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A Quest for Innovation Drivers with Autometrics: Do These Differ Before and After the COVID-19 Pandemic for European Economies?

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Abstract: The literature regarding innovation drivers is usually based on variables taken from some theoretical approach and validated within a methodology. Some authors have included COVID-19 as a driver for innovations. In this paper, we address the pandemic from a different viewpoint: trying to find if innovation drivers for European countries are the same in pre- and post-pandemic years. The automated general-to-specific model selection algorithm—Autometrics—is used. The main potentially relevant drivers for which data were available for both years and two proxies of innovation (patents and the Summary Innovation Index) were considered. The final models provided by Autometrics allow for valid inference on retained innovation drivers since they have passed a plethora of diagnostic tests, ensuring congruency. The attractiveness of the research system is the most impactful driver on the index in both years but other drivers indeed differ. SMEs' business process innovation and their cooperation networks matter only in 2022. We found crowding-out effects of public funding of R&D (in both years, for the index). Sustainability was a driver in both periods. The ranking of common drivers also changes. Non-R&D innovation expenditures, the second most relevant before COVID-19, concedes to digitalization. Surprisingly, when patents are the proxy, digitalization is retained before COVID-19, with the attractiveness of the research system replacing it afterwards. Explanations for our findings are suggested. The main implications of our findings for innovation policy seem to be the facilitating role that the government should have in fostering linkages between stakeholders and the capacity the government might have to improve the attractiveness of the research system. Policies based on the public funding of R&D appear ineffective for European countries.

Keywords: innovation; innovation measure; COVID-19; general-to-specific; crowding-out; intangibles; summary innovation index

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1. Introduction

Economic theory has a long tradition regarding the relevance of innovation and the role of its drivers. Despite some of the views on Malthus (1817), considering that he disregarded the role of innovation, he is now perceived to have had a deep understanding of technological progress. Malthus (1817) noticed that this progress had been extensive in agriculture over the previous century. Moreover, in his debate with other classical economists, Mathus considered that innovations in agriculture were fundamental in Political Economy (e.g., Tunzelmann, 1991). Classical and neoclassical economics have devoted significant attention to technological progress and innovation in the ensuing years. Marshall (1890) discussed industrial districts, where vicinity would lead to a rise in innovation and the knowledge level of the regions. Almost a century after Malthus, the model known as Schumpeter Mark I placed innovations at the core of economic dynamics, generated and developed by new "entrepreneurial" firms. Innovating entrants replaced obsolete incumbents in a process described as "creative destruction". Free market competition and low barriers to entry facilitated what essentially was the interaction between competing technologies, with a pivotal role for entrepreneurship (Schumpeter, 1911). On a later approach, Schumpeter developed what has been labelled as the Mark II model (Schumpeter, 1942), with market power and property rights creating the conditions for innovation in a low competition environment. The weight of Solow's residual in "growth accounting" (Solow, 1957) has driven mainstream economics to pay attention to the drivers of Total Factor Productivity (TFP). Romer (1990) placed innovation and technological change at the core of the so-called endogenous growth models, with Research and Development (R&D) activities being the result of intentional investments by profit-maximizing firms. A large amount of literature on this ensued, emphasizing several distinct aspects of innovation (e.g., the quality ladder model of Grossman and Helpman (1991) has brought R&D to incremental improvements on the range of existing products). More recent literature has deepened the acknowledgement of the relevance of innovation both for the growth of firms and for that of countries (e.g., Timmons & Spinelli, 2004; Popescu, 2014; Rose et al., 2016; Omidi et al., 2020).

On 11 March 2020, the World Health Organization (WHO) stated that the COVID-19 outbreak had become a pandemic. The SARS-CoV-2 virus was highly contagious and easily transmissible. Extreme measures of social containment were taken worldwide: lockdowns, declines in physical consumer attendance, border shutdowns, travel restrictions, social distancing, and other measures had a notorious negative economic impact on demand, productivity, and income. The pandemic quickly became a major economic crisis (e.g., Liu et al., 2021; Costa et al., 2024). In this context, there is no doubt that the way societies and businesses prioritized resources and organized themselves shifted during the pandemic period. There were cases of effective joint collaborative effort between firms in innovation to face the increased requirement for ventilators and medical equipment (Harris et al., 2020). Moreover, there is a wide range of innovations that either appeared or gained relevance: vaccines, telehealth, contactless deliveries, online education, cashless transactions, and OTT (Over-the-Top) entertainment were some of the commonly adopted ones (Sampat & Shadlen, 2021). Clearly, it was to be expected that some changes to social and business models that occurred in the COVID-19 period would prevail and be enhanced in the post-pandemic period, possibly including innovation drivers, bringing to fruition gains from the pandemic experience.

The research question in this paper emerges from a relevant literature failure. Indeed, the paper addresses the problem of whether innovation drivers at the country level differed before and after the COVID-19 pandemic. There are empirical pieces of literature that explore the role that COVID-19 played as an innovation driver (Rishi et al., 2024), pieces of literature on the drivers of innovative solutions to face the issues raised by COVID-19 (Silveira et al., 2024), and on what factors determined broad innovation under COVID-19 (Gong et al., 2024). Notwithstanding, to the best of our knowledge, there is no study on the changes that COVID-19 might have brought about to innovation drivers.

The reference population in our research is European countries, with the subset of EU countries being our sample. Albeit differentiated, European countries share a common objective of fostering innovation and building knowledge-based economies (Ahmad &

Zheng, 2023). A knowledge-based economy is deemed to be the foundation of good innovation performance. The sample is representative since, despite some common policy strategies (e.g., the Lisbon Strategy, aimed at making the EU the leading innovation-based economy), the EU is sufficiently heterogeneous with respect to innovation performance, comprising emerging innovators, moderate innovators, strong innovators, and innovation leaders (European Commission, 2023).

To compare pre- and post-pandemic periods, this paper has adopted 2019 as the pre-pandemic year and 2022 as the post-pandemic year in Europe. COVID-19 emerged in December 2019; therefore, it could not have produced relevant effects in that year. This choice as a reference pre-pandemic year should be unproblematic. The choice of 2022 as the post-COVID-19 year needs further clarification. For EU member states, vaccination was already well underway in 2021. Two further arguments can be put forth to strengthen the view of 2022 as being post-pandemic: an institutional argument and an academic one. Firstly, from the institutional perspective, on 16 September 2021, the European Union's Health Emergency Preparedness Authority (HERA) was created as a new Directorate-General (WHO, 2022). The European Commission has stated that HERA was implemented in the aftermath of the COVID-19 pandemic as a key pillar of the European Health Union with the mission of preventing, detecting, and rapidly responding to health emergencies (after COVID-19). Secondly, from the academic viewpoint, in 2022, there were already extensive pieces of literature treating the pandemic as a past event in the context of the EU (e.g., Quaglia and Verdun (2022); Boin and Rhinard (2022); Brooks et al. (2022)).

This paper adds to the previous literature also at the methodological level, assessing possible drivers coming from a variety of literature streams, taking advantage of the advancements in automated General-to-Specific (GETS) model selection literature (e.g., Hendry, 2024) and of its machine learning algorithm embodied in Autometrics (Doornik, 2009). We use Autometrics (Doornik, 2009) in conjunction with the impulse indicator saturation (IIS) method (Santos et al., 2008). Neither the GETS methodology nor IIS had been previously applied to studies of innovation drivers. As shall be explained in detail in the methodology section, our approach guarantees that inference is conducted with congruent models.

Finally, our paper is also original in that it combines two innovation measures. We seek to determine, both for the pre- and the post-COVID-19 periods, drivers of both the number of requested patents (suitably normalized) and of a synthetic index reflecting the multi-dimensionality of innovation.

As an outcome of our analysis, relevant conclusions were obtained. We find that innovation drivers differ for European countries and for both innovation measures between the pre- and the post-COVID-19 periods. Even drivers that are common to both periods vary in their relative importance. The use of two innovation measures proved to be justified, as even within the same period, the determinants of the single dimensional indicator are not the same as that of the index.

This paper is organized as follows. The next section discusses the relevant literature, raising the research hypotheses throughout. A brief connection between each hypothesis and the variables defined is anticipated. Section 3 discusses in detail the methodology and data. The earlier referred variables are detailed. Section 4 presents the results. Section 5 discusses these in connection with the research question and the research hypotheses. Section 6 concludes the paper.

2. Literature Review and Research Hypotheses

In this section, we shall discuss the relevant literature on innovation drivers. A final and brief section on the measure of innovation is also included. The research hypotheses shall be presented throughout this section. Thus, each hypothesis is substantiated by each specific body of literature in the subsection (this is also true for the subsection on innovation measures). Furthermore, following each hypothesis, a reference to the relevant variable(s) that shall be used to test it is made (despite a better characterization of the data in Section 3.3). Hence, the section is organized to facilitate the correlation between theory and each of the hypotheses and the correlation between the hypotheses and the variables.

2.1. An Overview of the Literature on Innovation Drivers

2.1.1. Research and Development

A widely referred to factor in the literature as a classical driver of innovation is the investment in research and development (R&D) (see, inter alia, Greenhalgh and Longland (2005); Hauser et al. (2018); Fernández-Sastre and Montalvo-Quizhpi (2019); Rochina-Barrachina and Rodríguez (2019)). According to Greenhalgh and Longland (2005), products and services have an increasingly shorter life cycle due to market changes and technological advances. As such, firms need to continuously improve their offer to consumers to maintain or increase their market share. This is only possible through innovation and investment in R&D. The latter is inherent to organizations' commitment to innovation, as it allows them to identify opportunities and meet market needs better than their competitors. According to the Frascati Manual (OECD, 2015), R&D can be carried out with specific or general objectives. By its nature, the process has an uncertain outcome. It aims at discoveries that may be completely original or based on existing concepts. In order for R&D activities to be designated as such, they must meet five criteria: the activity must be innovative, creative, uncertain, systematic and capable of being reproduced and/or transferable. R&D may be carried out by different entities, public and private (profit or non-profit), as well as by higher education institutions. Regarding its financing, it is also public or private in nature (OECD, 2015).

R&D has been fostering innovation in different periods and territories (Kim et al., 2012; Park, 2005). Nevertheless, the relationship between innovation and R&D is contingent on other factors, such as firm size, organizational structure, ownership type, and industrial branch (Shefer & Frenkel, 2005). Parrilli and Radicic (2021) analyzed and compared two strategies firms use to innovate: an innovation mode based on the application of science and technology drivers—STI—(e.g., R&D; collaboration with universities) and the mode based on learning-by-doing (e.g., teamwork; collaboration with suppliers). The authors have distinguished between internal and external drivers and investigated the impact of these on innovation output across European and American firms of different sizes: micro and small, medium-sized and large. Investment in R&D proved to be an excellent driver for micro and small companies, with very efficient and visible results. However, these results do not mean that many of these companies invest in R&D but rather that those that manage to do so have obtained good results. In the reality of medium-sized companies, investment in R&D is more common, more evolved and frequent, and equally rewarding for the companies that do so. Parrilli and Radicic (2021) also added that medium-sized companies combine investment in R&D with collaboration with universities and science and technology organizations, which proves to be beneficial. For large companies, investment in R&D enhances success and acts as an inductor of product innovation, process innovation, marketing and organizational innovation. The study concluded that there is effective adoption of internal STI drivers across micro and small firms and an extensive approach taken by medium-sized firms. Large firms show a more limited efficacy of external drivers, which seems to be linked to a selective approach to innovation.

The OECD's (2015) perspective on the irrelevance of whether R&D is privately or publicly funded has been questioned in the literature. There is a crowding-out hypothesis, where recipients of public funding would simply substitute the investment they were planning to make with private funds instead of increasing it (Marino et al., 2016). The authors find evidence of a lack of additionality of public investment in R&D. Marino et al. (2016) also discuss cases of no crowding-out but mere irrelevance of public investment in R&D (the so-called no additionality effect). In a different direction, Francois et al. (2024) find evidence of crowding-in for public investment in R&D.

It follows from the literature discussed above that the following would be an interesting research hypothesis:

H_1: *Investment in R&D is an innovation driver, regardless of whether it is carried out with public or private funds*.

Section 3.3 presents four variables that shall be used to assess the hypothesis. This is the case because H_1 entails that R&D matters and that such a result does not depend on the source of the funds (public vs. private). As such, the four variables are the percentage of total expenditure in R&D carried out by the public sector ($X_{2,i}$); the percentage of total expenditure in R&D carried out by the business sector ($X_{3,i}$); the Government budget allocation for R&D ($X_{12,i}$); the gross domestic expenditure in R&D ($X_{13,i}$). Further details on each of these variables may be found in Section 3.3.

2.1.2. Technological Advances and Digitalization

Digitalization involves the integration of digital technologies into business operations to optimize processes, enhance customer experiences, and drive innovation. Kroll et al. (2018) state that digitalization combined with other variables, such as automation, positively impacts the performance of companies in terms of their productivity efficiency and their innovative performance. Albeit acknowledging this role for digitalization, Kroll et al. (2018) alert that, with respect to innovative performance, the impact of digital transformation may be lagged. Contrary to other technologies, digitalization does not, in general, induce immediate innovation but rather a gradual evolution over time.

A number of authors (e.g., Gong et al. (2024); Silveira et al. (2024); Al Issa and Omar (2024)) consider that digital advances allow innovation in management models and strategic planning of firms. Furthermore, they also foster globalization, as reaching new markets is easier with e-commerce. Digital transformation allows firms to anticipate problems and carry out more organized and efficient management. Thus, it is fundamental that management works on adapting and nourishing its human resources with the necessary digital capabilities. The changes triggered by digitalization, combined with the lockdowns and social distancing that have existed during the pandemic, have induced more firms to update their practices and to be aware of the new technologies available (Veza et al., 2022).

