coefficients) Additional positive effects from: - No. of private patents → Gov. funding - No. of private patents → Gov. ownership - Gov. funding → N. of priv. patents - Gov. R&D cited → No. of private patents Lost significant effects (effects that were significant in our main model but not here): - Gov. funding → Complexity - Gov. R&D cited → Complexity	As in our main model, government support drove the number of private patents, which was the main driver of the increase in technological complexity. We observed this effect within time (B0) and over time (B1 and B2, corresponding to a period of 4 years).
3	4-year periods (561 technologies), 2 lags	Gov. ownership, No. of private patent, Gov. funding, Gov. R&D cited,	500 samples, 151 with same order (30%)	B0: Nearly equal significance of coefficients (equal effect direction of significant coefficients). One additional significantly positive effect from - No. of private patents → Gov. funding One lost significant effect from - Gov. funding → No. of private patents	As in our main model, government support drove the number of private patents, which was the main driver of the increase in technological complexity. We observed this effect within time (B0) and over time (B1, corresponding to a period

		Complexity (different than in our main model)		B1: Nearly equal significance of coefficients (equal effect direction of significant coefficients) Two additional significantly positive effects from - Gov. ownership → No. of private patents - Gov. funding → Gov. ownership Two lost significant effects from - Gov. funding → No. of private patents - No. of private patents → No. of private patents (negative autocorrelation) B2: Differences in the significance of coefficients (equal effect direction of significant coefficients) Additional positive effects from: - No. of private patents →Gov. funding - Gov. ownership → Gov. R&D cited - Gov. funding → Gov. ownership Lost significant effect from - Gov. R&D cited → Complexity - Gov. R&D cited → Gov. funding - Gov. funding → Complexity	of 4 years). In this specification, government ownership was relevant for an increase in private patents. We found no relationship between government support and complexity over a longer period (B2, corresponding to a period of 8 years).
4	3-year periods, only with technologies for which the unit root test runs in which at least one variable per technology was stationary → 326 technologies), 2 lags	Gov. ownership, Gov. funding, No. of private patents, Gov. R&D cited, Complexity	500 samples, 205 with same order (41%)	B0: Nearly equal significance of coefficients (equal effect direction of significant coefficients). One lost significant effect from - Gov. ownership → Gov. R&D cited B1: Nearly equal significance of coefficients (equal effect direction of significant coefficients). Two lost significant effects from - Gov. R&D cited → Gov. funding - No. of private patents → Gov. ownership B2: Differences in the significance of coefficients (equal effect direction of significant coefficients). - Now positive autocorrelations (all variables apart from no. of private patents) instead of negative (as in the main model) Two lost significant effects from - Gov. funding → Complexity - Gov. R&D cited → Gov. funding Additional significantly positive effects from:	As in our main model, government support drove the number of private patents, which was the main driver of the increase in technological complexity. We observed this effect within time (B0) and over time (B1, corresponding to a period of 3 years).

				- No. of private patents → Gov. funding	
5	3-year periods, pre-process: estimation of median regression with technological field dummies and taking the residuals for the estimation (561 technologies), 2 lags	Gov. ownership, Gov. funding, No. of private patents, Gov. R&D cited, Complexity	500 samples, 326 with same order (65%)	B0: Equal significance of coefficients and effect direction. B1: Equal significance of coefficients and effect direction B2: Nearly equal significance of coefficients (equal effect direction of significant coefficients). Two lost significant effects from - Gov. funding → Complexity - Gov. citing → Gov. funding	As in our main model specification, we observed government support driving the number of private patents, which was the main driver of the increase in technological complexity. We observed this effect within time (B0) and over time (B1, corresponding to a period of 3 years). The technological field did not influence this relationship.
6	Same as in 5 with the addition of standardization of growth rates with a mean of 0 and deviation of 1 (561 technologies), 2 lags	Gov. ownership, Gov. funding, No. of private patents, Gov. citing, Complexity	500 samples, 204 with same order (40%)	B0: Equal significance of coefficients and effect direction B1: Equal significance of coefficients and effect direction B2: Nearly equal significance of coefficients (equal effect direction of significant coefficients) Two lost significant effect from - Gov. funding → Complexity - Gov. R&D cited → Gov. funding	As in our main model specification, we observed government support driving the number of private patents, which was the main driver of the increase in technological complexity. We observed this effect within time (B0) and over time (B1, corresponding to a period of 3 years). We observed a change in coefficient size due to the standardization, but the relationship between the coefficients in terms of size corresponded to our main model.

