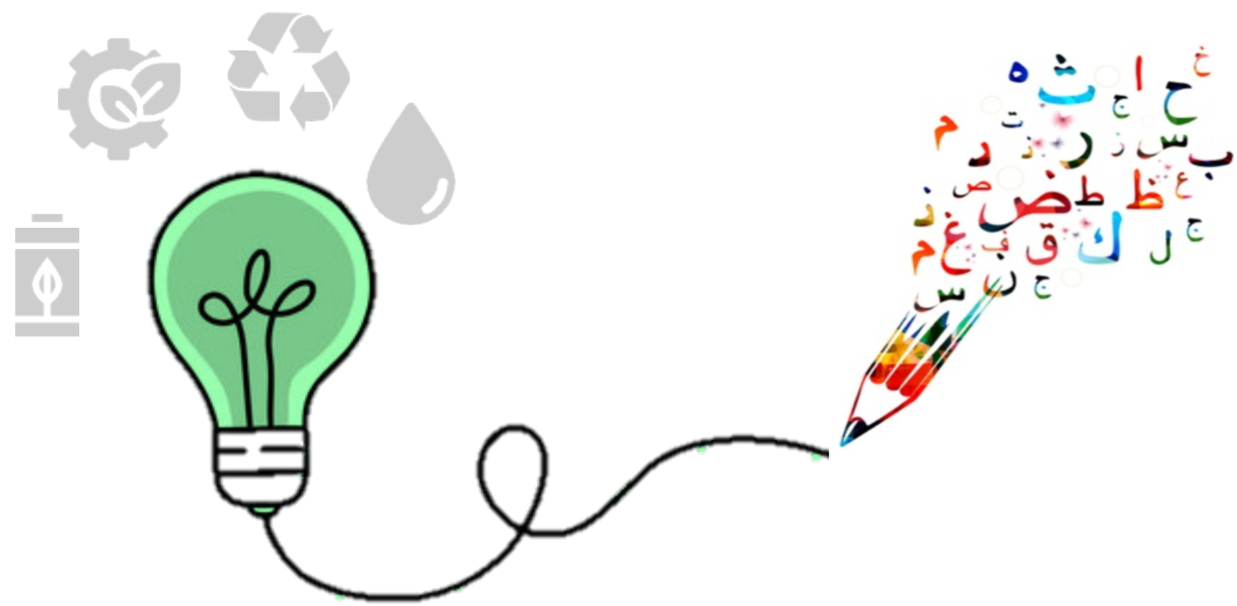
Focusing on the **Bright** Sides of Innovation

Three essays on the role of National Knowledge Dynamics, Inclusive Innovation Teams and Policy Monitoring



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Focusing on the Bright Sides of Innovation: Three essays on the role of National Knowledge Dynamics, Inclusive Innovation Teams and Policy Monitoring

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I dedicate this thesis to the Palestinians in Gaza.

My parents finished their education in times of war. I finished mine in flights traveling from one European city to another. My education became my safety and my privilege. I am working and hoping for a world where it becomes everyone's safety and privilege.

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Thesis Abstract

Innovation theory and policy are most beneficial when they reflect shifts in societal priorities. Traditionally and initially focused on technological change, we see innovation policy currently grappling with the increasingly necessary task of addressing negative externalities, especially in the context of social and environmental sustainability. This is best embodied in the case-example of the Smart Specialization innovation policy in Europe. In contribution to the current debate in the field on the intersection of innovation and sustainability, this thesis targets three different research questions focused on how innovation policy can be leveraged to achieve equality, sustainability, and inclusivity. Each chapter asks a unique question, embarks on a specific literature review, and employs a tailored methodology to answer the question at hand and accordingly contribute to our understanding of the broad theme of innovation for sustainability. The thesis ends with the literature and methodological contributions of the research questions in addition to the policy recommendations at the firm level, regional level and policy design and implementation level.

Resumen de tesis

La teoría y las políticas de innovación son más beneficiosas cuando reflejan cambios en las prioridades sociales. Centradas tradicionalmente e inicialmente en el cambio tecnológico, vemos que las políticas de innovación actualmente enfrentan la tarea cada vez más necesaria de abordar las externalidades negativas, especialmente en el contexto de la sostenibilidad social y ambiental. Esto se materializa mejor en el caso de ejemplo de la política de innovación de especialización inteligente en Europa. Como contribución al debate actual en el campo sobre la intersección de la innovación y la sostenibilidad, esta tesis aborda tres preguntas de investigación diferentes centradas en cómo se pueden aprovechar las políticas de innovación para lograr la igualdad, la sostenibilidad y la inclusión. Cada capítulo plantea una pregunta única, se embarca en una revisión de la literatura específica y emplea una metodología personalizada para responder la pregunta en cuestión y, en consecuencia, contribuir a nuestra comprensión del amplio tema de la innovación para la sostenibilidad. La tesis finaliza con la literatura y las contribuciones metodológicas de las preguntas de investigación, además de las recomendaciones de políticas a nivel de empresa, nivel regional y nivel de diseño e implementación de políticas.

Chapter 1: Introduction

To innovate or not to innovate is never a question. And if it were, the answer is always: "Of course innovate!". Ask the scientist with a crazy idea that may make life easier for others, the scientist will certainly want to innovate. Ask the firm which has the input required to bring an innovation into market and make some extra profit, the firm will certainly want to innovate. Ask the policy makers about the type of output they want from their policy efforts, the policy makers will always strive to improve local innovation. And yet, innovation cannot and should not be understood as a pure positive goal which should be strived for always with no considerations. The literature on the "Dark Sides of Innovation" (Meijer & Thaens, 2021; Coad et al., 2022) within the innovation literature underscores the understanding that even the most well-thought of and beneficial innovation can have negative repercussions which should, at least on the policy levels, be understood and alleviated. On the other hand, vast amounts of literature on sustainable innovation (*amongst others* Loorbach, 2010; Steward, 2012; Mazzucato, 2017; Schot & Steinmueller. 2018; Tödtling et al., 2022) have decided to otherwise look at how innovation can be used within a sustainability framework, to ensure it leads to positive contributions and non-negative ones. Understanding how innovation can be used in a sustainable manner requires a large amount of research and collaboration from academics, policy makers and firms. While recognizing that no type of innovation can be stopped, nor should it be, this thesis contributes to our understanding and our needs for innovation as a source of good. It learns from vast amounts of research and experience which has already been developed and presents the argument for why this type of research needs to continue, the space left to contribute to it, and its role at the intersection of innovation literature and innovation policy.

Various definitions of innovation exist, spawned across streams of literature studying innovation at different scales and in reference to specific needs (*see* Baregheh et al. 2009; Edison et al., 2014). After collecting 35 of those definitions (*see* Table A1.1), we create a Word Cloud, Figure 1.1, to highlight the repeated words and phrases. The most prominent word is: "new", which is the reflection of the novelty that is introduced in innovation - arguably the most important asset of it. The second most important group of words consist of; "product", "process" and "service" reflecting the different types of use-cases in which innovation can be present. Other repeated words represent the "technology" and "knowledge" that is required for innovation to be successful, and the scales at which innovation may occur: "firm", "individual", "business", "market", "organization".

Figure 1.1: Innovation Definitions World Cloud

As it stands, there is an urgent and increasing need amongst governments to address, through all means possible, issues like climate change, rising inequality, poverty and pollution. We see this urgency being translated at the level of innovation policy as well. Certain initiatives have looked at this challenge as a creation of opportunities for science, technology and innovation. Initiatives such as Horizon 2020, the 2015 Lund Declaration and the universal Paris climate change agreement (Schot & Steinmueller, 2018) have supported the vision of aligning innovation methods within the Sustainable Development goals, focusing on greener forms of production and creation, directing local efforts towards more sustainable, inclusive and just patterns of creation and consumption. At the European Union level, the conversation is increasingly focused on the "twin challenges" and "twin transitions" of technology and sustainability. The European Commission writes that neither challenge can succeed without the other and both are equally important for Europe's future and success[1]. There are many reasons for the increased focus on sustainability policies. One stark illustration of this is "Earth Overshoot Day" which represents the date of each year when the forecasted global demand for ecological resources and services becomes higher than

[1] https://www.euronews.com/next/2023/07/12/how-sustainability-is-shaping-the-future-of-tech-innovation-and-viceversa

what Earth can sustainably generate within that year. After that date, the world becomes in deficit and is using more resources than can be replaced and creating more emissions than can be expelled from the atmosphere. Since 1971, the date has been arriving earlier and earlier. In 2023, Earth Overshoot Day was on August 2nd. In 2024, it is projected on July 25th[2]. In itself, this day is typically used as a communication tool to reflect the urgency of addressing ecological imbalances and the need for a global shift towards more sustainable and regenerative practices to ensure the well-being of the planet for future generations.

Baregheh et al. (2009) highlight how the various definitions of innovation change with the "dominant paradigm of the respective discipline" (p. 1323). The definition of innovation within the literature changes alongside the dominant societal needs and perspectives towards it. In turn, the implementation of innovation itself adapts to dominant local circumstances, challenges and goals. To illustrate, Nelson and Winter (1982) acknowledge that economic processes continue to create externalities that eventually become too significant to be ignored or denied. This is particularly true the faster the pace of technological change becomes. The authors discuss how: "Long-lasting chemical insecticides were not a problem eighty years ago. Horse manure polluted the cities, but automotive emissions did not. The canonical 'externality' problem of evolutionary theory is the generation by new technologies of benefits and costs that old institutional structures ignore" (Nelson and Winter, 1982, p. 368). Innovation policy and studies may have purely focused on technological change 80 years ago, as this had been the more urgent and pressing need. However, as externalities arise, and local circumstances switch focus, sustainability issues have become more urgent and demanding. Thus, innovation and innovation policy became no longer understood purely as a tool to achieve technological change but were increasingly utilized to reduce the cost of these technological externalities or even contribute to more positive ones.

Innovation theory - our understanding of innovation - and innovation policy - our efforts to implement it - are influenced by each other through dual roles. As our understanding of innovation dynamics develops, the policy recommendations change to account for those literature advancements. At the same time, sometimes our policy priorities change and that expands the way

[2] https://nationaltoday.com/earth-overshoot-day/#:~:text=We%20are%20observing%20Earth%20Overshoot,resources%20at%20a%20finite%20rate.

we study, analyze and understand innovation. For example, as the innovation literature evolved from understanding innovation in a linear manner into a network perspective, the policy recommendations and procedures evolved accordingly. However, as we currently witness the paradigm shift around the world highlighting the growing urgency to integrate innovation and sustainability, we also see a shift in the literature on how we can study and understand innovation for the sake of sustainability purposes.