Technology and digitalization are currently closely interconnected, even in the most traditional industries. Simioni et al. (2015) studied the impact of new technologies as a driver of innovation in the wood industry. Technological innovation in this industry is induced by internal and external factors, such as customers, suppliers, competitiveness and production costs. For the authors, the expected results of the increase in digital technology in this sector are an increase in quality, reduced losses, augmented productivity, reduced costs, better working environment, less need to rework the product, lower environmental impact and fewer workplace accidents (Simioni et al., 2015). The results from the introduction of new technologies in some sectors may act as a benchmark, encouraging others to do the same. Veza et al. (2022) also claim, on the basis of this type of evidence, that digital transformation is an innovation driver.

In conclusion, the literature allows us to posit the following research hypothesis:

H_2: *Digitalization and digital transformation are innovation drivers*.

Section 3.3 will clarify that we can test the hypothesis since we have country-level data on two variables of interest: the % of ICT specialists in total employment ($X_{5,i}$); a composite measure of broadband penetration, and the level of digital skills in the population ($X_{7,i}$). Again, details on the precise definition of the variables may be found in Section 3.3.

2.1.3. Ecological Sustainability

Following El-Kassar and Singh (2019), the internal and external pressures that exist in organizations to make their activities and processes eco-friendly are factors that induce innovation. This innovation will result in the maintenance and improvement of ecological, economic, and competitive performance in the market. Management's commitment to developing these practices leads to a better contribution to society and a better reuse of resources, possibly resulting in a reduction in the company's current expenses, allowing greater profit margins.

The growing concern with ecological and sustainable issues, together with the circular economy increasing its presence on the agenda of governments and regulatory entities, is becoming central in firms' management processes (Pieroni et al., 2019). The authors claim that these two issues have enough societal weight to be considered a factor that induces innovation in business models.

Godil et al. (2021) refer to the need to reduce CO_2 emissions into the atmosphere as a factor that induces innovation. In this case, innovation arises through the need to solve a specific problem. This will happen using innovative technology and with the emergence of technological solutions associated with renewable energy.

Sustainability is also highlighted by Nidumolu et al. (2009) as the main factor inducing innovation. For the authors, there is no alternative to sustainable and ecological corporate development. They argue this is the path in which visionary and socially responsible companies are already invested. Innovation is not only aimed at guaranteeing competitiveness but also allows a solution to the environmental crisis. The compliance of firms with this is an opportunity to create or reinvent products and services, processes and business models, and enhance their position relative to competition, as they satisfy consumer needs and demonstrate social and ecological responsibility. Moreover, firms would also be meeting demands from the governments and public entities (which support the creation and growth of sustainable companies).

Sustainable innovations were investigated by Hermundsdottir and Aspelund (2021) with the aim of understanding the relationship between sustainability and competitiveness. The authors concluded that the impact of sustainable innovation is influenced by the market and industry in which the firm is located, as well as by internal factors. In most scenarios, it has a positive effect on the organizations' competitive advantage, resulting from variables such as cost reduction, value creation and an increase in intangible and non-financial assets. At a different level, Gault (2018) put forward that innovation promotes social cohesion, and that is one of the main factors in fighting climate change, as it provides ecologically sustainable development in organizations.

Given the importance of these issues, there are studies about green, eco and sustainable innovations and their drivers. For example, Román et al. (2021) carried out a qualitative study about sustainable innovation drivers using data from multinational food manufacturers. Their results suggest that sustainable innovation drivers (corporate innovation culture, strategic management, operational initiatives and external factors) do not seem to operate individually. Alternatively, the drivers follow a particular pattern, where external factors motivate transformations at the strategic and operational levels. Barba-Aragón and Jiménez-Jiménez (2024) analyzed the relationships between training, knowledge acquisition, green innovation and firm performance using a sample of 373 Spanish firms from a variety of sectors. The authors concluded that training is a driver of green innovation. Furthermore, they found evidence that green innovation and knowledge acquisition improve firm performance and that knowledge acquisition has a mediating effect between training and green innovation.

Arranz (2024) presented a system dynamics approach to eco-innovation drivers using machine learning. For that purpose, the author used Spanish data for the periods 2010–2011 and 2012–2013 and studied the drivers discussed in the literature and how these drivers act and interact in promoting innovation. Specifically, the author analyzed internal drivers (innovation capabilities, environmental corporate management, cooperation agreements), governmental drivers (regulation, public financial support) and drivers related to the market (new for the market).

Castellano et al. (2022) used an SME sample and demonstrated that, at the green innovation level, their choices are influenced by cultural elements, the prospect of obtaining economic advantages over competitors, and stakeholder solicitations.

In conclusion, this subsection allows us to posit the following research hypothesis:

H$_3$: *Sustainability, climate change and pressures for a circular economy are innovation drivers*.

Section 3.3 will detail that we have a relevant variable to assess H$_3$: at a country level, a composite variable measuring the above items. The variable $X_{8,i}$ includes the efficiency of resource consumption in manufacturing, pointing to a circular economy; atmospheric emission of fine particulate matter, pointing to concerns with greenhouse effects and climate change; the development of environmental-related technologies.

2.1.4. Proximity and Networks

It has long been recognized that the geographic location of firms may influence their innovation performance (Porter & Stern, 2001; Musella et al., 2023). Albeit not with a fatalistic view, the authors recognize that geography matters to the extent that it is related to the proximity of suppliers and resources, the available knowledge and the greater possibility of collaboration with other firms and academic institutions. In their view, areas with higher population and industrial densities offer more opportunities to innovate due to the physical proximity to innovation stakeholders and a higher probability of attracting talent.

Araki et al. (2024) studied the influence of regional innovation networks (RIN) and their relationship with the availability of technological entrepreneurship. The authors showed that strong RIN allows for a much faster dissemination of knowledge due to the strong connection between the members and the surrounding environment, encouraging knowledge sharing, the rapid dissemination of information, and access to cutting-edge technologies as well as to new discoveries. These factors facilitate innovation, unlike the typical characteristics of weak RIN. Their results confirmed the positive relationship between strong RIN and rapidly growing technological entrepreneurship. Evaluating the spatial heterogeneity of innovation drivers, Musella et al. (2023) studied 287 European regions between 2014 and 2021. They concluded in favor of spatial variability in innovation drivers. The relevance of collaboration between SMEs, scientific research producers, and other stakeholders suggests a possible engine of local innovation generating process. This is of the utmost relevance, namely for SMEs' competitiveness.

Boschma (2005) was more cautious in the view of networks and vicinity. He argued they should be examined in connection with other dimensions of proximity (cognitive, organizational, social, institutional) since the variety of stakeholders and variables might generate a problem of coordination failure. Moreover, proximity may also have negative impacts on innovation due to the problem of poor technological lock-ins.

The previous paragraphs support the relevance of testing the role of the degree of collaboration between SMEs and between these and other stakeholders. As such, we posit the following research hypothesis:

H_4: *SME management practices favoring external collaborations are an innovation driver*.

Section 3.3 shall provide detailed information on the proxy we shall use to test this hypothesis. The "linkages" composite variable ($X_{9,i}$) includes the % of innovation active SMEs that cooperated with other firms or other organizations. The number of public–private co-authored research publications is also included.

2.1.5. The Science Sector

The previous subsection pointed to the relevance of collaboration with scientific institutions. Hence, a robust and attractive science sector should be relevant. In fact, the literature suggests scientific collaborations to be considered a most relevant innovation driver (Ganau & Grandinetti, 2021). Pepe et al. (2024) analyzed the characteristics of networks of publication and their relationship with a country's innovativeness. They suggest that the creation of knowledge and international collaboration within science networks play a key role in improving a nation's innovation capacity.

It follows from the above paragraph that one should consider the following research hypothesis:

H_5: *Scientific research and scientific collaborations, namely international ones, are innovation drivers*.

Section 3.3 shall provide details about the variable we use to test this hypothesis, labelled "attractiveness of the research system" ($X_{10,i}$). In essence, it is a composite indicator comprising the percentage of scientific publications with at least one international co-author, the percentage of foreign doctoral students, and the percentage of scientific publications among the 10% most cited worldwide.

2.1.6. Intellectual Property Protection

The need for intellectual property protection (IPP) and the possibility of this also being an innovation driver is often discussed in the innovation literature. Beynon et al. (2023) carried out a longitudinal study to evaluate innovation readiness drivers across European regions, covering 25 countries. They also made a country-level analysis. Using principal component analysis and a constellation graph index approach, they identified three drivers of innovation: innovation system, absorptive capacity, and IPP. Nguyen et al. (2023), using firm-level data from Vietnam, concluded that the need for IPP is a robust driver for open innovation, regardless of whether the firm is in a more or less competitive context. Also, they concluded that this is a stronger driver for small firms than for larger ones.

In the opposite direction, Lyu and Xu (2024) found that investors in publicly listed firms react differently to patent issuance, depending on its novelty. A misreaction has a deep impact on such firms' future innovation. The authors present causal evidence that firms change their innovation behavior from novelty-seeking to incremental or copycat if an experience of disappointing stock returns after patent issuance exists. R&D-intensive firms are already considered riskier in the stock market, and complex patents, unclear to non-expert scientists, add to that uncertainty. The authors' findings highlight that investor misreaction to patent novelty has redirected firms' innovation, turning them away from higher-valued, groundbreaking research.

It follows from the literature that the following research hypothesis concerning IPP should be investigated:

H$_6$: *Intellectual Property Protection is an innovation driver.*

Section 3.3 provides details about the variable we use to test this hypothesis: "intellectual assets" ($X_{11,i}$). In essence, it is a composite measure of suitably normalized patents, trademarks and new design applications at the EU Intellectual Property Office.

2.1.7. Management of Organizations

Meroño-Cerdan and López-Nicolas (2013) refer to organizational innovation as an inductor of intangible changes that facilitates even product and service innovation. Since such organizational innovation is a form of business model innovation, the authors are suggesting that business process innovation may be a facilitator of the introduction of new products and services by firms. In fact, it combines new business processes and practices, changes in the work environment and external relations, with the aim of improving response time, product and service quality, reducing costs, and expanding innovative practices and knowledge sharing within the organization. Oyadomari et al. (2013) reinforced that organizational change, departing from the more conservative perspectives rooted in the company, makes it less resistant to change and to engage in the discovery of new processes, products and methods. Thus, the authors reinforced that the new business process is a factor that induces innovation. Rose et al. (2016) point out that this is of relevance for SMEs. They claim that SMEs that have changed to a more open organizational culture are very keen to take advantage of the knowledge from the surrounding environment and use it to their advantage. Moreover, Brancati et al. (2022) show that for SMEs located in Italy, competitiveness is enhanced by the existence of an innovative culture. In addition to a better supply of goods to customers, this results in increased productivity, which brings, in the long term, a better competitive position internationally. Moreover, the expansion of the range of products offered by the firm, along with the firm's innovative organizational process, increases the ability to penetrate the foreign market. Therefore, innovation fosters external competitiveness. Indeed, it is considered that innovation inputs go well beyond scientific discoveries.

The literature reviewed above translates to the following two research hypotheses:

H$_7$: *Business process innovation in SMEs is an innovation driver.*

H$_8$: *Investment in non-R&D innovation expenditures also induces innovation.*

These hypotheses shall be studied with the assistance of two variables $X_{4,i}$ and $X_{6,i}$. The former refers to non-R&D innovation expenditures. The latter refers to the fraction of SMEs in a country that introduced business process innovations. More details on the variables are provided in Section 3.3.

Finally, considering the type of leadership within firms, it is widely acknowledged that the behavior of leaders is critical but contingent on the quality of the surrounding institutions (Acemoglu & Robinson, 2000; Ferreira et al., 2024). A research hypothesis as follows should be posited concerning this:

H$_9$: *Institutional arrangements matter at the country level for innovation performance.*

Although there exist variables that try to proxy institutional quality, we choose to take a different path. Given that this paper innovates using a methodology based on model selection and an IIS, the selected country-specific dummies in a model will point us to countries that need specific indicators to capture institutional differences. The measure of institutional differences between countries shall be based on the estimated indicator coefficient of a country for which an impulse indicator was retained. This shall be clearer with the methodology discussion in Section 3. Our approach is based on Hendry (2001). It is a very different option from, say, that of Ferreira et al. (2024), where institutional quality is inferred from a variety of suppositions, translating into composite proxy variables going from public administration to terrorism and global security metrics.

2.2. Measuring Innovation

There is no consensus in the literature on how best to measure innovation. Adams et al. (2006) considered that measuring innovation is a complex and challenging process for organizations and academics due to the multi-dimensionality of factors that potentially perform as indicators of innovation and due to the different types of innovation. Hagedoorn and Cloodt (2003) state that the use of just one innovation measure can be limitative and that innovation can be measured differently, presenting two categories: innovative performance and inventive performance (potentially measured by patents). However, using only patents would be incorrect, according to the most recent literature. Fontana et al. (2013), following Basberg (1987), argue that many innovations are not patented: because the inventor consider the innovation in question does not represent suitable patent matter; because the inventor considers that the inventive step embodied in the innovation is not sufficiently high; because the inventor may decide not to patent and follow other strategies, such as industrial secrecy, to extract some rent from the innovation. Koh et al. (2022) argue that the absence of patenting or R&D data for a firm does not necessarily imply a lack of innovative activity. Faurel et al. (2024) suggested that trademarks are a more adequate measure of innovation. Innovation indices, combining several indicators, were used in several recent studies (e.g., Katuščáková et al. (2023); Dworak (2024); Janoskova and Kral (2019).

As referred to in the introduction to this paper, our analysis is original also because it seeks to determine innovation drivers using different innovation measures. Following the literature in this subsection and the explanation in the introduction, the following final research hypothesis emerges:

$\mathbf{H_{10}}$: *A single dimension innovation measure is led, before and after the pandemic, by the same drivers as a synthetic innovation index.*

The variables used in this paper to measure innovation are the common one-dimensional indicator number of patent applications (P_i), and a synthetic innovation index aggregating many indicators. For the latter, we use the Summary Innovation Index (SII_i). Detailed information on each of these variables and their sources may be found in Section 3.3.