Table A12. Detailed information on robustness models.

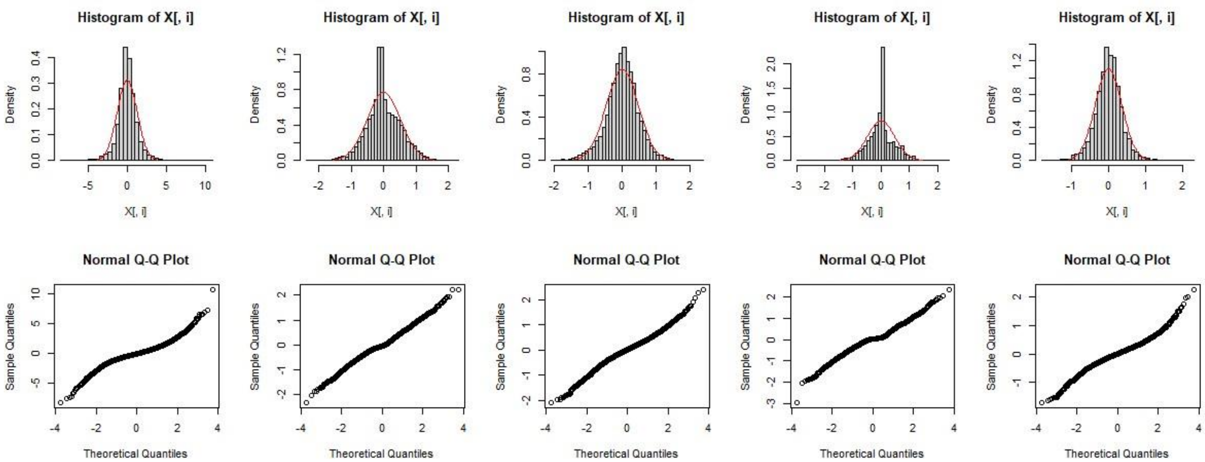
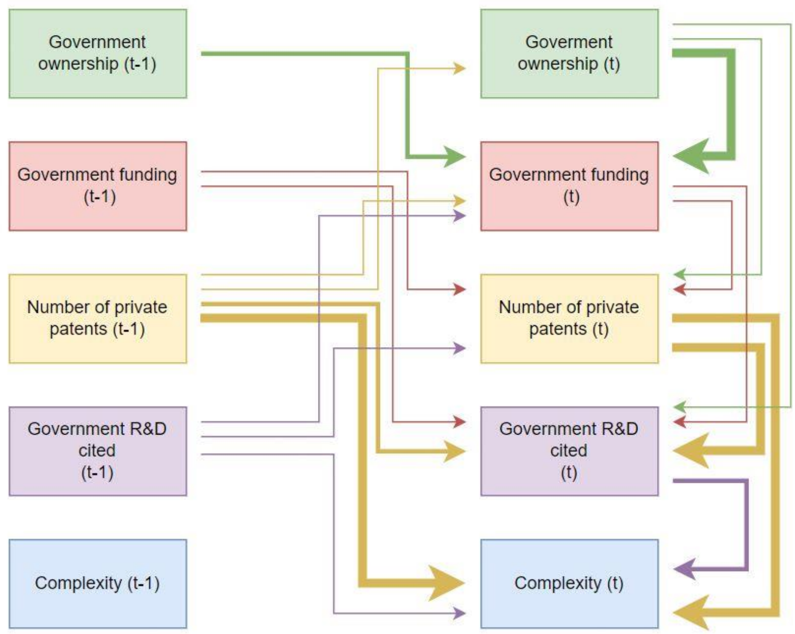
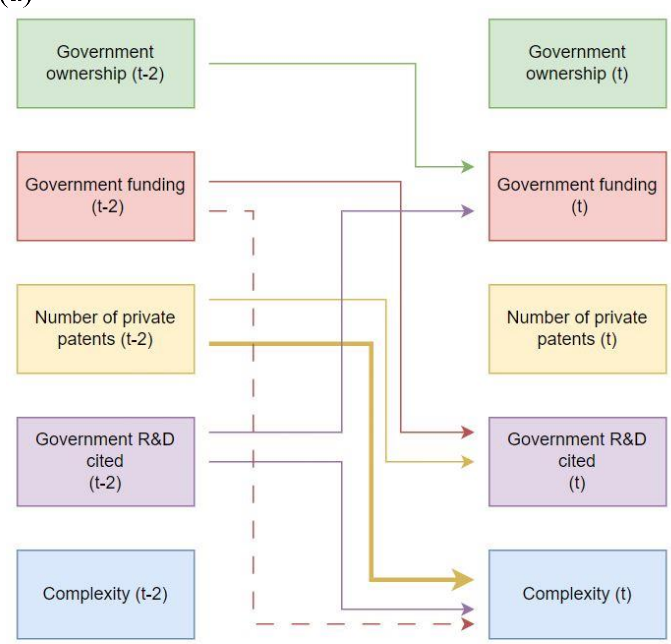


Figure A1: Histograms and quantile-quantile (QQ) plots to confirm non-Gaussian distribution.