1.1. Innovation Literature and Policy

Schot & Steinmueller (2018) summarize the evolution of innovation literature and policies into three different frameworks. The earliest and simplest framework is the linear vision of innovation. Eventually, this approach was abandoned after recognizing that the process from R&D spending to new technological developments is not automatic. Then the network framework (*e.g.:* regional and national systems of innovation) became the dominant perspective. The third and final framework, and the more recently relevant one, focuses on the framing of innovation policy within societal and environmental challenges and for the sake of achieving social needs.

It is important to position this thesis amongst our understanding of the evolution of the innovation literature, the three frameworks described above, and how such frameworks inspired the current innovation policy debate. To begin, the first view for innovation followed the *Schumpeterian concept* where the implementation of innovation relied purely on the entrepreneurial spirit from people who are aware of new business opportunities and invest time and resources to benefit from those opportunities (Schumpeter Mark I). From the 1950's onwards, the dominant view of innovation became that of "neo-classical economists" who followed the definition. According to this theory, policy intervention is deemed unnecessary since the returns of innovation on their own would be enough motivation for entrepreneurs to innovate (Samuelson, 1973). However, even within this line of literature, it was eventually argued that some form of "market-failure" would exceptionally justify policy interventions. This market-failure exists due to the "public-goods" nature of knowledge. Once innovation does occur and new knowledge is created, this knowledge becomes free of charge and readily available to be exploited by everyone. Thus, the return on investments for the innovators, the people creating this knowledge, reduces. This could lead to an underinvestment by individuals themselves in the R&D process (Edler & Fagerberg, 2017). Even after acknowledging some role of public policy in innovation dynamics, the above view of innovation was still considered too simplistic in its approach and inconsistent with various empirical findings and tests about this topic (Kline, 1985; Todtling & Trippl, 2005; Edler & Fagerbeg, 2017). The literature began focusing on how the process of innovation occurs in a non-linear manner (Kline, 1985). In addition, geographically specific case studies showed that local contexts play a huge role in whether or not, and how, innovation occurs. These contexts include, but are not limited to, agglomeration forces, proximity to large industry players, variations in institutional capacity and international positioning within the supply chain (*amongst others:* Niosi & Bellon, 1994; Rodríguez-Pose & Crescenzi, 2008; Rodriguez-Pose, 2013; Lundvall, 2016).

The role of innovation policy grew fundamentally after the 1970's during the aftermath of the OPEC oil crisis. The global economy was struggling with a phase of slow growth, high unemployment and obvious and persisting structural problems. As traditional economic policies were proving to be of little impact, policies focused on innovation, in the broad sense, were hailed as mechanisms of achieving economic success (Fagerberg, 2018). At the time as well, national innovation systems as a "term" became quite popular. This is a good portrayal of the popular perception and understanding of innovation at the time. Innovation policies developed from a simple understanding of the need to achieve innovation, into a more focused effort of understanding the local contexts and failures of why innovation is not being achieved. Since countries have different knowledge and economic industries in which they specialize in, and different social norms on how interactions amongst these industries occur (Fagerberg, 2016), the policies following national innovation systems were expected to be quite globally diverse and context specific.

Specifically, from the 1990's onwards, the literature on innovation increasingly focused on a network, non-linear and locally specific perspective of understanding innovation. This is based on the understanding that innovation depends on the interplay and the complementarities between various stakeholders within a complex context (sectors, regions, countries). Stakeholders include firms, private and public research institutes, government regulations, academic institutions, etc. (Edquist, 1997; Weber & Truffer, 2017). The National Systems of Innovation (NIS) literature

(Freeman, 1982; Lundvall, 1988; Lundvall, 1992; Nelson, 1993) focused on this theory from a national perspective, while the Regional Systems of Innovation (Cooke et al., 2004) recognized that innovation tends to happen at smaller and more urban-structured scales and thus focused on the network theory from a regional perspective. Both theories shed light on the role of socio-economic conditions and policies on innovation. In this context, policy intervention is justified specifically when deficiencies are detected in the core elements of the innovation system. Such deficiencies include (Todtling & Trippl, 2018) the absence of essential skills and resources amongst actors (*capabilities failures*), the inadequacy or absence of interactions between actors within the innovation network (*coordination failures*), the hindering of innovation through too harsh or non-existent regulations (*institutional failures*) and the absence of essential infrastructure for R&D performance and collaboration (*infrastructural failures*). Under this framework, policy interventions need to be adapted based on the system failures defined and to fit the local context. This portrays a change from a "one-size-fits-all" type of intervention. This establishes a need for "place-based" policy, which is tailored to the specific local interests and characteristics and thus places more responsibility on local actors.

The final framing for innovation lies at the intersection of innovation and sustainability challenges. Scholars (Schot & Steinmueller, 2018; Fagerberg, 2019) raised the concern that once the urgency of sustainability issues comes to light – connecting the policy world to the academic one – a question arises on whether the two first frames of innovation policy are sufficiently capable of contributing to these challenges. Are they even capable of dealing with the negative externalities that are generated directly because of economic growth? According to Schot & Steinmueller (2018), the frames are insufficient, describing the main issue with the fact that innovation lacks directionality through these frames and always represents innovation as positive, regardless of its externalities. Even if these framings recognize some dangers or negative outcomes in the short term, they also claim that the overall innovation benefits compensate for this. On the other hand, Fagerberg (2019) takes issue with the claim arguing that any policy should be anchored in the accumulated research. Nevertheless, building on the accumulated research, the third and most recent framework of innovation is attributed to the purpose of using innovation in order to achieve socio-technical system changes that may help solving the environmental and social challenges of our world. We can call this framework: innovation for sustainability. The literature differs in scope and implementation (and even to the type of policy recommendations they evoke), but essentially, they all contribute to the notion of introducing directionality into innovation policy. Concepts within this framing include eco-innovation policy (Kemp, 2011), transition management literature (Rotmans et al., 2001; Kemp et al., 2007; Loorbach 2010), mission-oriented innovation policy (Mazzucato, 2017), transformative innovation policy (Steward, 2012) and challenge-oriented regional innovation systems (Tödtling et al., 2022). Directionality in innovation policy means that the policy must be tailored to not only stimulate technological progress. Such policies might be able to investigate the societal and environmental impacts of the different potential policy responses in question and eventually foster methods to enable the desired response and block the undesired ones. That perception of innovation has important implications on how policy interventions change. But also, important implications on when policy interventions become necessary. The need for innovation policy, under this framework, remains necessary when *capabilities failures, coordination failures, institutional failures* and *infrastructural failures* arise. However, Weber & Rohracher (2012) also expand on this to explain how policy interventions need to respond to additional failures within the ecosystem. These include the failure of producing innovations capable of contribution to systemic local transformational change (*directionality failure*), the disjunction between the supply of innovation and local demands (*demand-articulation failure*), the failure of innovation to positively contribute to, and in some cases undermining, other local policy initiatives (*policy coordination failure*) and the ecosystem's failure to adeptly monitor and enhance itself (*reflexivity failure*). Innovation policies, under this framework, need to work towards prioritizing a specific type of innovation and ensuring that the outcomes of any policy intervention lead to overall changes capable of responding to sustainability challenges and demands. The literature on innovation for sustainability became necessary in response to both our recognition of the dark sides of innovation and to the overwhelming need to integrate innovation policy within a sustainability framework. Thus, while the two earlier frameworks were themselves influential in changing the innovation policy debate, this particular framework is an example of how the innovation literature progressed in response to a policy crisis and in anticipation of how innovation policy can be achieved to alleviate it.

This thesis is grounded in the evolution of innovation literature but strategically situated within the ultimate framework that emphasizes the application of innovation for addressing sustainability challenges. In the ongoing academic and policy discourse, this body of literature holds significant relevance. Arguing that innovation policy should play a role in achieving sustainability transitions becomes more difficult when moving from a theoretical sense to a practical one. It is particularly challenging to provide good model examples on how to integrate the two (Mowery et al., 2020). This difficulty contributes to a broader sense of friction between these two domains. The absence of compelling case studies further fosters hesitancy within the innovation community, generating concerns about how an abundance of sustainability constraints might impede the local progress of technological advancements. The imperative to translate theoretical insights into practical implementation, guided by policy measures, regional emphasis, and organizational initiatives, is not only crucial but also holds considerable influence.

1.2. Dark Sides of Innovation

The third frame of innovation policy came as the dark sides of innovation became too obvious to be ignored. The Dark Sides of Innovation is a term already popular amongst the innovation literature (Meijer & Thaens, 2021; Coad et al., 2022) to understand and manage the potential harms and risks associated with any innovation project. Meijer & Thaens (2021) further define these effects as the "perverse effects" of innovation since they may or may not be directly related to key features of the innovation process. It is crucial and equally challenging for the innovation literature to be able to update its understanding of innovation as local and global priorities change. Indeed, when the field of innovation studies was quite recent, in the 1960's, most innovations were technology-based, developed by large firms with large R&D departments, and frequently involved patenting. Nowadays, the reality is different; innovation is not always patented (and not all patents are a sign of innovation) and happens in an incremental fashion which may or may not involve formal R&D (Martin, 2015). The literature on the dark sides of innovation recognized that empirical analysis of innovation studies, and thus innovation policy, did not keep pace with the changing world and its changing needs (ibid). The way innovation was defined, measured, and operationalized seemed to be rooted in the past, had a very simplistic vision of what innovation entailed and did not consider the urgent need for sustainability.

Numerous instances underscore the dark repercussions of innovation, encompassing public health issues like lung cancer and allergies stemming from novel products, the global weight of pollution, and the inadvertent fallout of heightened plastic usage (Coad et al., 2021). At the socio-economic echelon, we witness widespread joblessness and escalating inequality. The benefits of innovation on a firm level, regional level and global level resonate strongly and are constant things to aspire for. Yet, the negative consequences, specifically on a local level, can no longer be disregarded. Both the innovation literature needs to discuss them and innovation policy efforts need to be focused on reducing them.

We understand from various examples that the intentions that one has at the start of an innovative project rarely project the eventual consequences. A vast number of inventions that originated from the military industry are being widely used in our day to day lives; for example, the internet, GPS satellite navigation, and microwave ovens.[3] All these inventions were developed through military research in the intention of creating assets to help win wars. Despite their initial aims, their final use-case has become an every-day necessity. Unfortunately, we also see inventions that had positive intentions that were eventually used for dangerous purposes. For example, dynamite, which was invented for construction and building purposes eventually came to be used as weaponry. Another example is the creation of robots, which was envisioned as a tool to help people in their daily lives and make companies more efficient and faster. Gradually, robots became useful as drones for high-precision weaponry[4]. In addition, the growing possibilities of using robots in autonomous land and sea-based weapons is dangerous enough that the UN has called to ban them[5].