3. Data and Methodology

As argued in the introduction, the methodology used is one of the main novelties of this paper. In fact, to the best of our knowledge, no other paper on innovation drivers explores the possibilities posed by the automatic General-to-Specific (GETS) machine learning model selection algorithm Autometrics (Doornik, 2009). Further, no study in this field has taken advantage of the Impulse Indicator Saturation (IIS)[1] outlier detection test (Santos & Hendry, 2006; Santos et al., 2008; Santos, 2008). As such, a summary explanation of these methods and how they relate to our research question needs to be provided. Section 3.1 describes the Autometrics algorithm in the context of the GETS approach, detailing some of the hypotheses tests it performs in the selection process. The properties of GETS selection are discussed. The baseline models for our research are presented. Section 3.2 describes the IIS test and the resulting modified baseline models to be used when searching for innovation drivers. Section 3.3 presents our sample and discusses the variables' definitions.

3.1. GETS Model Selection and Autometrics

It would be misleading to say this paper relies on regression analysis as the main research method. Regression analysis is fundamental but not from the mainstream approach, where a model is specified, with an assumed functional form taken as given, and a set of covariates included to explain the variable of interest. Usually, in that framework, a certain theory leads to the choice of covariates, and these are tested within the regression framework. Possible issues with residual diagnostics are dealt with in a bottom-up (or specific-to-general) strategy, adding other variables, such as lags of the dependent variable or of the covariates, to try to circumvent possible problems. Clearly, starting from a reduced form model that is being corrected as the diagnostic tests suggest is a method without an upper bound (e.g., lags of variables could continuously be added until the diagnostics would be satisfactory, with no rejection of the null in residual-based diagnostic tests).

Instead of merely referring to regression analysis, it is far more correct to say that this paper relies on automatic GETS model selection as its primary method.[2] It rests on the latest generation of the GETS approach software and on the use of impulse indicator saturation (IIS). A detailed account of the evolution of GETS may be found in Hendry (2024). Automated GETS model selection has been having major successes since the early 21st Century.

Broadly speaking, GETS does not previously choose a particular take on economic theory, emphasizing the role of some drivers in explaining the variable of interest while neglecting others. Sargan (1957) pioneered the approach and emphasized the need for proper model selection. He noticed that while economic data often features complexities, economic theory is too abstract. As a result, in a time when theory was dominant in model building, estimated regression models often excluded relevant variables. Using a GETS approach, the econometric model is viewed as a representation of the unobservable Data Generating Process (DGP). Any loss of information moving from the DGP to its representation must be irrelevant to the problem at hand. Using Hendry's terminology (Hendry, 1985), the representation would then be congruent. Each reduction from the DGP is more complex than simply deleting the least significant variable. F-tests are performed on blocks of variables, as deleting the least relevant is not conducted if the variable is critical, e.g., to maintain global significance (F-Global). A variable that fails the individual significance test might also be retained if dropping it would imply a loss of congruency. A series of residual-based diagnostic tests is used to assess the congruency of the model at each reduction stage. Hendry (2024) reiterates the fundamental role of misspecification tests. Failures of these would eliminate a model from consideration, as it was non-congruent. If a stage of reduction induces rejection in a misspecification test, the process goes back. Favero (2001) made a similar claim regarding GETS. As expected, the vector of residuals should not depart from a vector drawn from a multivariate normal distribution. Otherwise, the model is mis-specified and not congruent (Favero, 2001).

For explicit model design, GETS suggests a starting point: the so-called general unrestricted model (GUM). This is the most general, estimable, statistical model that the researcher might reasonably start with, based on the present sample, all variables used in previous empirical and theoretical research, and any institutional measurement information (Hendry, 1995). As pointed out by Hendry (1995), estimable implies that the GUM must be such that the parameters must be uniquely determined from empirical evidence. The path from the GUM to the empirical model is sustained by the theory of reduction (e.g., Hendry & Richard, 1982). In practice, each reduction operation must avoid a loss of congruency. Therefore, an automatic GETS procedure needs to check this at each stage. Hendry and Krolzig (2001) further define the local DGP (LDGP) as the representation such that, for the subset of variables under analysis, the outcomes could be predicted up to an innovation error (white noise residual). The LDGP is the best representation one can obtain given the selection of variables, so it must be the target for model selection. Hence, the GUM should be the best approximation to the LDGP (Hendry, 2024). In the current century, automated GETS procedures gained traction as the properties of the underlying algorithms were unveiled. Campos et al. (2003) showed the consistency of the PcGETS (Hendry & Krolzig, 1999) model selection algorithm. That is, as the sample size grows to infinity, the probability that the PcGETS algorithm would select the true DGP converges to unity. In more general terms, White (1990) endorsed Hendry's progressive research strategy (GETS), showing that with sufficiently rigorous testing, the selected model should converge to the DGP. White's argument also contradicts those who criticized GETS for performing too many tests. In fact, these are crucial in the procedure. Hendry and Santos (2010) also provide Monte Carlo evidence that testing on a model, where variables were selected from prior testing in an earlier stage does not induce "pretest biases", as the empirical rejection frequencies of the tests on the later model coincide with the postulated nominal significance, when the null hypothesis holds. There is no overfitting. Clearly, though, the sample size matters when choosing the significance level for selection. As discussed by Hendry (2000), one should respect the condition $\alpha N \geq 3$. A tight significance combined with a small sample size (say $\alpha = 1\%$) would risk severely undersized individual significance tests, failing to ever reject the null hypothesis (Hendry & Santos, 2010), since possibly no variable would be picked at a reduction stage. Using a bigger significance level α in a GETS-based procedure may spuriously retain some irrelevant variables, but it is deemed that the cost of not retaining relevant ones is much higher. This is a cost of inference and not a cost of search (e.g., Hendry, 1995). Thus, it is unavoidable for any non-zero significance level (Castle, 2005). Finally, the PcGETS algorithm performed multiple multipath searches; therefore, the outcome does not depend on the arbitrary choice of a particular non-significant variable to start reduction. Pagan (1987) considered that avoiding path dependency was critical for model selection.

The field of automatic GETS model selection jumped forward with the automated machine learning algorithm to unveil a viable empirical model provided in Autometrics (Doornik, 2009). The root of the algorithm is the GUM, which entails all potentially relevant variables, including the possibility of searching over more variables than the available sample size. The parameters in the GUM are estimated by OLS, with all statistically insignificant covariates being removed, and the compact model's reliability is tested at each individual stage to guarantee consistency with the test diagnostics. Autometrics employs a tree–path exploration strategy that involves multistep simplifications. Every node and subnode represents a model containing fewer variables than the GUM. Within each branch, until the end node or subnode, the most insignificant variables are the first to be eliminated. Notwithstanding, at each reduction, a battery of residual diagnostic tests is conducted. Thus, if a terminal model does not pass such tests, Autometrics backtracks until a valid model is found. If a high number of terminal models are discovered, a novel GUM is formed, merging the "surviving" ones into a union model, permitting another tree-path search repetition. The whole search procedure is completed by reexamining the terminal models and their consolidations. If many models pass all the tests, the final decision is made on a specified information criterion. The multipath technique in Autometrics also identifies multiple breaks and outliers effectively while preserving reduced estimator variance (Muhammadullah et al., 2022).

The analysis in this paper considers each of the models in Equations (1)–(4) as a candidate GUM. Given our research objective, each GUM below is built for each measure of innovation (each y_i) that we shall use. Furthermore, for each y_i and each GUM, Autometrics is used twice: one for data from a pre-COVID-19 year, and another for data from a post-COVID-19 year. The X_i are taken from a wide variety of drivers suggested in the literature assessed in Section 2, without favoring any theory a priori (thus, in a proper GETS analysis). Section 3.3 will provide further details on the data.

$$y_i = \beta_1 + \beta_2 X_{2,i} + \beta_3 X_{3,i} + \ldots + \beta_k X_{k,i} + u_i \quad (1)$$

$$lny_i = \gamma_1 + \gamma_2 X_{2,i} + \gamma_3 X_{3,i} + \ldots + \gamma_k X_{k,i} + v_i \quad (2)$$

$$y_i = \theta_1 + \theta_2 lnX_{2,i} + \theta_3 lnX_{3,i} + \ldots + \theta_k lnX_{k,i} + \varepsilon_i \quad (3)$$

$$lny_i = \delta_1 + \delta_2 lnX_{2,i} + \delta_{3ln} X_{3,i} + \ldots + \delta_k lnX_{k,i} + \omega_i \quad (4)$$

k is the number of variables included in the GUM. Autometrics copes with situations where $k > N$, with N being the sample size, but that shall not be the case here. After running each of the GUMs in Autometrics, the resulting terminal model is assessed with the battery of diagnostic tests to check for congruency. Hendry (2024) emphasizes the role of diagnostic tests, asserting that empirical models that fail misspecification tests must be non-congruent.

It should be noted that models (2)–(4) are linearized versions of non-linear specifications. Hence, parameter interpretation shall also change, from marginal effects on y_i, to elasticities and semi-elasticities.

With respect to the diagnostic tests implemented in Autometrics, it is important to be aware of the choices made. These appear to be the best solutions in terms of real size and power, but different testing methods might lead to different results. Autometrics tests the Gaussian white noise properties of the residuals. For a cross-section sample, the diagnostics amount to checking normality, homoscedasticity and the model's functional form.

For heteroscedasticity testing in single equation models, White's (1980) Lagrange Multiplier (LM) test has been a long-time favorite. The procedure requires regressing the squared residuals of the model under study on a constant, the k covariates, their squares, and possibly also the cross-products. White's test statistic is of the form NR^2, which under the null of homoscedasticity (entailing all coefficients of the variables in the auxiliary regression being zero) has an asymptotic distribution χ^2_s, with $s = \frac{k(k-1)}{2}$. However, Kiviet (1986) showed that an $F(v_1; v_2)$ provided a better approximation in small samples. Godfrey and Orme (1994) corroborated that the χ^2_s version has significant deviations from the nominal size for non-normal error distributions. Doornik (1994) provided a discussion for single-equation and multi-equation models. Most importantly, for this paper, where impulse indicator variables are critical, Hendry and Santos (2005) established that the presence of even a few impulse dummies in single-equation regression models leads to size distortions in White's LM heteroscedasticity test. All things considered, Autometrics (Doornik, 2009) checks for congruency using, with respect to homoscedasticity, an $F(v_1; v_2)$ approximation suggested in Doornik and Hendry (1994). Both the versions, including cross-products and the one without cross-products of the test, are used. Autometrics identifies these as "hetero-X test" and "hetero test", respectively.

With respect to normality, Autometrics uses the improvement on the Jarque and Bera (1987) test suggested by Doornik and Hansen (2008). Still, the idea rests on the Bowman and Shenton (1975) line of tests, where asymmetry and kurtosis are the basis of the statistics used to assess departures from normality. Under the null hypothesis that the random errors follow a normal distribution, the asymptotic distribution of the test statistic is $\chi^2_{(2)}$, as with the Jarque and Bera (1987) test. For models with many impulse indicators, such as some that are assessed in the next section, Hendry and Santos (2005) show that the Bowman and Shenton type of tests retain good power against leptokurtosis but not so much against mesokurtic distributions, which might be the ones with near impulse saturation. Notwithstanding, this is a finite sample problem, and the authors advise looking at it cautiously. As the approach in this paper, and that within Autometrics, is to use IIS as an outlier detection test, we would be concerned with power in the non-problematic setting of many impulse indicators and excess kurtosis (leptokurtic distributions). As argued above, tests of this family retain good power properties in this scenario, even in small samples.

Finally, with respect to functional form testing in the GUM and at each reduction stage, Autometrics (Doornik, 2009) uses Ramsey's (1969) RESET test. The null hypothesis is that of the lack of relevance of adding two variables (the square and the cube of the estimates of the dependent variable) to the original regression. Rejection of the null, although pointing to a misspecification of the original model, does not provide indicative solutions. As discussed previously, we shall use several specifications of the GUM's functional form to avoid coming to a solution of not knowing how to improve the model, in case Autometrics cannot find a reduced form congruent model. Furthermore, we take advantage of the empirical findings in, inter alia, Castle (2005), Oliveira and Santos (2010), and Santos and Oliveira (2010). Indeed, the authors concluded that the presence of outliers in the residuals might lead to a false conclusion of non-linearities. As such, we used the impulse indicator saturation test (IIS) for outlier detection. IIS is discussed in Section 3.2.

In conclusion, reductions are checked for congruency using several tests: the Doornik–Hansen normality test, the Doornik–Hendry F-Snedcor approach to White's heteroscedasticity test, and the RESET test. Should rejection occur in any of these, the IIS test for outliers is used.

All hypotheses' tests in our analysis shall use a significance level $\alpha = 10\%$. This choice is a result of the small sample size (as shall be seen in Section 3.3: $N = 27$), to approximate the condition $\alpha N \geq 3$ (Hendry, 2000). Using $\alpha = 10\%$, a GETS-based procedure may spuriously retain some irrelevant variables, but it is deemed that the cost of not retaining relevant ones is much higher. This is a cost of inference and not a cost of search (e.g., Hendry, 1995). Thus, it is unavoidable for any non-zero significance level (Castle, 2005).

3.2. Impulse Indicator Saturation (IIS)

The theoretical basis of IIS is discussed in the GETS model selection literature (Santos et al., 2008). It follows the work of Hendry and Santos (2005), who established the properties of inference on impulse indicators and the non-excess retention of indicators in nearly saturated models. Santos and Hendry (2006) and Santos (2008) establish the properties of IIS as an outlier detection test. We shall discuss this procedure below. Castle (2005) made seminal use of IIS to test outliers in a cross-section sample. In this paper, we do not just take rejections of the null in the normality test as a possible indication of outliers. Following Castle (2005), rejections of the null of the RESET test might also be due to outliers and not to non-linearities.