Note: The top row shows histograms of the residuals overlaid with the Gaussian distribution with the same mean and variance. In all plots, the histograms deviate from this reference distribution. The bottom row shows QQ plots of the same residuals. Both plots indicate non-Gaussianity of the residuals. The variable order of the plots is (1) technological complexity, (2) government funding, (3) government R&D cited, (4) government ownership, and (5) number of private patents.



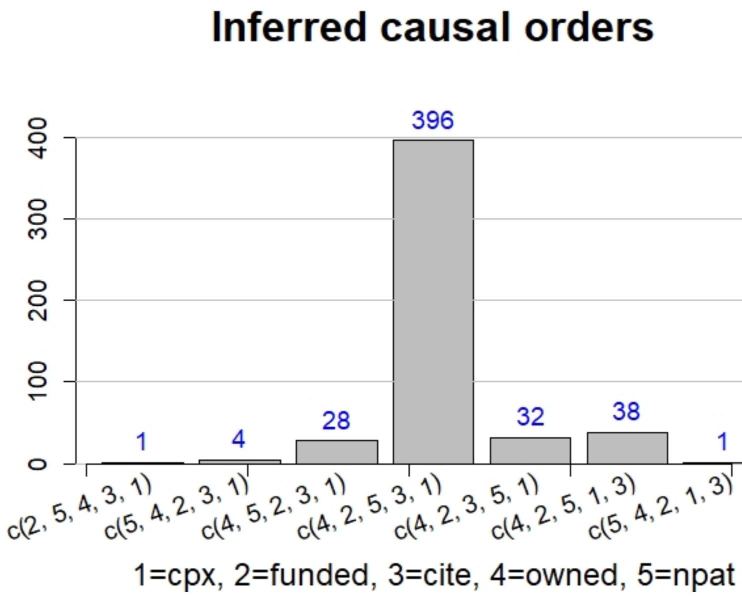
(a)



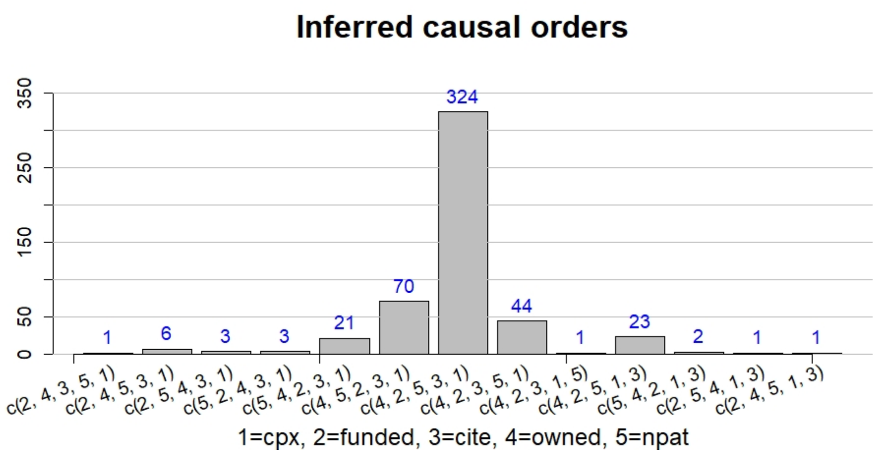
(b)

Figure A2 (a and b): Full graphical representation of structural vector autoregression results from Table 2.

Notes: Solid arrows indicate significant positive effects, dashed arrows significant negative effects. The size of the arrow reflects the magnitude of each effect (thin: 0.03–0.19; medium: 0.2–0.39; thick: ≥0.4; equivalent for the negative scale thin: -0.03 to -0.19, etc.). For simplicity and to maximize visibility, this figure does not show autocorrelations. Instantaneous effects are shown on the right side of Figure A2a, and lagged effects on the left side (with a lag of one period in A2a and with a lag of two periods in A2b). The row order corresponds to the empirically inferred causal ordering: government ownership first, followed by government funding, number of private patents, government citing, and, lastly, complexity.