Sometimes the damages that innovation may create may not have anything to do with the use case of the product, but rather the unanticipated accidents - e.g. Chernobyl - or the end-of-product-life considerations on how best to dispose of the use of such products (ibid, p. 104). During the exploration phases of innovation cycles, negative consequences tend to be ignored or accepted at a small scale. However, those consequences may expand in intensity once such explorations become fully-fledged products used at a large scale. Congestion and pollution are an example of this (Coad et al., 2021). Another example is the increase in the demand of Cobalt for the production of lithium-ion batteries and how that has caused social issues of corruption, extreme poverty and child labour (Conca, 2020).

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[3] https://www.nato.int/cps/fr/natohq/declassified_215371.htm?msg_pos=1
[4] https://www.seeker.com/10-good-techs-turned-bad-1767944010.html
[5] https://www.seeker.com/un-calls-for-ban-on-killer-robots-1767569699.html

It becomes thus clear that innovation cannot be viewed as always good or always bad. The environments in which "bad" innovation arise cannot always be foreseen, nor controlled, nor should they always be limited. This adds an entire layer of complexity to innovation policy; how should innovation policy intervene? Should it intervene at all? At what levels should the intervention happen? This thesis contributes to some of these essential questions to be discussed.

1.3. Innovation Policy in Europe; the case of Smart Specialization

The Smart Specialization policy case serves as a practical illustration of how innovation policy and objectives can be molded by the broader policy landscape and the scholarly comprehension of innovation's diverse outcomes. Smart Specialization policy is Europe's most recent and one of the biggest innovation policies to date. The first phase of policy began as of 2014 when the European Commission made the disbursement of European Regional Development Funds conditional on the existence of a regional strategy. The fundamental logic of the Smart Specialization Strategy (S3) program is outlined in multiple sources by the European Commission (2012), Barca (2009) and by Foray et al. (2009). The strategy was meant to implement innovation development initiatives that focus on the involvement of local stakeholders in both the design and the implementation of the process. The approach is intended to be place-based; allowing regions to leverage their local competitive advantages and assets to diversify their knowledge industries into technologies and activities that are related to their knowledge base. In its design and implementation, S3 is a multi-level governance process, carried out across various territorial scales through a bottom-up approach. While the EU establishes the rules, general objectives and the funding criteria, the ground-level implementation is conducted by lower levels of governments, either the national or the regional ones. For example, Hungary and Bulgaria have chosen to specify S3 priorities on the national level. Meanwhile, Finland and Sweden have implemented it on the NUTS-3 level. In addition, countries such as Germany, Denmark and Greece have complemented regional implementation of S3 strategies with national projects effective to the whole country[1] (Marrocu et al., 2020). This ground-level implementation allows objectives to be adapted to the socio-economic context (Barca, 2009).

In the implementation of S3, stakeholder involvement is expected to begin with identifying priorities for each region to focus their innovation efforts on. This is referred to in the literature as the "Entrepreneurial Discovery Process" (Foray et al., 2009). For regions to gain access to the European Regional Development funds, regions should prioritize actions in sectors where: regions have a competitive advantage or the potential to generate knowledge-driven growth. The priorities set by regions will naturally be in the interception of local and global technological, industrial and societal needs (Marinelli et al., 2019). The concept of priority setting is intended to concentrate intervention on a few economic activities, specifically those that match the local reality of each region, and can guarantee, with less risk, an effective response to social and economic challenges. In fact, this approach was in part motivated by the failure of many regions in creating industrial "technology miracles" and dedicating large portions of investments in sectors that are economically and locally infeasible. Priority setting, as a mechanism, instead attempted to mitigate the gaps between European regions by identifying unique assets that practically create a potential for innovation in such areas (Rodriguez-Pose et al., 2014).

The first phase of Smart Specialization was between 2014 and 2020. Driven by shifts in policy interests around the time of its second phase (2021 - onwards), the strategy became known as: "Smart Specialization for Sustainability". Regions were encouraged to align their technological priorities with their own regional sustainability goals, and wider sustainability goals across the EU (McCann and Soete 2020). It was understood that locally focused regional innovation efforts based on stakeholder involvement could play a large role in gaining local sector to target important and timely urgent challenges (European Commission 2012b; Coenen and Morgan 2020). While there may be considerable overlap in the foundational literature and backing for both policies, nuanced distinctions must be implemented to accommodate the evolving confluence of objectives related to innovation and sustainability (McCann and Soete 2020).

The Smart Specialization approach, since its inception and until its second phase of implementation, has shown a lot of weaknesses and strengths. While its logic is rooted in place-based policies, evidence has shown that the local implementation reflects the lack of local resources to implement the vision. Marrocu et al., (2022) show that throughout the Smart

Specialization Strategies, only a few regions selected priorities which are in line with their current specializations. Many regions, in fact, selected combinations of unrelated and unspecialized sectors. In addition, the place-based focus was done to avoid the trap of unachievable goals and to use place-specific assets for successful policies, however, the overwhelming perspective within the literature is that Smart Specialization still fails in less-developed regions due to some form of combination of the weak initial technological endowments, scattered social and business networks and institutional failures (Barzotto, 2020; Marques & Morgan, 2020). Finally, while the policy reasoning to align with sustainability goals is clear, the method of implementation may not be as straightforward. Both literature and policy efforts need to be made to ensure that the implementation results in practical and local beneficial results.

It remains to be seen what lessons will be learnt from the second phase of Smart Specialization, as it aligns with sustainability goals. Nonetheless, as this phase unfolds, it is clear that the EU direction is committed to finding policies capable of achieving the twin transitions of sustainability and digital transformations. We can hypothesize that future iterations of this policy would remain in line with this overarching objective.

1.4. Research Questions

Driven by the progress of the literature on innovation studies and inspired by the specific use-case of the regional and place-based policy of Smart Specialization in Europe, this thesis studies various dimensions of how we can achieve sustainability within innovation. While this is the general theme of the thesis, each research chapter tackles it in a very specific way. The thesis contributes to the field of innovation by studying different ways and scales (regional, local and policy level) through which the positive sides of innovation can be harnessed. Each chapter asks a specific research question and uses a relevant methodology in order to answer the question, contribute to the literature and highlight the potential policy implications. Throughout the different questions, the common link is the aim of analyzing how different avenues, research policies and assets can be leveraged to practically achieve sustainable innovation.

Throughout this thesis, we define innovation in a broad sense, as is common in previous literature on innovation (Fagerberg, 2004). Here, innovation includes the full spectrum of innovation activities; from the creation of new ideas, to its implementation and eventual adoption within the economic and societal system including the policy environment guiding or hindering this process. Such broad definitions are essential specifically when discussing sustainability within innovation because in this context, the practical aspects (execution and diffusion) of innovation hold paramount importance (Mowery et al., 2010). In addition, we also define sustainability in the broad sense, allowing the range of different definitions to be valid. In fact, we connect our research questions and analysis to one or many of the UN's 17 Sustainable Development Goals[6]. As diverse as these goals are, they contribute in their own way to a definition of sustainability and when applied in a context-specific manner, each goal is essential in its own way to sustainable development.

The thesis is organized into five chapters. This introduction chapter discusses the aim of the thesis and positions it within the field of innovation research and innovation policy. The next three chapters correspond to the big research questions that this thesis intends to study.

The second chapter of this thesis offers a new perspective into the relationship between innovation, knowledge complexity and inequality. We study what type of innovation leads to higher or lower levels of inequality at the national level. To further contextualize the dynamics of the innovation-inequality relationship, this chapter utilizes the Economic Complexity (Hidalgo & Hausmann, 2009; Tachella et al., 2012) framework. We model the knowledge complexity of each country as defined by the diversity of the industries in which the country patents successfully complemented by the ubiquity of such industries. The intuition behind this is that looking at the diversity of the knowledge ecosystem is not sufficient. To truly understand the extent to which this diversity offers a competitive advantage to the nation on the global scale, it is helpful to look into the ubiquity of the industries themselves at a global scale. We can hypothesize that the complexity of the knowledge core impacts the inequality of the local population through the type of skills required and the type of jobs and learning opportunities available (Hartmann, 2014, Milanovic, 2012; Hartmann et al., 2017; Chu & Hoang, 2020). We therefore look into how such knowledge

[6] https://sdgs.un.org/goals

complexity is associated with inequality dynamics on the national level. The complexity framework has often been used to understand local inequality dynamics (*for example;* Hartmann et al., 2017) but the contribution of this chapter is studying the connection with the knowledge ecosystem rather than the production/trade ecosystem. This allows us to contextualize the relationship further and to contribute to the literature focused on innovation and technological change. We study inequality dynamics by not only looking at the Gini Index, but also by studying different income percentile ratios. This is important as it offers insight into what part of the income distribution is affected and in what way by the complex knowledge ecosystem. This chapter discusses the 10th SDG Goals on "Reducing Inequalities" which includes reducing inequalities within countries[7].

The third chapter of this thesis studies the inclusivity of innovation. In that chapter, we target the question on sustainability within innovation at the organizational level. We believe that the inclusivity of the innovation ecosystem, in itself, is an asset that contributes to sustainability, overall. The reasons being that once females are involved within the labor dynamics of innovation production, we have higher equality, quality of life and access to opportunities throughout society. In addition, multiple research outlines the unanticipated drawbacks of inventing through a homogeneous perspective (Perez, 2019) and not considering female data, and points of views when inventing. Thus, we can hypothesize that both on the societal level and on the individual invention level, female involvement in innovation activities is desirable. Following from that, and deciding to focus on a timely relevant and growing industry, this chapter studies the gender dimension in Industry 4.0 innovation. First we look into how much gender diversity exists in the patents contributing to Industry 4.0, how this number has developed over time and in which technological sectors is this number greatest and lowest. Second, we look into what are the possible effects of having a more gender diverse team on the patent itself. We implement a Natural Language Processing model to create data-based indicators of novelty and impact based on the similarity to previous and future patents. This chapter discusses the 5th SDG goals on "Gender Equality"[8] and the 8th one on "Decent Work and Economic Growth"[9].