IIS initially generates impulse indicator variables (one for each observation). As a result, there are more variables than observations N. Santos et al. (2008) used subset selection (where the subsets are sample partitions, either in halves, thirds, etc.), followed by searches across the union of the terminal models. For a split of $N/2$, this entails saturating half the sample, storing the significant indicators and then examining the other half. Under the null hypothesis that no indicator matters, the impulse-saturation procedure is shown to have the correct null rejection frequencies (NRFs) precluding overfitting, independently of the number of splits used for the subsets. For individual tests conducted on each indicator at a significance level α, the average retention rate is αN, under the null hypothesis that no dummy matters, matching exactly the binomial result and showing low costs of search for low α (see Hendry, 2000). The asymptotic distribution of the post-selection estimators of the mean and variance, in a location-scale model with IID errors is derived, and extensive Monte Carlo evidence confirms the theoretical results (Santos et al., 2008). Under the alternative, Santos and Hendry (2006) and Santos (2008) showed that the IIS has good power against outliers and structural breaks in the sample. Further developments are made in Hendry and Santos (2010) and Castle et al. (2012). Extensions to trend indicator saturation are developed in Castle et al. (2015, 2019a) and to multiplicative indicator saturation (Castle et al., 2019b). Muhammadullah et al. (2022) confirmed that the IIS method outperforms other outlier robust methods (see Huber, 1964), such as trimmed least squares, the M estimator and the MM estimator. Johansen and Nielsen (2009) and Doornik and Hendry (2016) also debated outliers, robust statistics and automatic model selection in the context of IIS.

In this paper, IIS versions of the GUM are estimated. Letting I_i be the impulse indicator for observation i, such that:

$$I_i = \begin{cases} 1 <= i = s \\ 0 <= i \neq s \end{cases}, s = 1, 2, \ldots.., N \tag{5}$$

the IIS versions of the GUM are:

$$y_i = \beta_1 + \sum_{j=2}^{k} \beta_j X_{j,i} + \sum_{i=1}^{N} \tau_i I_i + u_i \tag{6}$$

$$lny_i = \gamma_1 + \sum_{j=2}^{k} \gamma_j X_{j,i} + \sum_{i=1}^{N} \eta_i I_i + v_i \tag{7}$$

$$y_i = \mu_1 + \sum_{j=2}^{k} \mu_j lnX_{j,i} + \sum_{i=1}^{N} \phi_i I_i + v_i \tag{8}$$

$$lny_i = \varphi_1 + \sum_{j=2}^{k} \varphi_j lnX_{j,i} + \sum_{i=1}^{N} \pi_i I_i + v_i \tag{9}$$

Equations (6)–(9) correspond to Equations (1)–(4) augmented by the complete set of country-specific impulse indicators. As with the candidate covariates, selection will determine which indicators are retained, if any. A specific interpretation for retained indicators is provided in Section 3.3.

Therefore, the steps to obtain the results in Section 4 pertain to the pre-pandemic period, the post-pandemic period, and each innovation capacity proxy y_i,

1. Using Autometrics to obtain reduced form models for each of the GUMs (1)–(4), and possibly of the IIS versions (6)–(9) if diagnostic tests fail with non-saturated GUMs;
2. Checking congruency via the residual diagnostics of the models in (1). We refer to the tests discussed in Section 3.1;
3. In the event of rejection of the null in a diagnostic test of a terminal model, the representation is deemed inadequate for the LDGP. Furthermore, if a model is such that a test statistic cannot be obtained due to insufficient degrees of freedom (this might occur with the heteroscedasticity test), we disregard the model since we cannot claim that the residuals suggest valid inference is feasible;
4. One might argue that a rejection of normality would still allow asymptotic inference. That is true in some cases, but to argue that $N \rightarrow \infty$. However, this would be a fallacy in our case: the number of European countries will not grow without an upper bound;
5. For a terminal model satisfying the diagnostic conditions, we conduct the analysis and inference. We use such congruent models to assess the relevance of the innovation drivers selected therein.

3.3. Data Definitions

In this paper, we aim to study the drivers of innovation for European economies using different innovation proxies and considering the impact of a natural shock. The shock is the COVID-19 pandemic. Hence, we have data for all the variables for a pre-pandemic year (2019) and a post-pandemic year (2022).

We innovate with respect to the existing literature by looking for effects on innovation drivers at the national level of a worldwide natural shock: the COVID-19 pandemic. The introduction to this paper provides details on the pandemic. There is a plethora of papers in the economic literature assessing behavior before and after some event, or some hallmark related to human behavior (e.g., Gillen and Lall (2003) with respect to the structure of the aviation industry, before and after the 11 September 2001 attacks; Oliveira and Santos (2015) with respect to financial markets behavior before and after a legislation shift; Oliveira and Santos (2018, 2022) with respect to the monetary policy before and after the European sovereign debt crisis, etc.). Notwithstanding, to the best of our knowledge, there is nothing in the field of innovation and with respect to a truly global natural catastrophe like the COVID-19 pandemic.

We use two different dependent variables to capture the effect of the pandemic shock at two levels. We search for drivers and, for COVID-19 impacts on these, for the variables below:

SII_i—The Summary Innovation Index (SII) for each EU country is calculated from the unweighted average of 32 re-scaled indicators (where the re-scaling takes into account the absence of an upper bound for some of them, possible heavy skewness [in which case, re-scaling would involve taking the square root of some variables], etc.). The value obtained for each member state for each year is divided by the value obtained for the EU and multiplied by 100 to obtain the country's SII. The Summary Innovation Index is obtained from the European Innovation Scoreboards (European Commission, 2023).

P_i—number of patents requested by country i under the Patent Cooperation Treaty (PCT). The variable is normalized by dividing the country's GDP (in billions of EUR, evaluated at Purchasing Power Standards). We chose patents requested under the PCT instead of those requested to the European Patent Office due to its broader protection, since the agreement covers 158 states. Patents requested from the EPO offer protection only in 39 states (WIPO, 2024).

The purpose of using both the SII and the number of patents requested by each country was discussed in Section 2.2.

We are interested in the results for European economies. As such, we retrieve a sample of European countries (in particular, the 27 EU economies[3]). We use data, as candidate innovation drivers, from two sources: the European Innovation Scoreboards (European Commission, 2023) and the statistical office of the EU (Eurostat). The variables were justified by the literature and first presented with each of the 10 research hypotheses in Section 2. We recall their specifications here, detailing each more carefully. The independent variables[4] for the pre-pandemic and the post-pandemic years of reference (2019 and 2022) are as follows:

$X_{2,i}$—R&D expenditure in the public sector as a % of GDP (this includes the government sector and higher education sector);

$X_{3,i}$—R&D expenditure in the Business Sector, as % of GDP;

$X_{4,i}$—Non-R&D innovation expenditures (as a % of turnover);

$X_{5,i}$—Information and Communications Technology (ICT) specialists as a % of total employment;

$X_{6,i}$—SMEs introducing business process innovation, as a % of SMEs;

$X_{7,i}$—digitalization (a composite measure of broadband penetration [ratio of enterprises with a maximum contracted download speed of the fastest fixed internet connection of at least 100 Mb/s, to the total number of enterprises] and of individuals with above basic overall digital skills [% on the total number of individuals aged 16–74]);

$X_{8,i}$—Environmental Sustainability (a composite measure of resource productivity [GDP in Purchasing Power Standard per unit of directly consumed materials, in kilograms], air emissions by fine particulate matter (PM2.5) in the manufacturing sector, in tonnes, as a ratio of the value added in the manufacturing sector; the percentage of environment-related technologies developed on the total number of technologies developed);

$X_{9,i}$—Linkages (a composite measure of: (1) the ratio of innovation-active Small and Medium-Sized Enterprises (SMEs) that cooperated in business with other firms or organizations, as a % of the total number of SMEs; (2) number of public-private co-authored research publications as a fraction of the total population; (3) job-to-job mobility in Science and technology as a % of the population aged 25 to 64);

$X_{10,i}$—Attractiveness of the Research System (a composite indicator of (1) the number of scientific publications, with at least one co-author abroad, as a % of total population; (2) scientific publications among the 10% most cited worldwide as a % of the total number of scientific publications; (3) foreign doctorate students as a % of all doctoral students);

$X_{11,i}$—Intellectual assets (a composite application of the number of trademarks applied for at the EU Intellectual Property Office (EUIPO) per billion GDP in purchasing power standards, and the number of individual designs applied for at the EUIPO, per billion GDP in PPS);

$X_{12,i}$—GBARD—Government Budget Allocations for R&D (in million EUR, according to the government budgets submitted by the member states of the EU to the Eurostat; it includes both current costs and capital expenditure; it is not limited to public expenditure, as other indicators, but to funding of expenditures by the private sector).

$X_{13,i}$—GERD—Gross Domestic Expenditure on R&D (contrary to other expenditure indicators, GERD includes non-profit organizations);

As discussed in Section 2.1, although we do pose a hypothesis related to institutional quality, no $X_{j,i}$ is defined in the above list as associated with it. Although some proxies do exist in the literature that we have referenced (e.g., Ferreira et al., 2024), we follow a different path, more in line with the approach in Hendry (2001). In our analysis, if a country-specific impulse indicator is retained by Autometrics, in a final congruent model, we associate its estimated coefficient to country-specific factors not included in all the variables entering the GUM. As such, the estimate of the coefficient of a country-specific indicator reflects intangible and non-measurable differences to other countries, such as institutional quality. In practice, this shall only be of relevance in one model in Section 4, and the exact interpretation is contingent on its functional form. Following the results, the role of the functional form in the interpretation of country-specific indicators will be clearer. In conclusion our approach lets the model speak for itself with respect to the need for institutional quality differences being relevant (through IIS and GETS), instead of building some artificial composite variable with items varying from property rights to organized crime (Ferreira et al., 2024).

The following section presents the results of our approach.

4. Results

In this section, we present the results of the automatic general-to-specific model selection, implemented via Autometrics (Doornik, 2009), as carefully outlined in the methodology section of this paper. Relevant concepts, such as congruency are also discussed in that section. We should emphasize that reductions from the GUM are only allowed if congruency is kept, which entails the necessary condition of data coherence. As explained in the previous section, this means that the residuals from the model must be white noise. Thus, mis-specification tests are of the utmost importance.

The structure of the tables reporting the results is identical. In the first column, the estimates $\hat{\beta}_2$ to $\hat{\beta}_{13}$ match the order of the covariates as presented in Section 3.3. $\hat{\beta}_1$ is the estimate of a constant term. The absence of an associated value for some model of a coefficient estimate implies that X_j was not retained by Autometrics, although it entered the matching GUM. For impulse indicator saturated GUMs, the estimates $\hat{\theta}_1$ to $\hat{\theta}_{27}$ match each of the countries in the sample. Again, the absence of a value for some of these coefficients indicates that the matching impulse indicator was not retained. Furthermore, the *p*-values for individual significance are given below each retained variable's coefficient estimate. For global significance and diagnostic tests, the value reported is the observed test statistic. Below each of these test statistics, the *p*-value is provided between parentheses. When no value is reported for the global significance test (F-Global), the model did not retain a constant term β_1, so R^2 was not calculated. As discussed in Section 3.1, the heteroscedasticity test might not be feasible to compute in some cases due to a lack of degrees of freedom. Should this occur, no value for such test (hetero and hetero-X) is given. Thus, we do not pursue the model, as its reliability cannot be guaranteed for inference purposes.

Table 1 is related to the models for the Summary Innovation Index (SII).[5] All variables are reported for 2019 (pre-pandemic data). The second column reports the final retained model and its diagnostic tests when the GUM matches Equation (1). The results for the retained innovation drivers are not worth discussing, as the model is not a valid representation of the unknown LDGP. In fact, the results for the RESET test (Ramsey, 1969) show a *p*-value of 0.0858, which is smaller than the significance level (as discussed in Section 3, we use $\alpha = 10\%$). Hence, the null hypothesis of correct specification of the functional form is rejected.

Table 1. Autometrics results for the SII with reference to 2019.

	Equation (1)	**Equation (6)**	**Equation (2)**	**Equation (7)**	**Equation (3)**	**Equation (8)**	**Equation (4)**	**Equation (9)**
1	2	3	4	5	6	7	8	9
$\hat{\beta}_1$ (*p*-value)			3.1622 (0.0000)	3.69472 (0.0000)	−216.9 (0.0000)	−164.64 (0.0000)		
$\hat{\beta}_2$ (*p*-value)								
$\hat{\beta}_3$ (*p*-value)	0.1238 (0.0002)	0.1338 (0.0000)	0.0009 (0.0655)		6.2576 (0.0032)	4.6742 (0.0000)	0.04013 (0.0162)	
$\hat{\beta}_4$ (*p*-value)	0.1658 (0.0000)	0.0849 (0.0013)	0.0035 (0.0001)				0.17816 (0.0000)	0.26009 (0.0000)
$\hat{\beta}_5$ (*p*-value)								
$\hat{\beta}_6$ (*p*-value)	0.0483 (0.0371)	0.0641 (0.0003)	0.0009 (0.0254)	0.0007 (0.0073)	2.0942 (0.3096)	2.3063 (0.0028)		
$\hat{\beta}_7$ (*p*-value)	0.1476 (0.0012)	0.1213 (0.0000)	0.0014 (0.069)	0.0025 (0.0000)	15.2648 (0.0044)	40.1848 (0.0000)	0.19109 (0.0000)	0.0668 (0.0012)
$\hat{\beta}_8$ (*p*-value)	0.1835 (0.0001)	0.1718 (0.0000)	0.0033 (0.0002)	0.0009 (0.097)	8.9119 (0.0292)	−9.7932 (0.0012)	0.18103 (0.0000)	0.22114 (0.0000)

Table 1. *Cont*.