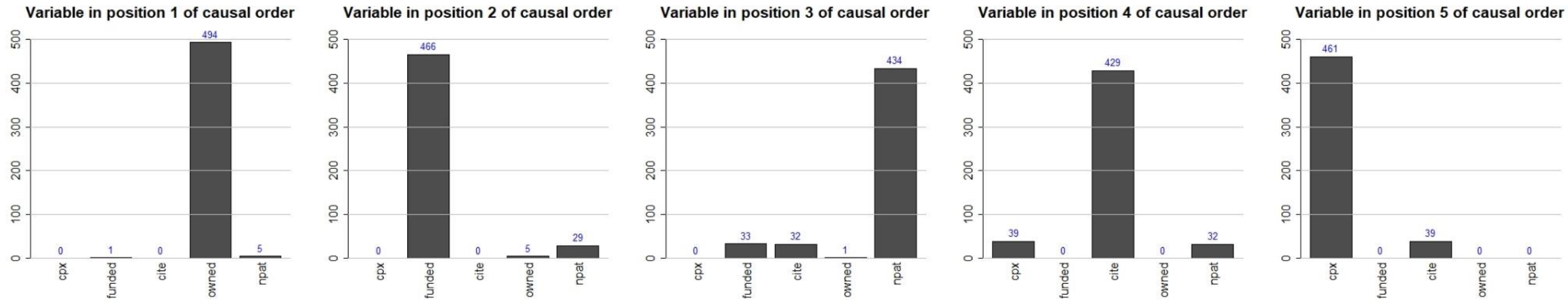
(a) Least absolute deviations (LAD) estimator



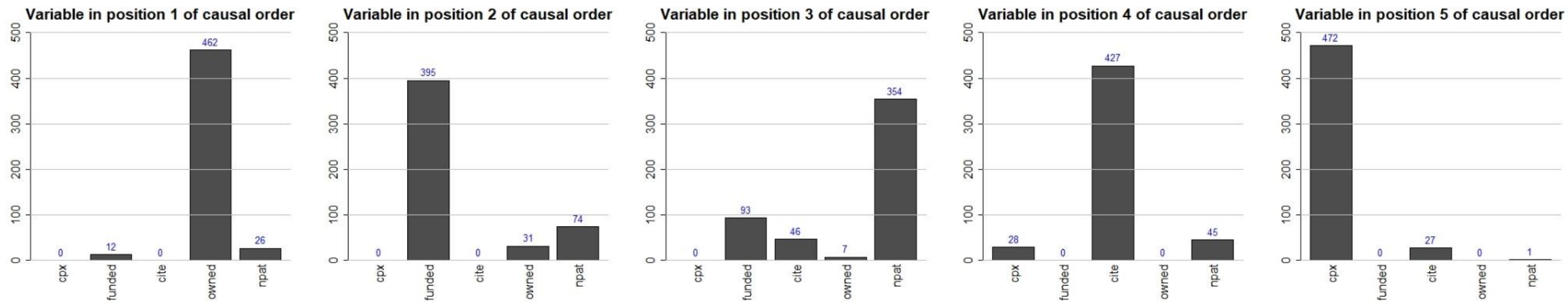
(b) Ordinary least squares (OLS) estimator

Figure A3 (a and b): Frequencies of inferred causal orders.

Note: The two panels show which causal orders were inferred among the bootstrap samples (for OLS and LAD). While there is no strict rule for what constitutes a “good agreement” in bootstrap samples, a higher percentage of consistent results generally indicates more robust findings. There are in total 120 possible orderings with five variables; therefore, inferring 65–80% of the times (with OLS and LAD) the exact same ordering is far beyond random (which would be less than 1% of the times, i.e., about 4 out of the 500 bootstrap samples). Some variability is expected when using bootstrapping, especially with smaller sample sizes.



(a) Least absolute deviations (LAD) estimator



(b) Ordinary least squares (OLS) estimator

Figure A4 (a and b): Variable positioning in the causal ordering.

Note: As mentioned before, some variability is expected when using bootstrapping, especially with smaller sample sizes. The key was to assess whether this variability significantly impacted the interpretations and conclusions of our study. These figures show how often each variable was at a particular position in the causal ordering (for OLS and LAD). Our key rankings of complexity (cpx in the plots) being the last and government ownership (owned in the plots) being the first in the causal order remain largely consistent across bootstrap samples (more than 90% for both OLS and LAD). We used this to indicate a trend despite the variability.