[7] https://sdgs.un.org/goals/goal10
[8] https://sdgs.un.org/goals/goal5
[9] https://sdgs.un.org/goals/goal8

The fourth chapter delves deeper into the case-study of Smart Specialization and responds to the apparent neglect of the direction of innovation in policy-making (Coad et al., 2021). Traditional indicators of innovation used for monitoring purposes or for performance comparison with other countries tend to take for granted that innovation is always good and thus, the higher the indicator the better. In this chapter, we question this notion, especially in the context of EU innovation policy increasingly focusing on innovation and sustainability collectively. In this chapter we look at the monitoring indicators that were used in the first phase of Smart Specialization and analyze them within the context of the first and the second phase of Smart Specialization. As we know in the initial phases, the Smart Specialization policy was focused on place-based regional innovation. In the second phase, the policy began to be acknowledged as Smart Specialization for Sustainability was encouraged to focus more on using place-based innovation in a directed manner towards achieving the EU's general sustainability goals. In line with such a change in the policy focus, this chapter studies how the monitoring indicators need to adjust to adapt both theoretically and practically to the new goals of the policy. This chapter contributes to our understanding of the 17th SDG Goal on "Partnerships for the Goals"[10] which includes strengthening the implementation for sustainable development goals.

The three chapters collectively contribute to the discussion on how innovation can be used to achieve sustainability, from different perspectives: regional, inventor team and policy level. Each chapter actively engages in the ongoing dialogue within the literature of innovation and economic geography, addressing specific gaps elucidated in subsequent chapters. Furthermore, the methodologies employed exhibit diversity across the chapters, carefully tailored to the unique contexts, ensuring the most effective and pertinent approaches to answer the posed questions.

While chapters 2, 3 and 4 conclude with their own contributions and policy recommendations, the fifth and final chapter of this thesis ends by a quick summary of the chapters and by clarifying their collective contribution to the literature and to the policy discussion.

[10] https://sdgs.un.org/goals/goal17

Chapter 2: What is the relationship between Knowledge Complexity and Income Inequality? A European analysis.

Disclaimer: This chapter is also a paper currently as a work in progress with Davide Consoli from INGENIO (CSIC – UPV).

2.1. Abstract

The chapter explores empirically the relationship between innovation and within country income inequality in a panel of European countries between 2005 and 2018. Using the complexity approach to patent data we find a self-reinforcing dynamics whereby more technologically complex countries exhibit lower inequality and, also, more equal countries have higher capacity to produce complex innovation. While this is robust for different measurements of inequality, we find that inequality at the 80:50 income percentile ratio increases as complexity increases although this is not a deterrent for future complexity.

2.2. Introduction

Widening income disparity is a growing local and global concern as it fuels economic instability and political tensions, damages trust and collaboration amongst citizens, discourages investments and, eventually, reduces consumption and growth (Acemoglu et al., 2012; Carvahlo and Rezai, 2014; Cingano, 2014; Kumhof et al., 2015; Rajan, 2011, Bourguignon and Dessus, 2009). These far-reaching consequences fuel intense academic and policy debates. The community of innovation studies has recently become the focus of much analysis on the relationship between inequality and technological change with different definitions, measures, and perspectives as well as, inevitably, different interpretations (Fragkandreas, 2022). The present chapter seeks to add to this debate by studying how knowledge accumulation and diversity contribute to income inequality across Europe. Prior literature shows that knowledge accumulates in different ways through technology, forms of business organization and institutions (Nelson,1994, p. 48). We argue that aggregate measures commonly used in previous literature oversimplify important nuances, especially considering recent empirical work showing that many social phenomena, including innovation, are better understood by accounting for the systemic interactions that drive their development (Balland et al., 2022). Accordingly, we measure knowledge diversity using a complexity approach (Hausmann and Rodrik, 2005; Hidalgo and Hausmann, 2009; Tacchella et al., 2012; Tacchella et al., 2013), and more specifically we use "Knowledge Fitness" (Tacchella et al., 2012) as a proxy of the multiple forms of know-how that make up an economy.

Previous literature shows that the complexity of the activities of an economic system is a positive predictor of economic growth (Hidalgo & Hausmann, 2009; Tacchella et al., 2018) but, arguably, disregards distributional aspects. Our chapter is motivated by the paucity of evidence on the association between knowledge diversity and within-country inequality. We believe that complexity approaches provide useful insights by offering more nuanced indicators – relative to standard measures such as GDP and patent aggregates – to capture the granularity of activities and of the underlying knowledge bases that fuel (or hamper) economic growth (Hidalgo & Hausmann, 2009; Hartmann et al., 2017; Sbardella et al. 2017 *and others*). Our conjecture is that growth is associated differently to inequality depending on qualitative, or structural, features, and we seek to understand whether and to what extent inequality is an undesired consequence of higher knowledge complexity, or whether higher complexity can yield growth with no increases in inequality.

We study the relationship between knowledge diversity, proxied through a measure of *knowledge fitness*, and inequality in a panel 30 European countries in the period 2005-2018. While existing empirical literature uses trade data to study the association between complexity and income inequality both at national (Hartmann et al., 2017; Sbardella et al., 2017; Lee & Vu, 2020; Lee & Wang, 2021) and regional level (Zhu et al., 2021; Bandeira-Morais et al., 2021), we rely on patent data. Patents capture a substantial part of the local innovation ecosystem, especially in relation to technological change and local capabilities, thus allowing to focus more closely on the innovation component of economic growth. Following Tacchella et al. (2012), knowledge fitness is used as a proxy to measure the complexity of national innovation ecosystems. The indicator allows us to capture a nuanced indicator of knowledge diversity, while correcting and taking into consideration how this diversity is competitive compared to the global knowledge economy. Income quantile ratios, complementing the GINI index, are used as measures of inequality to provide nuance on how inequality is distributed over the income spectrum (Milanovic, 2006). While reducing overall inequality is a key policy goal, nuances matter. A change in the GINI coefficient may not carry the same implications as a change in inequality at the top or the bottom of the income quantiles. Accordingly, to acknowledge the mutual relationship between the two main dimensions of interest, we implement a System of Simultaneous equations to analyse the mutual relationship between knowledge complexity and income inequality.

The main finding is that there is a positive and mutual correlation between knowledge fitness and lower levels of income inequality. Higher complexity is associated with lower inequality at the 80:20 and the 50:20 income percentile ratios. Lower inequality in these income percentiles is also a predictor of higher knowledge complexity. However, we also find that complexity is positively correlated to higher inequality at the 80:50 income percentile ratios. The finding of higher disparities in the middle portion of the income distribution is novel and undoubtedly calls for further policy attention.

The remainder of the chapter is organised as follows. Section 2.3 presents the theoretical context and main evidence and is followed by a description of the methodology (Section 2.4) and the empirical analysis (Section 2.5). Section 2.6 concludes.

2.3. Literature Review

2. 3. a. Knowledge Complexity

Knowledge is typically measured by means of quantitative indicators (e.g.: patent counts and R&D percentages) which are arguably incomplete, since not all knowledge accrues the same level of competitive advantage and industries and technologies differ in the knowledge bases as well as in the infrastructures and tools they employ. Economic Geography scholars have recently explored these qualitative aspects of knowledge growth and innovation by means of novel methods based on network theory, spectral analysis and complexity science that allow efficient and influential dimensionality reduction of large data (Balland et al., 2022). The proxy used in this chapter - *Knowledge Fitness* – intuitively captures the set of innovative capabilities (skills, knowledge, infrastructure) of an economy, specifically those contributing to create and maintain competitive advantage.

Fitness is a measure of diversity that accounts for differential competitive advantage due to technology based on its degree of spatial ubiquity. This literature stems from the works of Hausmann and Rodrik (2005), Hidalgo and Hausmann (2009) and Tacchella et al. (2012) based on international trade data, which were subsequently extended to other measures such as patent and employment data (Hidalgo, 2021, p.1). Metrics that were aimed at predicting economic growth performance (Hidalgo & Hausmann, 2009; Tacchella et al., 2018) have recently been used to study other issues such as income inequality, human development (Lapatinas, 2016; Ferraz et al., 2018), environmental development (Lapatinas et al., 2021; Boleti et al., 2021; Romero & Gramkow, 2021) and the intersection of environmental development and income inequality (Napolitano et al., 2022).

The complexity approach has also made headway in the policy domain. To illustrate, the EU Smart Specialization policy (Foray et al., 2009; European Commission, 2012b) shares common ground with complexity methods due to the focus on qualitative components of regions asset endowment in relation to diversification strategies (Rigby et al., 2019). Also, complexity indicators are now prominent in policy analysis of territorial development and industrial competitiveness by the EC Joint Research Centre[11], in WIPO's Global Innovation Index[12], and the International Finance Corporation's study of Asian industrial development (Lin et al., 2020).

2. 3. b. Theoretical Discussion

Knowledge complexity measures capture the technological capabilities of an innovation ecosystem and, therefore, its main structural features. We propose that the relationship with inequality is threefold, as outlined below.

Q1: Does Complexity reduce Income Inequality?

While we take the cue from the literature on trade complexity and inequality, the theoretical underpinnings are adapted to our focus on patents and innovation. We put forth that complexity leads to lower income inequality through higher-quality institutions, employment, occupational and learning opportunities, and resilience to external shocks.

Early studies show that comparing countries with similar income, more complex ones tend to be more equal (Hausmann & Hartmann, 2017). For countries to be competitive in complex industries, various dimensions – including institutions and educational structures – need to co-evolve with the mix of local capabilities (ibid, p. 85). From the innovation perspective, the same logic applies. Local institutions capable of combining efficiently the ensemble of local capabilities is a ley prerequisite to a highly diversified, viz. complex, innovation ecosystem. The 'Varieties of Capitalism' literature (Hall, 2015) contends that some countries have secured substantial growth and national comparative advantage with relatively equal income distribution, contrary to the belief that greater economic prosperity only comes at the cost of higher inequality. Rather, more egalitarian institutions , such as Coordinated Market Economies (Hall and Soskice, 2001), allow firms to achieve growth and innovation through strategic coordination by leveraging business association networks and trade unions as well as specialized vocational training. Labour laws in

[11] https://iri.jrc.ec.europa.eu/complexity
[12] https://www.wipo.int/edocs/pubdocs/en/wipo-pub-2000-2022-appendix3-en-appendix-iii-global-innovation-index-2022-15th-edition.pdf

these settings can boost more specialized labour markets. Social security, generous unemployment benefits and availability of long-term labour contracts incentivize commitment to continuous vocational training on industry-specific skills, thus fuelling the innovation capacity of the business ecosystem. Once individuals possess appropriate skills, firms have an incentive to offer competitive wages to secure workers with skill that are specific and not -easily replaceable. As Hartmann et al. (2017) argue, while a country may enjoy considerable income growth regardless of the institutional structure and relying on natural resources, it is more likely that high income is coupled with inclusive institutions once the economic ecosystem is based on sophisticated, diverse and interlinked industrial structures.