	Equation (1)	Equation (6)	Equation (2)	Equation (7)	Equation (3)	Equation (8)	Equation (4)	Equation (9)
$\hat{\beta}_9$ (p-value)		0.0836 (0.0000)			9.9645 (0.0159)	−6.7458 (0.0091)	0.0631 (0.0187)	
$\hat{\beta}_{10}$ (p-value)	0.3053 (0.0000)	0.1719 (0.0001)	0.0037 (0.0000)		17.624 (0.0011)	27.728 (0.0000)	0.34497 (0.0000)	0.43022 (0.0000)
$\hat{\beta}_{11}$ (p-value)		0.1172 (0.0045)		0.0047 (0.0000)	9.3461 (0.0342)			
$\hat{\beta}_{12}$ (p-value)				-4.4×10^{-5} (0.0107)				−0.0905 (0.0010)
$\hat{\beta}_{13}$ (p-value)				1.5×10^{-5} (0.0072)				0.0921 (0.0001)
$\hat{\theta}_1$		−9.9024 (0.0072)				9.0803 (0.0003)		
$\hat{\theta}_2$				0.1609 (0.0082)				
$\hat{\theta}_3$				−0.4242 (0.0000)		10.417 (0.0004)		
$\hat{\theta}_4$								−0.0813 (0.0178)
$\hat{\theta}_5$								
$\hat{\theta}_6$						22.845 (0.0000)		
$\hat{\theta}_7$		−14.047 (0.0005)						
$\hat{\theta}_8$								
$\hat{\theta}_9$								
$\hat{\theta}_{10}$						−22.351 (0.0000)		
$\hat{\theta}_{11}$								0.11464 (0.0003)
$\hat{\theta}_{12}$						−7.1267 (0.0004)		
$\hat{\theta}_{13}$		−5.9887 (0.0656)						−0.0994 (0.0042)
$\hat{\theta}_{14}$						−6.4776 (0.0026)		−0.1661 (0.0000)
$\hat{\theta}_{15}$		16.3389 (0.0001)		0.2609 (0.0002)				
$\hat{\theta}_{16}$		−0.9271 (0.755)						−0.1135 (0.0007)
$\hat{\theta}_{17}$		−5.9277 (0.1264)				8.03282 (0.0044)		
$\hat{\theta}_{18}$								0.07289 (0.0494)

Table 1. *Cont.*

	Equation (1)	**Equation (6)**	**Equation (2)**	**Equation (7)**	**Equation (3)**	**Equation (8)**	**Equation (4)**	**Equation (9)**
$\hat{\theta}_{19}$		5.2906 (0.0545)		−0.2173 (0.0019)		−14.861 (0.0004)		
$\hat{\theta}_{20}$				−0.2971 (0.0001)				
$\hat{\theta}_{21}$								0.15661 (0.0001)
$\hat{\theta}_{22}$				−0.2411 (0.0011)				
$\hat{\theta}_{23}$						−35.915 (0.0000)		
$\hat{\theta}_{24}$				−0.6049 (0.0000)				
$\hat{\theta}_{25}$								
$\hat{\theta}_{26}$				0.1156 (0.0292)				
$\hat{\theta}_{27}$		6.7067 (0.0305)				7.8341 (0.0004)		
R^2			0.9573	0.9935	0.9727	0.9941		
F-Global (p-value)			74.75 (0.000)	132.4 (0.000)	91.7 (0.000)	946.9 (0.000)		
Normality (p-value)	1.0488 (0.5919)	3.4881 (0.1754)	0.80351 (0.6691)	0.71151 (0.7006)	0.72034 (0.6976)	17.145 (0.0002)	4.9721 (0.0832)	1.6269 (0.4433)
Hetero (p-value)	0.4357 (0.9216)		0.85891 (0.5999)		0.6311 (0.7935)		0.6764 (0.748)	0.35725 (0.9436)
Hetero-X (p-value)								
RESET (p-value)	2.803 (0.0858)	15.303 (0.0013)	15.78 (0.0001)	0.23082 (0.798)	5.69 (0.0136)	0.06677 (0.936)	0.44086 (0.6499)	0.07951 (0.9240)

The results in column 3 correspond to the Autometrics output with a similar GUM to that which is generated in column 2, but outlier detection through IIS is now active (that is, the GUM mimics Equation (6)). We shall not assess the individual significance of retained indicators or of innovation drivers since this final model is, again, an invalid representation of the LDGP. In fact, it is not a congruent model since the residual diagnostics fail. Firstly, for the RESET test, the p-value is 0.0013, which is smaller than the significance level. Secondly, as pointed out in the methodology section, when neither of the versions of the heteroscedasticity test can be computed due to insufficient degrees of freedom, we choose not to consider the model valid: we do not know if the random errors suffer from heteroscedasticity.

Column 4 is related to the GUM in Equation (2). Thus, we are now considering a log-linear model where the dependent variable is the log of the SII. The final model again points to failures in the functional form. A p-value of 0.0001, smaller than the significance level, is indicative of rejection of the null for the RESET test. Nonetheless, this could be the result of neglecting outliers. Thus, the reduced model with an underlying GUM mimicking Equation (7) is reported in column 5. The p-value for the RESET test is now 0.798, which is bigger than the significance level of 10%. As such, there is no statistical evidence of error in the functional form. Furthermore, the Doornik and Hansen (2008) normality test is shown to have a p-value of 0.7006, indicating that the null of normality in the random error is also not rejected. Notwithstanding, there is no information for the heteroscedasticity tests. The number of variables is such that the model could not compute the Doornik and Hendry (1994) F-Snedcor approximation to White's (1980) test. A congruent model should have homoscedastic errors, and we are in no position to make that claim. Thus, we do not pursue the analysis with this estimated reduced form log-linear model, even if it is impulse saturated.

Column 6 refers to the estimated reduced form model of the lin-log, or semi-elasticities, GUM (Equation (3)). A congruent representation is not achieved since the p-value of the RESET test is 0.0136. Column 7 presents results for a reduced form of the GUM in Equation (8): the estimated impulse-saturated lin-log GUM after selection. The non-rejection of the null in the RESET test (p-value of $0.9360 > 0.1$) is obtained but the normality test now fails. The p-value of the Doornik–Hansen test is $0.0002 < 0.1$. Thus, we reject the null of normality for the random errors of this model. Arguments in favor of asymptotic inference are hard to make with such a small sample. Furthermore, insufficient degrees of freedom to compute the heteroscedasticity test also advise in favor of concluding for non-congruency of this model. For these two reasons, we do not pursue this model.

In Table 1, column 8 presents results for the estimated model resulting from the GUM matching Equation (4). This is the log–log or constant elasticities model, where the dependent variable is the logarithm of the SII. An analysis of the diagnostic tests in column 8 reveals that the p-value of the normality test is 0.0832, which is smaller than 10%. Rejection of normality entails rejecting the model to be a congruent representation. Failures of normality often suggest there might be outliers in the data. Column 9 reports the after-selection estimated form of the GUM matching Equation (9): the impulse-saturated log–log model. The resulting model exhibits a p-value of 0.4433 for the Doornik–Hansen test (the null of normality is not rejected), a p-value of 0.9436 for the heteroscedasticity test (not rejecting the null of homoscedasticity), and a p-value of 0.924 for the RESET test (not rejecting the null of a correct functional form). The model underlying Equation (9) is, therefore, a congruent representation of the LDGP for the SII in 2019. Therefore, this should be the model used to conduct a valid analysis of the estimates of the regression coefficients.

The variables from the estimated after-selection IIS GUM pertaining Equation (9) are all individually statistically significant. This suggests that the innovation drivers for European economies, in a pre-pandemic world, would be the digitalization level, the attractiveness of the country's research system, the level of environmental sustainability, the country's innovation expenditures that are not related to R&D and the level of GERD. Albeit being significant, GBARD impacts negatively on R&D. In Table 1, column 9 shows that the logarithm of each of these variables has a p-value smaller than the postulated significant level of 10% (indeed the p-values are all smaller than 1% for the referred variables). The constant is not retained in the final model; therefore, no discussion on R^2 is feasible. With respect to the significant variables, the results in column 9 allow us to say that, in a pre-pandemic world, and for European economies, we estimate that on average, other things remaining equal, an increase in the digitalization measure of 1% leads to an increase in a country's Summary Innovation Index of 0.0668%; an increase in the attractiveness of the national research system of 1% increases the index by 0.430322%; an increase in environmental sustainability of 1% increases the innovation index by 0.22114%; an increase in innovation expenditures that are not related to R&D of 1% leads to an increase of 0.26009% in the innovation index; and an increase on GERD of 1% augments the innovation index in 0.0921%. All the estimated elasticities that we have just referred to are positive, which is also a sign of congruency since that was our prior expectation. As argued by Hendry (2001), in a congruent model, we expect estimated parameters of interest to be theory-consistent. One might argue that the elasticity for GBARD is estimated to be -0.0905%, entailing that a 1% increase in GBARD is expected to reduce the index by 0.0905%, other things remaining equal. We claim this is not theory-inconsistent, and an analysis of that result shall be conducted in Section 5 of this paper.

With respect to column 9 of Table 1, it should also be noted that seven impulse indicator variables were retained in the final model. The indicators would be kept even at a 5% significance level, which adds to showing this is not a spurious result of a loose significance level. It is worth noticing that we can relate the outliers identified to the countries in our sample. Also, countries with positive estimated impulse indicators' coefficients would outperform others, with the same values for the other retained variables, with respect to the innovation index. A negative estimated impulse indicator coefficient would mean that the country would underperform another with the same values for the variables discussed in the paragraph above, in terms of the Summary Innovation Index. As such, we should notice that Cyprus, Croatia, Hungary, and Italy have negative estimated impulse indicator coefficients. Finland, Luxemburg and the Netherlands have positive estimated impulse indicator coefficients. To interpret the coefficients of an impulse indicator retained in the final log–log model for the SII in 2019, we take the example of Cyprus. The estimated coefficient for that country-specific indicator is $\hat{\theta}_4 = -0.0813$. This implies that for country j, with the same values for the retained variables as Cyprus, but for which no impulse indicator was retained:

$$lnSII_4 - lnSII_j = -0.0813 \Longleftrightarrow ln\frac{SII_4}{SII_j} = -0.0812 \Longleftrightarrow ln(1+\delta) = -0.0812 \qquad (10)$$

Therefore, $\delta \times 100$ is the percentage difference between SII_4 and SII_j.

Taking a first-order Taylor series approximation to $ln(1+\delta)$ in the vicinity of zero, $ln(1+\delta) \sim \delta \Longleftrightarrow \delta \sim -0.0812$. In short, we estimate that the Summary Innovation Index would be 8.12% smaller in Cyprus than in country j. In the same way, we estimate that the SII would be 9.94% smaller in Croatia than in an identical country with respect to all retained covariates, but for which IIS did not lead to the selection of the matching impulse indicator. For Hungary, the SII is estimated to be smaller by 16.61% than for a corresponding comparable country. For Italy, the estimated penalty in the SII is 11.35% relative to a comparable country. Thus, we estimate the SII for Finland to be bigger than that of a country with the same values for the relevant variables but without a country-specific dummy retained by 11.464%. For Luxemburg, the SII is estimated to be bigger than that of a country with the same value for all variables and without retention of the matching indicator by 7.289%. For the Netherlands, the bonus in the SII with respect to an otherwise equal country for the variables retained is 15.661%. These results are discussed in Section 5. In short, from the retained indicators in Equation (9) and their estimated coefficients, we infer that the quality of institutional arrangements was positively affecting the SII for Luxembourg, Finland and the Netherlands. Differently, institutional arrangements had a negative effect for Cyprus, Hungary, Croatia and Italy.

Table 2 also uses data from 2019, a pre-COVID-19 year. The difference relative to Table 1 is that the proxy for innovation is the number of requested patents. As such, the dependent variable for the models in Table 2 shall be either the number of requested patents or its logarithm. Table 2 reflects the same search for a congruent representation of the dependent variable as explained in detail above.

Table 2. Autometrics results for requested patents with reference to 2019.