Furthermore, individuals living in more complex economies have access to more employment opportunities (Hartmann, 2014, Milanovic, 2012). Intuitively, complex knowledge ecosystems are diverse and possess various technological capabilities, and the connections between them create local occupational opportunities due to their global competitive advantage[13]. Of course, the extent to which technology diversification yields higher-quality human capital depends on the transferability of skills (Gathmann & Schönberg, 2010) or on the institutional capacity to upskill or reskill the labour force. Notably, education may not adapt as quickly as technological change, thus leading to skill mismatches or skill gaps. While exploring this issue is beyond the scope of this chapter, we do control for time dynamics to account for the possibility that skill supply may not adjust as in synch with technology.

Following the assumption that it is unlikely for a country to achieve higher complexity without the coevolution of the underlying institutional and education structures (Hartmann et al., 2017), we expect the technological infrastructure to reflect the skill endowment and the availability of opportunities to develop or adapt the competence base. Put otherwise, complex innovation ecosystems are more likely to feature high capacity to develop skills (Chu & Hoang, 2020), offer life-long learning and earning potential (Constantine and Khemraj, 2019; Hartmann et al., 2017, Lee & Wang, 2021) thus making workers less bound to one type of job and accruing more

[13] Competitive advantage is captured by the fact that complexity indicators are measured based on the ubiquity of the technological structures in comparison with the rest of the world.

bargaining power.[14] Back to the focus of the present chapter we expect that when job and learning opportunities are well distributed and not power-grabbed, inequality is lower in highly complex economies. Conversely, we expect less complex economies with low technology implementation, low skills and limited knowledge transfer to exhibit narrow employment opportunities, vertical occupational structures and overall higher socio-economic disparities (Constantine & Khemraj, 2019). That said, the extent to which inequality is more or less prominent within different portions of the income spectrum, and thus beyond the aggregate level captured by global indicators (i.e., Gini's) remains unexplored.

Finally, a diverse knowledge-based economy is arguably more resilient against volatile global markets and unexpected shocks (Barnes et al., 2016; Joya, 2015). Some studies show that while diverse industrial structures are more exposed to economic shocks, the risk of negative local reactions is less concentrated since local industries exhibit differential dependence on external factors (Belke and Heine, 2006; Davies and Tonts, 2010). A sector-specific shock impacting the whole economy is less probable than in more narrowly specialized economies (Essletzbichler, 2007). Resilience thus lowers the probability of massive unemployment and wage contraction (Frenken & Boschma, 2007). Here again, the local institutional structure matters. Two caveats are in order. First, the evidence is still mixed. Fusillo et al. (2022) for example find that technological diversity, thwart a region's short-term capacity to develop new paths and withstand economic shocks. Second, a lot of the above research is at the sub-national rather than at national level.

In a nutshell, we hypothesize that complexity reduces income inequality through the institutional framework, the presence and access to job and learning opportunities and resilient economic structures.

Q2: Does complexity increase Income Inequality?

Bearing in mind the above, the source of regional diversification, the nature of complex systems, the risk of declining industries and stickiness of complex knowledge could entail a positive association between complexity and inequality. Diversifying local knowledge, in fact, occurs

[14] An important caveat here is that there is little literature on how education responds to and/or leads to complex innovation, and whether it is through secondary education, tertiary education or adult learning.

through the specialization of the local labour force (Balland et al., 2022). Specialized individuals may thus have access to different opportunities. Chu & Hoang (2020) argue that although higher complexity provides wider occupational opportunities, higher premia for workers with specialized and qualified knowledge (p. 47) can increase inequality. While their empirical work is based on trade data, the same logic applies when thinking of innovation ecosystems. Opportunities and rewards are not equally distributed between differently skilled workers. Also, more complex systems tend to be naturally more unequal due to self-reinforcing preferential attachment, multiplicative processes and feedback loops (Balland et al., 2022). Applied to innovation ecosystems, we therefore expect that highly skilled, powerful and privileged entities (organizations and/or individuals) reap higher rewards to the point that, eventually, returns may be decoupled from talent and effort and are instead shaped by complicated dynamics in the division and ownership of labour and capital (ibid, p. 1; see also Braverman, 1974).

Furthermore, as new and more sophisticated knowledge is produced pre-existing know how may be less relevant (Cadot et al., 2011). As a result, labour specialized in declining industries will suffer from less opportunities and be more dependent on opportunities to re-skilling, lacking which results in widespread skill mismatches or underemployment (Glyde, 1977). As new sectors continue to emerge and replace traditional ones, firms with limited experience, resources and opportunities due to economies of scale suffer the most (Qian & Yasar, 2016). All these scenarios have in common the growing gap between those that benefit from the growth of new industries and those that are left behind due to skill obsolescence.

Spatial stickiness of knowledge further reinforces the relationship between complexity and inequality. Balland & Rigby (2017) find that patent citations decrease as geographical distance grows, more so for patents in complex technologies, thus implying that more complex knowledge struggles to diffuse over space. This is unsurprising as we consider how complex knowledge concentrate and “agglomerate” through space more disproportionately than less complex knowledge (Balland et al., 2020). This spatial dimension implies that the opportunities due to higher complexity are not equally available to workers and may lead to higher inequality even within territories with similar language and institutional structures (Zhu et al., 2020).

Q3: Does Income Inequality inhibit Complexity?

There is one additional source of non-linearity in the between inequality and innovation complexity which can be ascribed to limited collaborations and social mobility, unfair distribution of rewards and local risk-aversion.

To begin with, the social structure of places with high inequality inhibits collaboration between socially and cognitively diverse actors and thus stifling the potential for innovation (Fragkandreas, 2012; Barnes and Mattsson, 2016) which instead requires a broad variety of cognitive and social assets (Page, 2019). Second, inequality undermines social mobility, the ability of citizens to improve beyond the social class they were born into (Nel, 2006; Corak, 2013). By limiting access to quality education, high inequality suppresses the latent potential of local capabilities and reduces the quality of local knowledge (Stiglitz, 2015). In addition, in places with high inequality, some entities may occupy positions that allow them access to capital, power and eventually benefits resulting due to technological changes. They are capable of accruing benefits whether deserved or not (Balland et al., 2022). This eventually reduces both the incentive and the ability to pursue innovation opportunities. Finally, inequality increases people's aversion towards risks in their careers, spending time developing a new skill, experimenting into new technological sectors and/or entering entrepreneurship opportunities. Through these mechanisms, inequality hampers the innovation and complexity of the local knowledge ecosystem.

This complicated two-way relationship complicates the analysis. Some authors simply acknowledge the co-evolution of inequality and complexity (Hartmann et al., 2017), while others implement more complicated methods to address reverse causality issues (Lee & Vu, 2020; Chu & Hoang, 2020). This motivates us to adopt an empirical strategy that explicitly addresses the mutual relationship between complexity and inequality.

2. 3. c. Empirical Evidence

The literature on the relationship between economic complexity and inequality is primarily based on trade data, which allow to proxy for the ensemble of local capabilities in an economy. The seminal work of Hartmann et al. (2017) was the first to explore empirically the idea that product sophistication and complexity impact countries' social and economic structures. Using data that cover up to 91% of the total world population (excluding countries with small populations and low export volumes) they find that more complex countries exhibit lower income inequality on account of institutional and educational structures capacity to "co-evolve with a country's product mix" (p. 85).

Lee & Vu (2020) report that as economies structurally transform towards more sophisticated products, income inequality increases. Chu & Hoang (2020) support this finding by observing that the positive relationship is lower as education, government spending, and trade openness increase. Finally, Lee & Wang's (2021) empirically examine the role of "country-risk"- financial, economic and political and find that only under low risk conditions, an improvement in the productive structure results in more equal income distribution. This indicates that industrial policies are insufficient, especially when adequate social policies are absent. Both papers are at a global country level depending on data availability (96, 88 and 43 countries respectively). By arguably conflating many incomparable institutional nuances these studies oversee the role of historical and geographical context.

Acknowledging the limitations of taking a global approach, a complementary stream of literature, Zhu et al. (2020), Banderia-Morais et al. (2021) and Sbardella et al. (2017) study the relationship between economic complexity and income inequality at subnational level, in China, Brazil and the US respectively. These papers motivate the geographical approach while studying inequality and complexity to provide more contextual depth. While this literature is undoubtedly interesting, we observe a bias in the gap in the opposite direction, namely due to selecting countries that are diverse albeit comparable.

Some literature focuses on the role of the geographical scale (i.e.: national vs. regional) on the relationship between complexity and innovation (Hartmann & Pinheiro, 2022), an issue that is beyond the scope of the present chapter. Thus, while acknowledging the richness of regional level studies, we believe that focussing on a panel of European countries that share several commonalities but also exhibit strong institutional diversity adds to the debate.

The only study that applies the complexity approach[15] to patent data, by Napolitano et al. (2022), finds that inequality hampers innovation in green complex technologies. Our chapter explores similar territory by focusing on the innovation-inequality dynamics and its two-way relationship, yet looks at the complexity of the national innovation ecosystem without limiting to a specific sector.

2.4. Research Question

The chapter addresses the following question: "What is the relationship between Local Income Inequality and Knowledge Complexity in Europe?". It diverts from prior literature in four ways; two major theoretical diversions and two minor empirical ones.

Typically, income inequality has been associated with complexity using trade data. Nonetheless, the ring structure of patent network data (Hidalgo, 2021) and the high amounts of data involve benefits from complexity approaches. Patents provide a reliable, if incomplete, indication of the knowledge in an economy (Griliches, 1990; Jaffe and Trajtenber, 2002). Patenting is a proxy of the institutional and scientific infrastructure in place and of the business focus and orientation at a specific time. Using these data allows us to unveil a little explored dimension of the relationship between innovation and inequality. While a country may successfully trade due to a variety of location, cost and human capital advantages, capacity to innovate calls on different premises. Patenting competitively in a technological field requires an ecosystem capable of stimulating new ideas. While patents do not capture the entire capacity of the ecosystem and have well known limitations (Griliches, 1990), they still provide a useful, highly detailed and structured way to focus on technological knowledge and its transfer into useful inventions (Nesta, 2008; Strumsky et al., 2012; Boschma et al., 2015). Patent data is widely used in economic geography literature as their granularity elucidates the structure of and the connections across different knowledge domains and (Popp, 2005). In the present chapter patents are a proxy for activities within a technological field and the number of patents within each field only matters to the extent it produces comparative advantage. Whether a country tends to patent more and whether the propensity to patent is higher in some fields does not impact our analysis. What matters is the relative share of a technological field across different countries.

[15] Economic Fitness and Complexity (Tacchella et al., 2012)

Second, the chapter studies the relationship at the European national level. Europe exhibits both significant cross-country heterogeneity - as regards knowledge ecosystems, distributional configurations and institutional frameworks – as well as coherence in terms of shared history, supranational coordination of markets and currency. Inequality in Europe is articulated by shared policies on convergence, Social Cohesion, Single Market and Single Currency rules (Filauro and Fischer, 2021). Still, the key actors in economic redistribution policies in Europe remain the Nation State (Blanchet et al., 2019), which motivates our decision to focus on the national level. For context, inequality in European countries is higher than other countries with established welfare models such as Australia and Japan but significantly lower than the US. Nearly all European countries have failed their commitment to the UN-SDG[16] goal of ensuring that the bottom 40% of the population grows faster than the average between 1980-2017 and so, income inequality has been increasing in nearly all European countries (ibid). Income inequality in Europe is mostly driven by inequality within countries rather than between countries and this significance has been growing over time (ibid, p.4) additionally motivating the relevance of this chapter.

Third, this chapter uses income quantile ratios to identify aspects of inequality that would otherwise be lost if one only focussed on global indicators such as Gini's. Our focus affords a closer look at income gaps between different portions of the income spectrum, which potentially allows for more nuanced policy insights. The reliance only on the GINI index may yield an imperfect picture as two countries with different income distributions at the tails may exhibit the same GINI measure "on-average" (Trapeznikova, 2019). The presence (or lack of) differences within specific income ratios may provide useful indications as on where inequality has risen, be it in the top-bottom scale of the mid-scale. Variations in where inequality occurs imply variations in policy conclusions. Finally, this chapter models the mutually enforcing relationship between complexity and income inequality accounting for the literature on inequality hampering innovation. The relationship is modelled by using a Systems of Simultaneous Equations Model, a method which permits correlations across several equations and estimates all coefficients of interests simultaneously.

[16] United Nations Sustainable Development Goal

2.5. Methodology

2. 5. a. Measuring Knowledge Complexity

Our proxy of knowledge is computed using the Economic Fitness algorithm (Tachella et al., 2012; Cristelli et al., 2013). Complexity indicators allow us to proxy innovation through an average measure of whether a country specialises in certain technological domains more than the global average. This is corrected by how common-place these classes are around the world highlighting that some advantages are more impactful than others.

This class of indicators were initially developed by Hidalgo and Hausmann (2009) using the method of moments and subsequently refined by various studies (Tacchella et al., 2012; Broekel, 2019; Sciarra et al., 2020). Our study relies on the Economic Fitness methodology (Tacchella et al., 2012), an iterative scheme which corrects weighting so that low fitness countries are more heavily considered. The authors considered that computing the complexity of a technology class as a linear average of the complexity of the countries that produce it is imperfect, as high-complex countries' economies patent in a lot of products of both high and low complexity. Thus Fitness assigns differing weights to countries based on how many classes they specialize in. Fitness[17] is calculated using the four-year moving averages of patent data from PATSTAT 2020 and implemented in Python using the "epackage3[18]". First, patent families[19] are extracted at the national level and attributed to their 4-digit CPC Codes[20]. We distribute each patent family as a fraction to its corresponding countries and technology codes. Then, an initial measure of the Revealed Comparative Advantage for country *c* in the technological class *t* is calculated. RCA occurs when a country has a larger share of patents in a technological class in comparison to the reference region (Rigby et al., 2019). In our case, the reference region is the world. Competition in innovation tends to occur across geographically distant boundaries and not at the European level.

$$RCA_{c,t} = \frac{patents_{c,p,t} / \sum_{p=1}^{N_p} patents_{c,p,t}}{\sum_{c=1}^{N_c} patents_{c,p,t} / \sum_{j=1}^{N_j} \sum_{c=1}^{N_c} patents_{c,p,t}}$$

[17] Thus referred to as Fitness
[18] Credits: Emanuele Pugliese
[19] Following the assumption that each patent family is an invention
[20] As in Rigby et al., (2019).

Following the literature, a coarse-grained measure of RCA is adequate and thus we use $M_{c,t}$ a binary value capturing whether or not a country is patenting more than “its fair share” within this technology class.

$$M_{c,t} = 1 \; if \; RCA_{c,t} > 1$$
$$M_{c,t} = 0 \; otherwise$$

The iterative algorithm couples the Fitness (F_c) of a country with the quality of its technology classes (Q_t) until a fixed point value defines them. F_c is proportional to the sum of the technology classes in which the country has a competitive advantage in, weighted by their technological complexity. While, the Q_t is inversely proportional to the number of countries which export it, with countries with low F_c contributing more strongly (Tachella et al.,2012).

The ideas are thus summarized in a series of iterative equations:

$$\begin{cases} \widetilde{F_c^{(n)}} = \sum_t M_{c,t} Q_t^{(n-1)} \\ \\ \widetilde{Q_t^{(n)}} = \dfrac{1}{\sum_c M_{c,t} \dfrac{1}{F_c^{(n)}}} \end{cases}$$

$$\longrightarrow \begin{cases} Q_t^{(n)} = \dfrac{\widetilde{Q_t^{(n)}}}{< \widetilde{Q_t^{(n)}} >_c} \\ F_c^{(n)} = \dfrac{\widetilde{F_c^{(n)}}}{< \widetilde{F_c^{(n)}} >_t} \end{cases}$$

During each iteration, two steps are conducted. First the intermediate values $\widetilde{F_c^{(n)}}$ & $\widetilde{Q_t^{(n)}}$ are calculated. Second, they are normalized. The initial conditions for the are $\widetilde{Q_t^{(0)}} = 1 \; \forall t$ and $\widetilde{F_c^{(0)}} = 1 \; \forall c$.

As the number of iterations (n) increases, the country and technological complexity indicators are refined by taking into account information from previous iterations and eventually converge to their mean.

Fitness is measured for all countries in the database at the same time and subsequently normalized to the European Average because the complexity of a technology class should be calculated according to its global ubiquity. To account for time dynamics, we use the four-year moving averages of patent counts, accounting for the randomness through which patents are published, especially between one year and another. Various time-lags are also used in the regressions (eventually we rely on the 3-year time lag) to account for time lags for patents to turn into products and businesses that may affect labour opportunities and propel the discussed theoretical mechanisms. We argue that this is the sufficient time needed to reconcile the slow state of changes to knowledge dynamics and ecosystems and specifically for it to affect the rest of the labour market the way we hypothesize. A longer time frame may create more noise and less accuracy in the results.

2. 5. b. Equation

Following the literature on innovation and inequality (Lee et al., 2016; Lee & Rodriguez-Pose, 2013), we expect education, government spending and globalization to impact the relationship between fitness and inequality operationalized in equation (1). Education is represented both by a measure of the percentage of population having attained tertiary education (*Tertiary_Education*) and the amount of spending by governments and businesses on Research and Development (*R&D_Spending*). While it is established that more educational spending is associated with better jobs and higher incomes (Campos et al., 2016; Dabla-Norris et al., 2015), this is only contextualized to the extent governments and companies provide adequate spending and local infrastructure to provide those jobs. While we expect institutional capacity, through social expenditure, to make a strong contribution to narrowing income gaps in society (Anderson et al., 2015; Goñi et al., 2011; Lustig, 2016), we argue that this is accounted for as much as possible through controlling for national effects. We also control for *Migration* and *Foreign_Employment* following literature on migration and inequality (Card, 2009; Glaeset et al., 2009). Migrations, through increases local competition for jobs and/or increasing demand for local resources, impacts inequality. Using both variables accounts for the type of migration that contributes both to inequality but also to the knowledge ecosystem. Clarification regarding the indicators used are found in Table A1.4.

$$
\begin{aligned}
(1)\quad Inequality_{i,t} &= \beta_0 + \beta_1 Knowledge\_Fitness_{i,t-n} + \beta_2 R\&D\_Spending_{i,t-n} \\
&+ \beta_3 Migration_{i,t-n} + \beta_4 Foreign\_Employment_{i,t-n} \\
&+ \beta_5 Tertiary\_Education_{i,t-n} + \alpha_i + u_t + \varepsilon_{i,t}
\end{aligned}
$$

Our fitness measure is standardized to the European average and lagged, along with all dependent variables. While equation (1) provides the baseline, a Granger test for panel data is then implemented to test for the presence of reverse Granger causality between the two variables of interest (Dumitrescu and Hurlin, 2012). Once this is established, a systems of simultaneous equations model (*hence* SEM) is implemented to account for the presence of mutual effects. The model is a combination of the Two Stage Least Squares Model and the Seemingly Unrelated Regression. SEM has a long tradition in the field of economics, having originated in the field of macroeconomics but been implemented in various literature in applied regional science and economic geography (see Mitze & Stephan, 2015).

In equation (2), components of fitness are used as explanatory variables and include educational attainment measured through the tertiary attainment of the population; institutional quality of the business market and how conducive it is to innovation (captured through the number of days required to open a business); percentage of foreign employment to account for knowledge coming from abroad and the employment rate of the labour market. Additional details are in Table A1.4. To the best of our knowledge, these variables control for potential confounding factors affecting fitness and can help clarify the relationship of interest.

$$(2) \quad Knolwedge\_Fitness_{i,t} = \gamma_0 + \gamma_1 Inequality_{i,t} + \gamma_2 Tertiary\_Education_{i,t-n} + \gamma_3 R\&D\_Spending_{i,t-n} + \gamma_4 Days\_to\_Open\_Business_{i,t-n} + \gamma_5 Foreign\_Employment_{i,t-n} + \gamma_6 Employment\_Rate_{i,t-n} + \alpha_i + u_t + \varepsilon_{i,t}$$

In the SEM, the dependent variable of one of the equations (*e.g.: inequality in equation (1)*) is used as an explanatory variable in another equation (*equation (2)*). The error terms of the two equations are clearly correlated and standard OLS estimation cannot be implemented as it does not satisfy the condition of independence of errors. SEM ensures that the independence of errors conditions is not violated (Zellner and Theil, 1962). The appendix explains the identification of the SEM model.