	Equation (1)	**Equation (6)**	**Equation (2)**	**Equation (3)**	**Equation (8)**	**Equation (4)**	**Equation (9)**
1	2	3	4	5	6	7	8
$\hat{\beta}_1$ (p-value)	−16.0846 (0.0299)	0.4781 (0.0840)	2.78478 (0.0000)	−183.28 (0.0002)	−239.85 (0.0000)		
$\hat{\beta}_2$ (p-value)				−12.9771 (0.0260)	−12.821 (0.000)	−0.17722 (0.0098)	
$\hat{\beta}_3$ (p-value)	0.4952 (0.0000)	0.4622 (0.0000)	0.00751 (0.0000)	31.1658 (0.0000)	31.761 (0.0000)	0.4513 (0.0000)	0.4364 (0.0000)
$\hat{\beta}_4$ (p-value)							
$\hat{\beta}_5$ (p-value)	0.0136 (0.0324)	0.02524 (0.0000)					
$\hat{\beta}_6$ (p-value)				6.6913 (0.1157)	8.5533 (0.0000)		
$\hat{\beta}_7$ (p-value)	0.2518 (0.0019)		0.00346 (0.0108)			0.29936 (0.0126)	
$\hat{\beta}_8$ (p-value)					16.1576 (0.0008)		
$\hat{\beta}_9$ (p-value)							
$\hat{\beta}_{10}$ (p-value)							0.1934 (0.0000)
$\hat{\beta}_{11}$ (p-value)	0.2042 (0.0272)	0.2638 (0.0000)	0.004238 (0.0102)	34.1277 (0.1157)	27.32 (0.0000)	0.3684 (0.0036)	0.1859 (0.0000)
$\hat{\beta}_{12}$ (p-value)							
$\hat{\beta}_{13}$ (p-value)							0.07534 (0.0000)
$\hat{\theta}_1$							
$\hat{\theta}_2$							−0.2069 (0.0009)
$\hat{\theta}_3$							
$\hat{\theta}_4$							0.23196 (0.0030)
$\hat{\theta}_5$		−15.195 (0.0012)			−24.9154 (0.0001)		−0.3204 (0.0000)
$\hat{\theta}_6$		−18.920 (0.0044)					
$\hat{\theta}_7$		24.40 (0.0001)			21.885 (0.0006)		
$\hat{\theta}_8$							
$\hat{\theta}_9$							−0.2619 (0.0001)
$\hat{\theta}_{10}$							

Table 2. *Cont.*

	Equation (1)	Equation (6)	Equation (2)	Equation (3)	Equation (8)	Equation (4)	Equation (9)
$\hat{\theta}_{11}$		39.4247 (0.0000)			35.7756 (0.0000)		0.26227 (0.0001)
$\hat{\theta}_{12}$					8.9372 (0.0565)		
$\hat{\theta}_{13}$							
$\hat{\theta}_{14}$					12.5192 (0.0265)		
$\hat{\theta}_{15}$		16.0890 (0.0008)					
$\hat{\theta}_{16}$					−7.89649 (0.0862)		
$\hat{\theta}_{17}$							
$\hat{\theta}_{18}$					−27.4002 (0.0001)		
$\hat{\theta}_{19}$		23.0678 (0.0000)			49.5019 (0.0000)		1.0224 (0.0000)
$\hat{\theta}_{20}$							0.4119 (0.0000)
$\hat{\theta}_{21}$		34.7911 (0.0000)			26.5583 (0.0001)		0.1647 (0.0033)
$\hat{\theta}_{22}$		−17.696 (0.0004)					−0.1768 (0.0052)
$\hat{\theta}_{23}$							−0.1912 (0.0012)
$\hat{\theta}_{24}$							−0.112 (0.0292)
$\hat{\theta}_{25}$		16.6524 (0.0019)					
$\hat{\theta}_{26}$					−20.2581 (0.0006		
$\hat{\theta}_{27}$							
R^2	0.9331	0.9953	0.903952	0.818367	0.996		
F-Global (p-value)	76.72 (0.000)	248.4 (0.000)	72.15 (0.000)	23.65 (0.000)	167 (0.000)		
Normality (p-value)	2.3919 (0.3024)	5.6700 (0.0587)	0.83158 (0.6598)	1.5129 (0.4693)	2.5017 (0.2863)	1.6286 (0.4430)	5.9487 (0.0511)
Hetero (p-value)	0.50168 (0.8393)	0.7038 (0.6534)	0.51263 (0.7917)	1.021 (0.4573)		2.2377 (0.0743)	
Hetero-X (p-value)	0.73502 (7117)	0.85243 (0.5946)	0.5934 (0.7853)	0.57516 (0.8362)		2.5813 (0.0537)	
RESET (p-value)	5.0968 (0.0163)	0.90262 (0.4313)	1.9686 (0.1646)	8.7087 (0.0021)	2.4121 (0.1514)	1.1239 (0.3438)	0.03276 (0.7281)

The estimated post-selection model resulting from the GUM underlying Equation (1) is presented in column 2. Indeed, the diagnostic tests reveal rejection of the null of correct model functional form, as the p-value for the RESET test is 0.0163, clearly smaller than the significance level of 10%. Congruency, evaluated by the plethora of diagnostic tests discussed in Section 3.1, fails. Thus, we do not pursue the analysis of this model. Column 3 reports estimation results for the post-selection impulse indicator saturated model when the GUM mimics Equation (6). Albeit not rejecting the null of the RESET test, the Doornik and Hansen test for normality is now an issue. The null of normality is rejected since the p-value of 0.0587 is smaller than $\alpha = 10\%$. Hence, we do not conduct inference on this model.

Column 4 reports post-selection results for the log-linear specification of the GUM matching Equation (2). The outcome exhibits data coherency, which is necessary for congruency. The null hypothesis is not rejected for the normality test (p-value = $0.6598 > \alpha$). The null of homoscedastic random errors is also not rejected for the Doornik and Hendry (1994) $F(v_1; v_2)$ approximation to White's (1980) test: without cross-products (p-value = $0.7917 > \alpha$), and when these are included (p-value = $0.7853 > \alpha$). The null of a well-specified functional form is not rejected for the RESET test (p-value = $0.1646 > \alpha$). Hence, there is no reason to impulse-saturate the GUM. Adding to this, the log-linear model exhibits global significance. That is, the null hypothesis that all variables are simultaneously irrelevant is rejected (p-value = $0.000 < \alpha$). R^2 suggests that 90.3952% of the total variation of the dependent variable (the log of requested patents) around its sample average is explained by the model. Given the congruence of the model found, we do not see the relevance of testing for outliers via IIS; therefore, the GUM matching Equation (7) is not even submitted to Autometrics.

The retained variables in the model, as innovation drivers, according to the individual significance tests, are the level of digitalization (p-value = $0.0108 < \alpha$), the level of expenditure in R&D undertaken by the business sector (p-value = $0.0000 < \alpha$), and the country's intellectual assets (p-value = $0.0102 < \alpha$). We estimate that, on average, when digitalization increases by one unit, the requested patents increase by 0.346053%, all other things being equal. We also estimate that, on average, the requested patents increase by 0.751055% when business sector expenditures in R&D increase by one, ceteris paribus. Finally, we estimate that a unit increase in the measure of intellectual assets increases requested patents by 0.4238%, everything else being equal. Section 5 shall discuss these results.

With respect to column 5, the lin-log specification of the GUM, matching Equation (3) is ruled out based on the diagnostic tests of the post-selection estimated model. Indeed, the null hypothesis of the RESET test is rejected (p-value = $0.0021 < \alpha$). Estimating the GETS reduced form of Equation (8), corresponding to the post-selection version of the impulse-saturated lin-log GUM, we obtain the results in column 6. This is a more difficult decision as there is no obvious rejection in the diagnostic tests presented. However, no version of the heteroscedasticity test could be computed. As such, we cannot confirm congruency as we do not have a basis to be statistically sure if homoscedasticity holds. We opt not to pursue the study of this model. In column 7, the results for the reduced form of the log–log model, resulting from the GUM matching Equation (4), are given. Rejection of the null of homoscedasticity using both the versions of the Doornik and Hendry (1994) test with and without cross-products occurs (p-value = $0.0743 < \alpha$ without cross-products; and p-value = $0.0537 < \alpha$ with these) invalidates congruency. The results for the post-selection impulse-saturated model, resulting from the GUM matching (9), are reported in column 8. Diagnostic tests show that the null hypothesis of the Doornik–Hansen normality test is rejected (p-value = $0.0511 < \alpha$). Furthermore, we cannot conclude as to homoscedasticity since neither version of the test can be computed. In short, the log–log version of the model should not be used.

Table 3 refers to models where the dependent variable was the Summary Innovation Index or the logarithm thereof. All variables used report data referring to 2022, which is the first post-pandemic year. The structure of the table follows Tables 1 and 2. Furthermore, as always in this section, the significance level is $\alpha = 10\%$ for all tests.

Table 3. Autometrics results for the SII with reference to 2022.

	Equation (1)	**Equation (6)**	**Equation (2)**	**Equation (7)**	**Equation (3)**	**Equation (8)**	**Equation (4)**	**Equation (9)**
1	2	3	4	5	6	7	8	9
$\hat{\beta}_1$ (p-value)	7.8285 (0.0434)	10.7328 (0.0071)	3.4804 (0.0000)	3.6079 (0.0000)	−243.93 (0.0000)	−270.242 (0.0000)	0.745222 (0.0000)	0.08926 (0.0000)
$\hat{\beta}_2$ (p-value)					−4.6832 (0.0416)	−4.3014 (0.0002)	−0.0298 (0.0116)	−0.0403 (0.0000)
$\hat{\beta}_3$ (p-value)	0.1542 (0.0000)	0.1229 (0.0000)	0.0015 (0.0034)	0.00088 (0.0001)	11.5622 (0.0002)	14.4127 (0.0000)	0.0921 (0.0000)	0.1055 (0.0000)
$\hat{\beta}_4$ (p-value)	0.1290 (0.0008)	0.0918 (0.0125)	0.0023 (0.0044)		6.7790 (0.0823)	17.3193 (0.0000)	0.0805 (0.0007)	0.0507 (0.0000)
$\hat{\beta}_5$ (p-value)				9.65×10^{-5} (0.0000)				
$\hat{\beta}_6$ (p-value)	0.0564 (0.0071)	0.0469 (0.0149)			7.0002 (0.0084)	2.3729 (0.0000)	0.0569 (0.0003)	0.0652 (0.0000)
$\hat{\beta}_7$ (p-value)	0.1249 (0.0007)	0.1131 (0.0011)			14.1513 (0.0231)	22.6931 (0.0000)	0.1095 (0.0016)	0.15337 (0.0000)
$\hat{\beta}_8$ (p-value)	0.1112 (0.0028)	0.1305 (0.0012)	0.0023 (0.0072)	0.0032 (0.0000)	5.7903 (0.1112)		0.0976 (0.0000)	0.1321 (0.0000)
$\hat{\beta}_9$ (p-value)	0.0647 (0.300)	0.1109 (0.0024)	0.0015 (0.0222)	0.0032 (0.0000)			0.1317 (0.0003)	0.1173 (0.0000)
$\hat{\beta}_{10}$ (p-value)	0.2204 (0.0000)	0.1757 (0.0002)	0.0025 (0.0071)		17.624 (0.0011)	33.5316 (0.0000)	0.2177 (0.0000)	0.1769 (0.0000)
$\hat{\beta}_{11}$ (p-value)					11.3045 (0.0072)		0.0749 (0.0031)	0.00376 (0.0086)
$\hat{\beta}_{12}$ (p-value)		0.00017 (0.0983)						
$\hat{\beta}_{13}$ (p-value)								
$\hat{\theta}_1$								
$\hat{\theta}_2$								
$\hat{\theta}_3$				−0.1321 (0.0011)		16.2207 (0.0000)		
$\hat{\theta}_4$								−0.0706 (0.0044)
$\hat{\theta}_5$				0.1045 (0.0028)		−7.02551 (0.0013)		
$\hat{\theta}_6$								
$\hat{\theta}_7$				−0.0893 (0.0108)				
$\hat{\theta}_8$								0.1189 (0.0000)
$\hat{\theta}_9$								

Table 3. *Cont.*

	Equation (1)	Equation (6)	Equation (2)	Equation (7)	Equation (3)	Equation (8)	Equation (4)	Equation (9)
$\hat{\theta}_{10}$						−15.257 (0.0000)		−0.0288 (0.0000)
$\hat{\theta}_{11}$								0.0347 (0.0000)
$\hat{\theta}_{12}$						−4.7636 (0.0125)		
$\hat{\theta}_{13}$								−0.0563 (0.0000)
$\hat{\theta}_{14}$						−14.1835 (0.0000		−0.04896 (0.0239)
$\hat{\theta}_{15}$								0.0512 (0.0047)
$\hat{\theta}_{16}$				0.0857 (0.0094)				
$\hat{\theta}_{17}$				−0.0880 (0.0063)				
$\hat{\theta}_{18}$								
$\hat{\theta}_{19}$						5.70837 (0.0160)		
$\hat{\theta}_{20}$								
$\hat{\theta}_{21}$								
$\hat{\theta}_{22}$				−0.0694 (0.0376)				
$\hat{\theta}_{23}$				0.1921 (0.0000)		−24.3279 (0.0000)		
$\hat{\theta}_{24}$				−0.2583 (0.0000)				
$\hat{\theta}_{25}$		9.7604 (0.0438)		0.3321 (0.0000)		−6.21512 (0.0166)		
$\hat{\theta}_{26}$				0.0837 (0.0083)				
$\hat{\theta}_{27}$								
R^2	0.9904	0.9929	0.953	0.9977	0.9733	0.9988	0.9948	0.9996
F-Global (p-value)	279.8 (0.000)	267 (0.000)	85.16 (0.000)	373.1 (0.000)	77.46 (0.000)	674.9 (0.000)	337.6 (0.000)	1337 (0.0000)
Normality (p-value)	5.21 (0.0743)	4.8 (0.0907)	0.5214 (0.7705)	4.1628 (0.1248)	0.76972 (0.6805)	1.488 (0.475)	0.26671 (0.8752)	7.594 (0.0224)
Hetero (p-value)	0.7344 (0.7097)	0.6370 (0.7933)	1.9078 (0.1202)		1.3033 (0.7935)		0.96971 (0.5562)	
Hetero-X (p-value)								
RESET (p-value)	1.4256 (0.2677)	1–537 (0.2471)	22.184 (0.0000)	1.2392 (0.3305)	5.8543 (0.0132)	0.17868 (0.8393)	2.3765 (0.1292)	0.94399 (0.4335)

Congruency is a problem with the reduced form models in columns 2 and 3 of Table 3. Research has started from the GUM provided in Equation (1), in column 2, and in Equation (6) in column 3. Irrespective of that, the null of the normality test is rejected in both models: p-value = 0.0743 $< \alpha$ in the first; p-value = 0.091 $< \alpha$ in the second. We do not pursue the analysis with these models. Column 4 refers to the after-selection log-lin model for the

Summary Innovation Index. The final output reveals problems with model specification (either due to the functional form, omitted variables, or outliers), since the null of a correct functional form is rejected. Indeed, for the RESET test p-value = $0.0000 < \alpha$. The model underlying column 4 should not be used, as it lacks congruency. The impulse-saturated log-linear GUM matches Equation (7). The estimate of the terminal version after GETS selection is reported in column 5. As previously explained, we choose not to use models where no information on the heteroscedasticity test is available. It is the case for the estimated final model in column 5, both for the cross-products and the no cross-products version of the heteroscedasticity test. Column 6 corresponds to the post-selection model when the GUM corresponds to the lin-log specification matching Equation (3). The null hypothesis of the RESET test is rejected (p-value = $0.0132 < \alpha$). Hence, congruency fails, and the model should be dropped. Running the impulse-saturation version of the previous GUM (Equation (8)) in Autometrics, the reduced form in column 7 is obtained. Again, the issue is that a valid claim on congruency cannot be made since heteroscedasticity cannot be tested. The log–log specification for the GUM, corresponding to Equation (4), is also estimated after automatic GETS selection. The results are given in column 8. All diagnostic tests point in the direction of a data-coherent model. In fact, the null hypothesis of normality of the random errors is not rejected in the Doornik–Hansen test (p-value = $0.8752 > \alpha$); the null hypothesis of homoscedasticity, in the F-Snedcor approximation to the distribution of White's test statistic, also fails to be rejected (p-value = $0.5562 > \alpha$); and the null hypothesis of a correct functional form, in the RESET test, is also not rejected (p-value = $0.1292 > \alpha$). Hence, the final congruent model delivered by Autometrics, for the Summary Innovation Index in the aftermath of COVID-19, in advanced economies, has a log–log specification, with no need for IIS.

The final model in the previous paragraph (column 8) is globally significant. In fact, the F-test, on all the coefficients (except for the intercept) being 0, leads to the rejection of the null (p-value = $0.000 < \alpha$). R^2 indicates that 99.4762% of the variation in the logarithm of the innovation index around its sample average is explained by the model. The retained innovation drivers are the linkages, the level of digitalization, the attractiveness of the research system, the level of environmental sustainability, the level of R&D expenditure carried out by the Business Sector, the country's intellectual assets, the expenditure with innovation in non-R&D related activities, and the level of the business innovation processes carried out by small and medium firms (SMEs). All the estimated coefficients point to a positive impact of these drivers on innovation. Nonetheless, the variable related to the public sector expenditure on R&D is also retained and has a negative estimated sign. In Section 5, we shall discuss this further. All retained variables are individually significant since the p-value for each of them is smaller than 10%.

Table 3 has led to the conclusion that the final congruent model for the innovation index in a post-COVID-19 context for advanced economies has a log–log or constant elasticities specification. Therefore, using the results in column 8 of Table 3, the estimated regression coefficients imply that, on average, other things being equal, we estimate that the impact of a 1% increase in:

- The level of public sector R&D expenditure would be a reduction of 0.0298% in the SII;
- The R&D expenditure of the business sector to be an increase of 0.0921% in the SII;
- The non-R&D innovation expenditure to be an increase of 0.0805% in the SII;
- The business process innovation in SMEs to be an increase of 0.0569% in the SII;
- The level of digitalization to be an increase of 0.1095% in the SII;
- The level of environmental sustainability would be a growth of 0.0976% in the SII;
- The level of linkages to be an increase of 0.1317% in the SII;
- The attractiveness of the research system would be an increase of 0.2177% in the SII;

- The country's intellectual assets would be an increase of 0.0749% in the SII;

Although we do not check for the after selection model resulting from an IIS GUM when the non IIS is congruent, we have chosen to report the results for the model resulting from (9) in Table 3 (column 9). Clearly, the model in column 9 is not congruent as we have no information on heteroscedasticity and the normality hypothesis is rejected (p-value = 0.0224 $< \alpha$). We should not conduct an analysis of this model. It is included here just to take notice that the retained indicators with negative estimated coefficients are Cyprus, Spain, Croatia and Hungary. With positive coefficients, we retained Finland, Estonia and Ireland. In Section 5, we will clarify the possible relevance of this information.

A discussion of these results, within the scope of the research question addressed in this paper shall be presented in the next section.

Finally, Table 4 refers to models of the requested patents or the logarithm thereof. All variables refer to 2022. We keep the significance level at $\alpha = 10\%$.

Table 4. Autometrics results for the requested patents with reference to 2022.

	Equation (1)	**Equation (6)**	**Equation (2)**	**Equation (3)**	**Equation (8)**	**Equation (4)**	**Equation (9)**
1	2	3	4	5	6	7	8
$\hat{\beta}_1$ (p-value)	−24.658 (0.0048)		2.8157 (0.0000)	−291.29 (0.0000)	−196.56 (0.0002)		−2.1951 (0.0000)
$\hat{\beta}_2$ (p-value)				−12.4911 (0.0391)			
$\hat{\beta}_3$ (p-value)	0.39818 (0.0000)	0.4208 (0.0000)	0.0056 (0.0001)	33.872 (0.0000)	27.188 (0.0000)	0.4418 (0.0000)	0.5651 (0.0000)
$\hat{\beta}_4$ (p-value)		−0.14096 (0.0037)			−9.0879 (0.1023)		
$\hat{\beta}_5$ (p-value)							
$\hat{\beta}_6$ (p-value)				2.7355 (0.5508)	2.2148 (0.3565)		
$\hat{\beta}_7$ (p-value)	0.2511 (0.0037)	0.1432 (0.0144)		25.0515 (0.0495)			0.1072 (0.030)
$\hat{\beta}_8$ (p-value)					15.671 (0.0026)		0.3056 (0.0000)
$\hat{\beta}_9$ (p-value)							
$\hat{\beta}_{10}$ (p-value)			0.0028 (0.0164)				0.07275 (0.053)
$\hat{\beta}_{11}$ (p-value)	0.3206 (0.0046)	0.30801 (0.0022)	0.00442 (0.0536)	31.727 (0.0148)	22.414 (0.0001)	0.4967 (0.0001)	0.3943 (0.0000)
$\hat{\beta}_{12}$ (p-value)	0.00075 (0.0188)	0.0037 (0.0304)	1.08×10^{-5} (0.0669)		0.9919 (0.4599)		
$\hat{\beta}_{13}$ (p-value)		−0.00103 (0.0834)					
$\hat{\theta}_1$							−0.2513 (0.0003)
$\hat{\theta}_2$							−0.2811 (0.0001)
$\hat{\theta}_3$							
$\hat{\theta}_4$							

Table 4. *Cont.*

	Equation (1)	Equation (6)	Equation (2)	Equation (3)	Equation (8)	Equation (4)	Equation (9)
$\hat{\theta}_5$					−26.698 (0.0016)		−0.5358 (0.0000)
$\hat{\theta}_6$					26.106 (0.0059)		
$\hat{\theta}_7$					21.173 (0.0095)		−0.1305 (0.0216)
$\hat{\theta}_8$							
$\hat{\theta}_9$							
$\hat{\theta}_{10}$							
$\hat{\theta}_{11}$		23.4021 (0.032)			41.3881 (0.0001)		0.1232 (0.0325)
$\hat{\theta}_{12}$							
$\hat{\theta}_{13}$							
$\hat{\theta}_{14}$							
$\hat{\theta}_{15}$							
$\hat{\theta}_{16}$							
$\hat{\theta}_{17}$							−0.2659 (0.0001)
$\hat{\theta}_{18}$							
$\hat{\theta}_{19}$					46.006 (0.0001)		1.0212 (0.0000)
$\hat{\theta}_{20}$							
$\hat{\theta}_{21}$					13.741 (0.0824)		
$\hat{\theta}_{22}$		−20.422 (0.0468)			−18.8278 (0.0429)		−0.4227 (0.0000)
$\hat{\theta}_{23}$							
$\hat{\theta}_{24}$							
$\hat{\theta}_{25}$					35.935 (0.0000)		
$\hat{\theta}_{26}$		−18.7368 (0.0783)			−21.077 (0.0003)		−0.2513 (0.0002)
$\hat{\theta}_{27}$							
R^2	0.9174		0.8809	0.8414	0.990649		0.9974
F-Global (p-value)	61.08 (0.000)		40.68 (0.000)	21.22 (0.000)	70.63 (0.000)		328.7 (0.000)
Normality (p-value)	0.52431 (0.7694)	0.0754 (0.9630)	0.7649 (0.6822)	0.0178 (0.9911)	6.3868 (0.0410)	0.5237 (0.7696)	0.7915 (0.6732)
Hetero (p-value)	0.71567 (0.6755)	0.1951 (0.9953)	1.6937 (0.1680)	1.8564 (0.1351)		1.1828 (0.1595)	
Hetero-X (p-value)	0.79994 (0.6586)		0.7145 (0.7285)			2.0357 (0.1149)	
RESET (p-value)	3.6659 (0.0440)	3.23 (0.0937)	0.6083 (0.5540)	13.341 (0.0003)	0.81108 (0.4778)	2.6384 (0.0930)	0.5699 (0.5829)

Column 2 corresponds to the reduced form of the model when the underlying GUM is given by Equation (1). The results point to non-congruency since the null of the RESET test is rejected (p-value = 0.044 $< \alpha$). IIS was used to account for the possibility that non-linearities might, in fact, be outliers. Notwithstanding, we choose not to use the estimated post-selection model when the earlier GUM is impulse-saturated (corresponding to Equation (6)). This option is due to insufficient improvement of the RESET test (p-value = 0.0937 $< \alpha$). The model cannot claim to be congruent. Column 4 reports the estimated post-selection model if the GUM matches Equation (2). The null hypothesis is not rejected in any of the diagnostic tests (hence, we have not enabled IIS). Indeed, we cannot reject the normality of the random errors (p-value = 0.6822 $> \alpha$), the null of homoscedasticity irrespectively of whether we use the test with cross-products (p-value = 0.7285 $> \alpha$) or not (p-value = 0.1680 $> \alpha$), nor the null of correct functional form (p-value = 0.5540 $> \alpha$). The F test leads to rejection of the null of no global significance for the model in column 4 (p-value = 0.000 $< \alpha$).

All the retained drivers of innovation in the log-linear model in column 4 are statistically significant at $\alpha = 10\%$: the attractiveness of the research system (p-value = 0.0164 $< \alpha$), the expenditure in R&D conducted by the Business Sector (p-value = 0.0001 $< \alpha$), the level of intellectual assets (p-value = 0.0536 $< \alpha$) and the GBARD (p-value = 0.0669 $< \alpha$). A unit increase in the attractiveness of the research system is estimated to augment the requested patents by 0.28%, other things constant. The estimated average impact of a unit increase in R&D business expenditure is an increase in the requested number of patents of 0.56%, ceteris paribus. With respect to the intellectual assets of the country, an increase in one unit is estimated to lead, on average, to a growth in the number of requested patents of 0.442%. Also, an increase in the GBARD variable of one, is, on average, estimated to increase the number of requested patents of 0.00108144%, other things equal. In Section 5, we shall discuss these results in detail.

The model reported in column 5 has an underlying GUM that mimics Equation (3). It lacks congruence, as we reject the null hypothesis of the RESET test (p-value = 0.0003 $< \alpha$). Once the same GUM is impulse-saturated (Equation (8)) and Autometrics performs its machine learning automatic selection algorithm, the estimates in column 6 are obtained. Again, the final model lacks congruence since the null of the normality test is rejected (p-value = 0.041). The log–log specification of Equation (4) leads, after selection, to the estimates in column 7. The null of a correctly specified model (RESET test) is rejected: p-value = 0.093 $< \alpha$. The model is dropped since congruency fails. Column 8 reports the estimated post-selection model when the underlying GUM is given by Equation (9). This is the IIS version of Equation (4). No heteroscedasticity test can be performed. We cannot claim the random errors of the model to be homoscedastic. Thus, the model should not be used.

5. Discussion

The Results Section led to conclusions with respect to the research hypotheses H_1-H_{10}. A tabular synthesis is presented in Table 5. A hypothesis is validated for a particular period (pre- or post-pandemic) and for a particular innovation measure (patents or the Summary Innovation Index) if the corresponding cell in Table 5 has a tick. The absence of a tick indicates a lack of validation. If a question mark appears in the relevant cell, the point has to be further debated.

A question mark does emerge for H_1 for the Summary Innovation Index in both periods. Indeed, the hypothesis postulated the role of R&D investment as an innovation driver, irrespective of the funding source being public or private. In the previous section, we learned that the elasticity of the SII with respect to Gross Domestic Expenditure in R&D was estimated to be 0.0921% in European economies before COVID-19. However, the same table showed an elasticity of −0.0095% of the SII with respect to Government Budget Allocations for R&D. While the first result suggests that R&D investment matters, the second challenges the usefulness of government funded R&D. The same conclusion is valid for 2022 (Table 3), with an elasticity of the SII to the business sector R&D expenditure 0.0921% and an elasticity of the SII to public sector R&D expenditures of −0.0298%. Hence, concerning the SII, our results strongly favor a crowding-out hypothesis, where recipients of public funding would simply substitute the investment they were planning to make with private funds instead of adding to it. Our results are in accordance with those of Marino et al. (2016), both with respect to the crowding-out hypothesis and with respect to the lack of additionality of public investment in R&D, as discussed in Section 2.1.1 of this paper.

Table 5. Results concerning the research hypotheses.

	Pre-Pandemic		Post-Pandemic	
	Patents	**SII**	**Patents**	**SII**
H_1	✔	?	✔	?
H_2	✔	✔		✔
H_3		✔		✔
H_4				✔
H_5		✔	✔	✔
H_6	✔		✔	
H_7				✔
H_8		✔		✔
H_9		✔		
H_{10}				

When patents are the innovation measure used, the question marks disappear. The post-selection final model for requested patents in Europe in a pre-COVID-19 setting did not retain GBARD (X_{12}), nor the R&D expenditures of the public sector (X_2) but did keep the business sector expenditure in R&D (X_3). For the requested patents in 2022, the coefficients for both the business sector expenditure and GBARD were retained with positive estimated coefficients. A possible additionality or crowding-in effect exists.