2. 5. c. Descriptive Analysis

Our dataset is an unbalanced panel of 30 countries between years 2000 and 2018. **Figure 2.1** shows a map of the regions and their average GINI index between 2005 and 2018[21]. Finland and Norway have, unsurprisingly, some of the lowest levels of inequality amongst European countries due to

[21] For completeness of our GINI measurements, we restrict our data for this time period for this graph

their social-democratic economies. Slovenia and Slovakia also display low inequality levels - a significant reflection of their government taxes and income transfer (OECD, 2016).

Within-country inequality is an important determinant of income trends across Europe. Before the great recession, income inequality in Europe had been declining with most of this decline attributed to the convergence process between countries. After 2008, the trend reversed. Although EU-wide income inequality slightly increased, local income inequalities within countries substantially increased due to income losses associated with unemployment (Vacas-Soriano & Fernández-Macías, 2017).

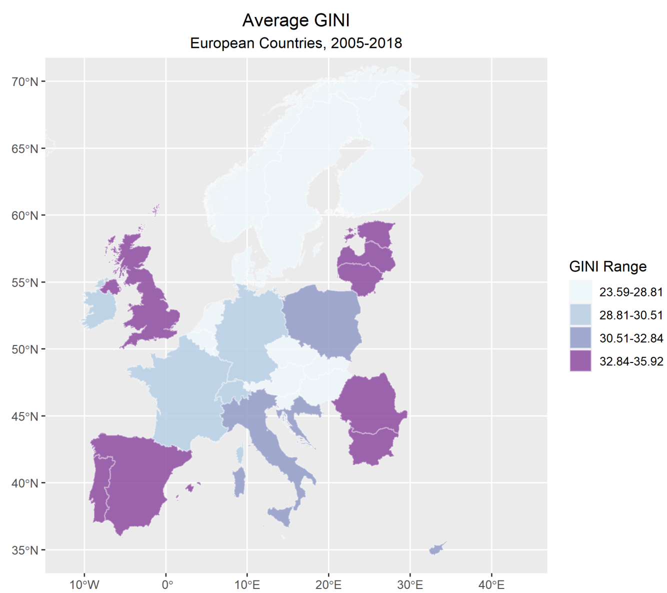


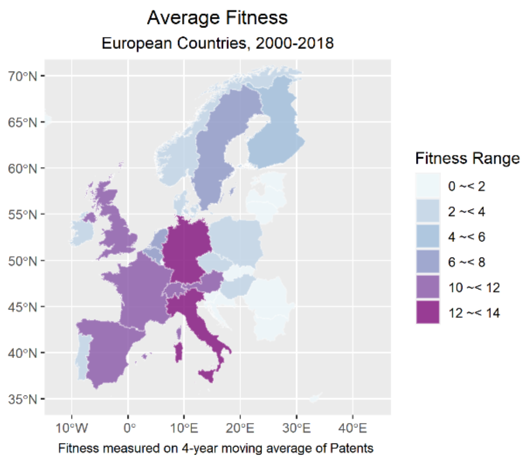
Figure 2.1: Average GINI

Figure 2.2 shows descriptive analysis on the GINI index in four of the most unequal and most equal countries in our sample. We see increasing inequality towards the middle of our time-frame (as a consequence of the great recession), but we do not see a unique pattern across all countries.

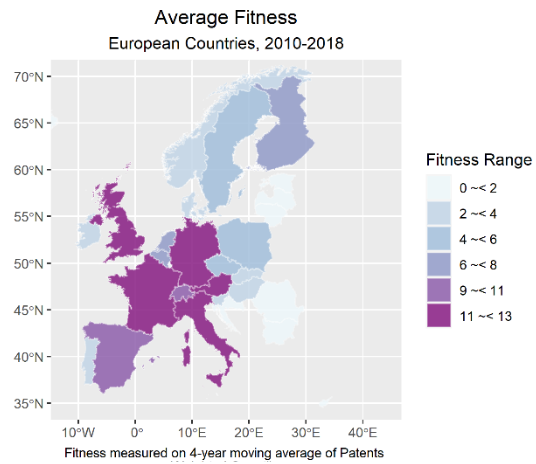
	Average Gini	% Change 06-10	% Change 10-14	% Change 14-18	Time Series
Latvia	35.92	−7.71	−1.11	0.28	
Bulgaria	35.61	6.41	6.63	11.86	
Romania	34.97	NA	4.48	0.29	
Portugal	34.89	−10.61	2.37	−6.96	
Finland	25.73	−1.93	0.79	1.17	
Slovakia	24.76	−7.83	0.77	−19.92	
Norway	24.66	−19.18	−0.42	5.53	
Slovenia	23.82	0.42	5.04	−6.40	

Figure 2.2: Summary of GINI Coefficient in Least & Most Unequal Countries

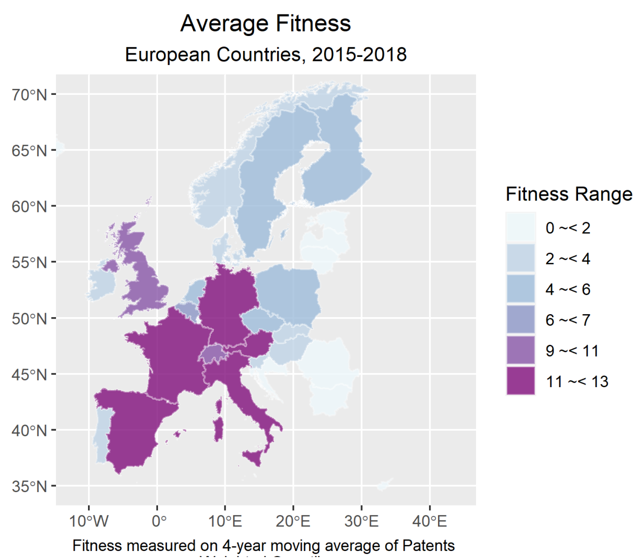
Descriptive analysis of the fitness measure is provided in **Figure 2.3 & 2.4**. **Figure 2.4** shows how the variable changed compared to the base year.



(2.3a)



(2.3b)



(2.3c)

Figure 2.3: Knowledge Fitness

a) Average between 2000 – 2018

b) Average: 2010 – 2018

c) Average: 2015 – 2018

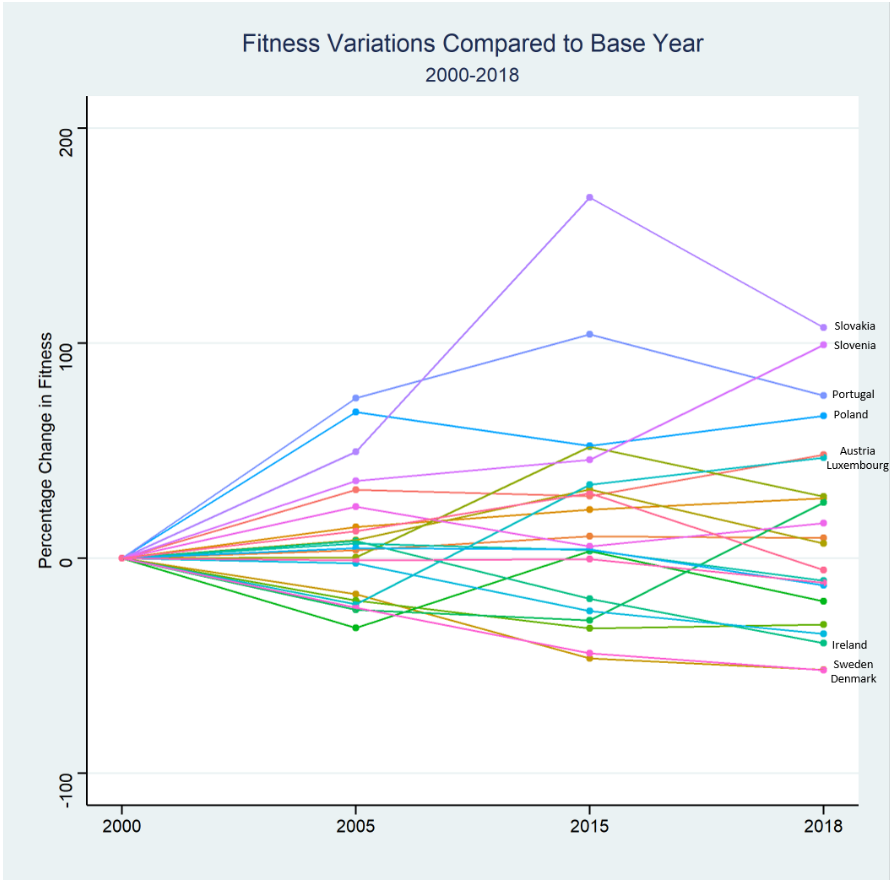


Figure 2.4: Knowledge Fitness Percentage Change

Overall, the most complex countries are Austria, Germany and Italy, followed by the UK France and Spain. Slovenia and Slovakia, having started with lower fitness measures have the highest growth but are not leading countries. Sweden and Denmark exhibit a percentage de-growth compared to the base year but remain in the top tier of fitness. The least complex countries are in the Eastern European regions.[22]

2.6. Findings

Tables 2.1 & 2.2 show that fitness is negatively and significantly correlated with inequality, as measured through the GINI index.

[22] Specific components of diversity and ubiquity are further dissected in the appendix (Tables A2.1 – A2.3, Figures A2.1 – A2.8).

VARIABLES	(1) GINI	(2) GINI	(3) GINI	(4) GINI
Fitness	**-1.101****	**-1.015****	**-0.978****	**-0.833****
	(0.443)	**(0.451)**	**(0.442)**	**(0.397)**
Constant	27.71***	27.33***	29.69***	29.03***
	(0.552)	(0.981)	(0.490)	(0.563)
Observations	463	441	430	424
R-squared	0.130	0.094	0.060	0.051
Number of country_code	30	30	30	30
Country & Time Fixed Effects	Yes	Yes	Yes	Yes
Robust S.E.	Yes	Yes	Yes	Yes
Fitness Time Lag	1 Year	2 Years	3 Years	4 Years

Table 2.1: Simple Panel Regressions with Country & Time Fixed Effects

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) GINI	(2) GINI	(3) GINI	(4) GINI
Fitness	**-1.058****	**-0.949****	**-0.899****	**-0.664***
	(0.412)	**(0.414)**	**(0.396)**	**(0.350)**
R&D_Spending	0.000832	0.000452	0.000862	0.000911
	(0.00159)	(0.00160)	(0.00143)	(0.00143)
Migration	0.280	0.271	0.218	0.207
	(0.277)	(0.289)	(0.285)	(0.291)
Foreign_Employment	-0.0349	-0.0358	-0.0289	-0.0283
	(0.0281)	(0.0280)	(0.0272)	(0.0278)
Tertiary_Education	-0.123	-0.108	-0.0851	-0.103
	(0.0804)	(0.0946)	(0.0812)	(0.0865)
Constant	32.64***	31.51***	33.08***	32.31***
	(1.641)	(1.944)	(1.797)	(1.837)
Observations	431	417	408	404
R-squared	0.125	0.104	0.082	0.072
Number of country_code	30	30	30	30
Country & Time Fixed Effects	Yes	Yes	Yes	Yes
Robust S.E.	Yes	Yes	Yes	Yes
Fitness Time Lag	1 Year	2 Years	3 Years	4 Years

Table 2.2: Full Model Panel Regressions: GINI

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The results are robust to the addition of controls for specific years (2008, 2009 and 2010) to ensure that the noise created due to the great recession does not influence our findings (see appendix *Table A 2.6*). The results are also robust when we include a dummy variable to control for the EU-15 countries, countries which have a GDP higher than 50% of the EU average and countries whose manufacturing industry contributes to more than 50% of gross value added compared to the EU average (*Table A2.7*).