Research hypothesis H_9 is addressed in an indirect way, as discussed in Section 4. We do not have a variable for institutional quality. Nonetheless, with respect to the SII, for the pre-pandemic period, econometric methodology does point to an answer. As discussed in Section 3.3 and in Section 4, with respect to Table 1, seven indicators are retained in the final congruent model, four of which have a negative estimated coefficient. As explained then, for each of these seven countries, when the logarithm of its SII is compared with that of a country with identical values for all retained variables but for which no country-specific impulse dummy was retained, the estimated impulse coefficient (multiplied by 100) would represent the percentage difference in the SII that cannot be explained by the quantitative variable in the model. Since we are following a GETS approach, the GUM is rich enough to preclude variables that were not selected for the final congruent model. Hence, we attribute the coefficients of retained dummies in congruent models to composite unobservable factors that surely include institutional quality. Our analysis has revealed, as discussed for Equation (9) in Table 1, that we estimate that the Summary Innovation Index for Cyprus, Croatia, Hungary and Italy suffers a penalty of the respective estimated magnitudes (8.13%, 9.94%, 16.61% and 11.35%) when compared to such hypothetical identical countries for which no dummy had been retained. Finland, Luxemburg and the Netherlands have an estimated increase in their SII when each of these countries is compared to a corresponding hypothetically identical country with no indicator retained of 11.464%, 7.289% and 15.661%. In order to further strengthen our interpretation, we look at the post-selection impulse-saturated model resulting from the GUM in Equation (9) for 2022 (Table 3). As discussed in the previous section, this is not a congruent model. Even so, we wish to highlight that retained impulse indicators with negative estimated coefficients match Cyprus, Croatia, Hungary and Spain. Finland remains with a positive estimated coefficient. We refer to this since institutional factors, by definition, might take time to change. In spite of the impact of COVID-19, it was not expected to observe major differences at this level. The fact that Cyprus, Croatia and Hungary remain with negative indicator coefficients suggests that, in fact, there are institutional difficulties in these countries. Neither possible heteroscedasticity nor failures of normality challenge the unbiased nature of OLS estimators. Thus, although inference cannot be conducted (e.g., claiming these coefficients are, in fact, significant), the fact that their estimates remain negative reinforces the view that they most likely reflect the institutional challenges of such countries.

With respect to research hypothesis H_{10} pertaining to the two different measures of innovation having the same drivers, the rejection should be explained. From Section 4, we know that requested patents are not even generated by a model with the same functional form as the Summary Innovation Index. Indeed, whilst models for the SII in both periods are log–log or constant elasticities models, those for the requested patents are log-lin in both periods. Hence, the estimated parameters do not even have the same interpretation, as seen in the Results Section. Furthermore, whilst one of the models for the SII retained impulse indicators, accounting, at least partially, to institutional differences between countries, the congruent models for requested patents do not retain country-specific dummies irrespective of the year under analysis. Adding to this, models for requested patents have clearly retained R&D business sector expenditures and intellectual assets as relevant drivers in both years. Additionally, digitalization was also retained for the model in Table 2, whilst for the model in Table 4, the attractiveness of the research system and the Government Budget allocations to R&D were retained. When compared to the six retained covariates (not counting the retained impulse indicators) in the model emerging from Table 1 and the nine retained covariates in the model emerging from Table 3, the evidence reveals that more drivers matter for innovation when measured using a synthetic multi-dimensional variable.

Finally, the research question of this paper, pertaining to whether the innovation drivers in European economies are identical before and after the pandemic, may be answered. As discussed in the introduction, this paper has adopted 2019 as the pre-pandemic year and 2022 as the post-pandemic year. Having said this, assessment of innovation drivers for both years should be carried out separately according to the innovation measure used since H_{10} was false, and the models for each of the two variables do not have the same functional form. From a statistical viewpoint, the drivers in one are included as such, and the other as their logarithm. A direct comparison of the drivers in the different functional forms would not be statistically sound since the dependent variable differs: lnP_i and $lnSII_i$. A congruent econometric model attempts to explain the variation of the dependent variable around its sample mean; therefore, models for lnP_i and for $lnSII_i$ are attempting explain two different things. In short, to assess whether COVID-19 changed innovation drivers or not, we look at the two different measures of innovation separately.

With respect to requested patents, the discussion of H_{10} already made clear that the drivers before and after the pandemic are not identical. The automatic GETS model selection algorithm in Autometrics has retained, for both periods, the R&D expenditure of the Business Sector and the Intellectual Property Protection variables in the terminal congruent models. However, one of the significant differences between the drivers of innovation (P_i) before and after COVID-19 was the retention in the model for 2022 of the Government Budget allocations for R&D. This variable was not retained in the model for 2019. The attractiveness of the research system was an innovation driver in 2022 but not in the year before the pandemic. Differently, digitalization was an innovation driver before the pandemic but not in the year immediately after. In our opinion, the fact that digitalization was not retained for 2022 is probably related to its already large increase during the pandemic (e.g., Veza et al., 2022). In fact, digital capabilities increased widely during lockdowns, mobility restrictions and social distancing rules. The demand for broadband connections was also likely to have risen, given the need to provide more stable connectivity for online meetings. In short, innovation drivers are not identical when innovation is measured by P_i, for European economies, before and after the pandemic.

Our research question might yet have a positive answer with the innovation measured using the Summary Innovation Index. However, the results from Section 4 and the summary of conclusions as to the research hypotheses in Table 5 already suggest that the congruent post-selection models for the SII do not maintain a precisely identical set of drivers before and after the pandemic. There are differences in retained covariates and on the magnitude of the elasticities of SII with respect to each of the common ones.

Regarding innovation drivers of the SII that are retained in 2022 but were not in 2019, we learn from Table 5 that we are referring to business process innovation by SMEs (X_6), linkages (X_9) and intellectual assets (X_{11}). With respect to intellectual property protection, the puzzle in our view is not its retention in 2022 but the fact that it was not deemed to be relevant in 2019. A possible explanation has to do with the rise in marketing and business process innovation during the pandemic, leading to a possible abnormal increase in applications for trademarks and individual designs.

Thinking in the opposite direction, variables that were retained in 2019 but not in 2022, firstly, the impulse dummies retained in the former that are not retained in the latter. Clearly, this was a result of using an impulse-saturated GUM for 2019 to obtain a congruent model. This necessity did not exist with the 2022 model. If we accept the interpretation that the post selection retained indicators in 2019 might reflect non-measurable country-specific factors, such as institutional quality, it could be argued that institutional quality is an innovation driver in 2019 but not in 2022.

The remaining variables (non-R&D innovation expenditures (X_4), digitalization (X_7), environmental sustainability (X_8) and attractiveness of the research system (X_{10})) retained in 2019 as innovation drivers are also retained in the model for the post pandemic period. However, if ranked according to their estimated impact on SII, there are some differences between the two periods. X_{10} is clearly the most impactful variable both pre- and post-COVID-19 (the estimated elasticity with respect to X_{10} has dropped from 0.43022% to 0.2177% with the pandemic, though). The second most impactful variable differs between the two periods: for 2019, the elasticity of SII with respect to non-R&D innovation expenditures was estimated to be 0.260009%, and it was the second most relevant variable; for the 2022 model, the estimated elasticity of the SII with respect to X_4 had lowered to 0.0805%, and the variable dropped to the sixth most relevant). The second most impactful variable in 2022 is one of the newly retained variables: linkages, with an estimated elasticity of the SII with respect to it of 0.1317%. The third most impactful innovation driver was environmental sustainability in 2019, and it ranked fourth in 2022 (third if we do not account for the new variables). The estimated elasticity of the SII with respect to X_8 is 0.221114% in 2019 but only 0.0976% in 2022. GERD was fourth in the 2019 rank whilst in 2022, the business sector expenditure in R&D was fifth. Most interestingly, digitalization was only fifth before COVID-19 but moved to the third most relevant driver in 2022. In fact, it is the only variable for which the estimated elasticity increased: 0.0668% in 2019 to 0.1095% in

2022. With respect to the remaining ones in 2022, business process innovation by SMEs was eighth, and intellectual assets were seventh.

We conclude this section with the directions of future research we wish to pursue. Firstly, we would wish to further investigate the crowding-out effects of public sector investment in R&D. Secondly, we intend to clarify the country-specific institutional differences that impact innovation as measured by the SII. Finally, we would like to conduct a panel data analysis of our research question. This shall be possible as information for the post-pandemic period accrues.

6. Conclusions

In this paper, we used a consistent model selection GETS algorithm (Autometrics) to investigate whether the pandemic period had changed innovation drivers. General-to-specific has the advantage of permitting us to start with a GUM with many candidate variables and even to impulse saturate it on top of that. We used two measures of innovation, a single-dimension one (requested patents to the PCT) and a multi-dimensional one in the form of a composite index (the Summary Innovation Index). We chose the 27 EU member states as a sample of European countries. The exercise was performed for a pre-COVID-19 year (2019) and for a post-COVID-19 year (2022). We allowed different functional forms for the GUM. We concluded that innovation drivers before and after the pandemic are indeed different. The final models provided by Autometrics allow for valid inference on retained innovation drivers since they have passed a plethora of diagnostic tests, ensuring congruency. SMEs' business process innovation, linkages and intellectual property protection are drivers of innovation (measured by the SII) after the pandemic that were not statistically relevant in the model for 2019. Both models provide evidence that investment in R&D is an innovation driver, but the origin of the fund matters: there is a crowding-out effect, with public expenditure in R&D diminishing the SII, while business investment in R&D has a positive effect. As a result of the retention of impulse indicators for 2019, we also claim to have found country-specific non-measurable factors, such as institutional quality that impacts the SII for 2019 but does not appear as a significant innovation driver in 2022. Furthermore, digitalization, environmental sustainability, non-R&D expenditures and attractiveness of the research system positively impact the SII in both years, but the ranking of the innovation drivers is modified with COVID-19. Both for 2019 and for 2022, the attractiveness of the research system is the most impactful innovation driver. However, digitalization was the least impactful before COVID-19 and the third most relevant in 2022. Linkages, retained only for 2022, occupies the second position in the ranking that year. Non-R&D innovation expenditures were the second most relevant driver of the SII in 2019 but dropped to sixth most impactful in 2022. In short, with respect to the SII, COVID-19 has impacted innovation drivers. When innovation is measured by a single dimensional variable, we also conclude that innovation drivers differ comparing 2019 and 2022. Digitalization was an innovation driver in 2019 but not a driver of patent requests in 2022. The attractiveness of the research system matters for 2022 but not for 2019. For 2022, there is also another different driver: government budget allocations for R&D. However, the estimated effect is extremely small. We explore possible explanations. Business sector expenditure in R&D and intellectual assets are innovation drivers for both years when innovation is measured by the single dimensional measure (patent applications). Nonetheless, the conclusion seems clear: innovation drivers for patents requested also differ before and after the pandemic.

The main implications of our findings for innovation policy seem to be the facilitating role the government should have in fostering linkages between stakeholders and the capacity the government might have to improve the attractiveness of the research system. Policies based on public funding for R&D appear ineffective for European countries. Promoting a culture of sustainability is also a relevant role the government might play. Public procurement policies could be an instrument to increase the need for environment-related innovations.

We are aware of the limitations of our study. The most relevant is that, despite the end of the pandemic period, there were other events in 2022 that may have affected the results for that year. The invasion of Ukraine by Russia disrupted the economic performance of countries, namely with supply shortages of several materials. Moreover, with inflation rising, the European Central Bank (ECB), as well as other central banks, raised their interest rates. Additionally, the ECB moved from an expansionary monetary policy (Quantitative Easing) to a restrictive one (Quantitative Tightening). The effect that a rise in interest rates might have had on innovation investments needs exploration.

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Notes

1 Autometrics is available as part of PcGive 15.0 in the Oxmetrics 8 Professional suite. Impulse saturation-based estimators with automatic model selection are also implemented in the R package Gets version 0.38 (Pretis et al., 2018) and in Eviews (since version 12.0). This paper uses PcGive 15.0 to implement Autometrics and IIS.

2 The general-to-specific methodology has also been referred to as the London School of Economics (LSE) approach since its origin dates back to Sargan (2001).

3 In Sections 4 and 5, it is of relevance to know the order in which countries are in our sample to understand which country we are referring to if a dummy is retained after IIS. The number associated with the impulse indicators match the country order. Our sample follows the order: Austria, Belgium, Bulgaria, Cyprus, Czechia, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxemburg, Latvia, Malta, Netherlands, Poland, Portugal, Romania, Sweden, Slovenia, and Slovakia.

4 Linear regression models are often represented in the matrix format $y = X\beta + u$ where X is the data matrix for independent variables, each matching a column. In models with a constant term, such as the GUMS discussed, the implication is that the first column of X, matching data for X_1, is a column vector of ones. Therefore, $X_{1,i} = 1$, $\forall i$. For that reason $X_{1,i}$ is not included when writing the extensive form, since $X_{1,i} \times \beta_1 = \beta_1$ (see, inter alia, Greene, 2003).

5 For all tables in this section, the encoding of Section 3.3 is valid. As such, the order of the countries in the sample matching the order i of the impulse dummies' coefficients $\hat{\theta}_i$ is: Austria, Belgium, Bulgaria, Cyprus, Czechia, Germany, Denmark, Estonia,

Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxemburg, Latvia, Malta, Netherlands, Poland, Portugal, Romania, Sweden, Slovenia, and Slovakia. The encoding of the covariates is also kept: $X_{2,i}$ refers to R&D public sector expenditure; $X_{3,i}$ refers to business sector R&D expenditure; $X_{4,i}$ to non-R&D innovation expenditure; $X_{5,,i}$ to ICT specialists; $X_{6,i}$ to SMEs' business process innovation; $X_{7,i}$ to digitalization; $X_{8,i}$ to environmental sustainability; $X_{9,i}$ to linkages; $X_{10,i}$ to the attractiveness of the research system; $X_{11,i}$ to intellectual assets; $X_{12,i}$ to GBARD; and $X_{13,i}$ to GERD.

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