The negative relationship indicates that places with higher-than-average fitness tend to have lower than average income inequality. This confirms similar findings on economic complexity and inequality. However, table 2.3 shows that when income quantiles are considered, we fail to find a significant relationship between complexity and inequality. A preliminary suggestion is that complexity might impact economies at the middle of the distribution, since the GINI coefficient, as a measure of inequality, puts the highest weight on the middle of the distribution (Trapeznikova, 2019). Potentially this is where most of the job opportunities and economic benefits are captured. Nonetheless, the model, in its current format, does not account for the mutual adaptation between the country's institutional capacity and the fitness of its knowledge ecosystem.

VARIABLES	(1) 80th/50th Percentile	(2) 80th/50th Percentile	(3) 50th/20th Percentile	(4) 50th/20th Percentile	(5) 80th/20th Percentile	(6) 80th/20th Percentile
Fitness	**-0.00227**	**-0.0215**	**-0.0411**	**-0.0101**	**-0.210****	**-0.140**
	(0.0230)	**(0.0259)**	**(0.0350)**	**(0.0360)**	**(0.0935)**	**(0.0936)**
R&D_Spending	-0.000114	-0.000122	-9.57e-05	-9.45e-05	7.72e-05	7.77e-05
	(0.000125)	(0.000127)	(0.000188)	(0.000187)	(0.000348)	(0.000349)
Migration	0.00984	0.00959	0.0262	0.0248	0.0629	0.0550
	(0.0184)	(0.0185)	(0.0223)	(0.0227)	(0.0731)	(0.0714)
Foreign_Employment	-0.00270**	-0.00269**	-0.00796***	-0.00810***	-0.00987	-0.0102
	(0.00109)	(0.00112)	(0.00254)	(0.00259)	(0.00742)	(0.00760)
Tertiary_Education	-0.00370	-0.00347	-0.0130	-0.0138	-0.0312	-0.0345
	(0.00546)	(0.00529)	(0.00921)	(0.00897)	(0.0210)	(0.0210)
Constant	1.814***	1.811***	2.267***	2.290***	6.018***	6.056***
	(0.111)	(0.108)	(0.242)	(0.239)	(0.522)	(0.528)
Observations	367	367	367	367	408	408
R-squared	0.903	0.903	0.878	0.877	0.091	0.082
Number of country_code	30	30	30	30	30	30
Country & Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Fitness Time Lag	1 Year	3 Years	1 Year	3 Years	1 Year	3 Years

Table 2.3: Full Model Panel Regressions: Income Quantiles

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

As argued before, the ability of a country to specialize in sophisticated and complex products depends on the regional institutional capacity to maintain diverse and strong social and professional networks (Fukuyama, 1996; Hidalgo, 2015). Under this perspective, it is clear why acquiring a competitive advantage in complex technologies tends to occur in nations with already inclusive institutions and eventually a more equal society (Hidalgo, 2015). We rely on a more robust empirical approach to explore further the simultaneous dynamics.

The Granger Causality test - adapted by Dumitrescu and Hurlin (2012) to be applied on panel-datasets for detecting Granger causality - is implemented to test whether one time-series is useful in forecasting another. The results (*Table A 2.8*) confirm the evidence that fitness Granger causes inequality, and inequality Granger causes fitness and motivate the use of the SEM to account for the mutual relationship. In economic phenomena and multifaceted relationships, it is common to expect variables to be interconnected and thus the error terms in their simultaneous equations to be correlated. In these cases, SEM models are efficient and utilize vast amounts of information[23]. The results of the SEM model (Table 2.4) confirm the negative relationship between GINI and Fitness, even as we account for the reverse relationship. All the control variables have the expected sign albeit the associated coefficients are not significant. The findings indicate that more equal societies are positively correlated with complex innovation. Intuitively this is understood as higher levels of inequality limiting people from taking further risks in their career, investing in skills, and spending time researching and developing novelty.

[23] https://spureconomics.com/3sls-three-stage-least-squares/

VARIABLES	(1) GINI	(2) Fitness	(3) GINI	(4) Fitness
Fitness	**-3.423****		**-6.611****	
	(1.550)		**(3.167)**	
GINI		**-0.120*****		**-0.154*****
		(0.0356)		**(0.0350)**
R&D_Spending	0.00327	0.000248	0.00457	0.000803*
	(0.00200)	(0.000332)	(0.00388)	(0.000475)
Migration	0.0550		0.0594	
	(0.169)		(0.264)	
Foreign_Employment	-0.0171		0.00359	
	(0.0205)		(0.0240)	
Tertiary_Education	-0.0182	0.00757	0.0975	0.0176
	(0.0829)	(0.0150)	(0.142)	(0.0218)
Time_to_start_Business		-0.00138		-5.52e-05
		(0.00133)		(0.000735)
Employment_Rate		0.00467		0.00136
		(0.00617)		(0.00644)
Constant	31.39***	4.327***	32.00***	4.718***
	(3.455)	(1.132)	(6.971)	(1.260)
Observations	332	332	322	322
R-squared	0.874	0.928	0.763	0.911
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Method	3SLS	3SLS	3SLS	3SLS
Time Lag of IVs	3 Years	3 Years	4 Years	4 Years

Table 2.4: SEM Regression: GINI

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Implementing SEM to other measures of income inequality yields a negative and significant relationship between fitness and the 80th vs. 20th percentile income ratios and the 50th vs. 20th percentile income ratios. The latter suggests that complex innovation benefits the bottom tier of the income spectrum in the form of lower disparities with both top and middle-level earners. While this issue deserves further scrutiny, these findings are unlikely to indicate that the middle class is shrinking since the coefficient of the GINI index is also negative. Nonetheless, disaggregated individual level data would allow us to examine this further.

Column (1) shows that high fitness increases inequality within a specific subset of the income distribution. The 50th income percentile is typically an average, economically comfortable, middle income individual and the 80th income percentile is situated at the top of the middle income or the beginning of the higher income percentile. In countries with higher technological fitness, the gap between the two is higher. Explanations could vary. Here, the mechanisms of high complex ecosystems (e.g.: preferential attachment) (Balland et al., 2022) might begin to make an impact. In these places competition may complicate the emergence of novel ideas to break out of the middle class. If preferential attachment in a complex system has gotten so bad that only people with power and money are being rewarded, regardless of where the work is being done, this would have negative consequences on the innovative potential of the country. Potential ideas and talent may be underutilized, and people's ambition would be accordingly low. Here, the second relationship, modelled in equation (2) allows us to further investigate. In this specification a higher income gap between the 80th and the 50th percentile is positively associated to fitness. This means that inequality is not large enough to stifle innovation. In fact, inequality in this part of the income distribution may motivate innovative risk takers and skill development, eventually increasing the knowledge complexity at the national level. Also, the income gap may be wider simply because earning potentials are higher, thus implying that, by increasing the earning capacity, higher fitness spurs innovation to be able to access the benefits of higher income rewards. Educational factors may also play a role. Either a specific type of education and/or training is required to break into the 80th percentile and that education is not adapting as quickly to technological change. Or, at that end of the income distribution, the power, money, and capital you have matters more than educational change. These potential mechanisms and explanations are, at this point, all hypotheses that call for future research and should be taken with a grain of salt.

VARIABLES	(1) 80th/50th Percentile	(2) Fitness	(3) 50th/20th Percentile	(4) Fitness	(5) 80th/20th Percentile	(6) Fitness
Fitness	**0.452*** **		**-1.106** **		**-1.084***	
	(0.0964)		**(0.433)**		**(0.631)**	
80th/50th Percentile		**2.131*** **				
		(0.363)				
50th/20th Percentile				**-0.891*** **		
				(0.180)		
80th/20th Percentile						**-0.309**
						(0.271)
R&D_Spending	-1.51e-05	6.40e-05	-0.000355	-0.000270	-0.000302	-0.000103
	(0.000184)	(0.000382)	(0.000357)	(0.000340)	(0.000593)	(0.000314)
Migration	-0.00393		0.00949		0.0621	
	(0.00861)		(0.0188)		(0.0566)	
Foreign_Employment	-0.000561		0.000228		-0.000422	
	(0.00117)		(0.00373)		(0.00701)	
Tertiary_Education	-0.0130	0.0307	0.0258	0.0248	-0.00666	0.0146
	(0.0104)	(0.0218)	(0.0216)	(0.0190)	(0.0241)	(0.0168)
Time_to_start_Business		0.000609		-3.31e-05		-0.000139
		(0.00195)		(0.00195)		(0.00360)
Employment_Rate		0.00330		0.00131		0.00860
		(0.00400)		(0.00315)		(0.00635)
Constant	1.034***	-2.400***	2.974***	2.521***	6.546***	2.247
	(0.272)	(0.817)	(0.590)	(0.618)	(1.088)	(1.524)
Observations	278	278	278	278	314	314
R-squared	0.836	0.917	0.515	0.948	0.875	0.939
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Method	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS

Table 2.5: SEM Regression: Income Quantiles

DVs are lagged by T = 3

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

2.7. Conclusion

This chapter contributes the literature on inequality and innovation. By using patent data, by extending the use of complexity approaches and by analysing various measures of income inequality, it adds novel insights to the current debate. Our study tests three different perspectives.

The first two are that innovation contributes to inequality either by providing more opportunities to people or by limiting these opportunities to a specific subset of people with certain skills and the final being that high and uncontrolled levels of inequality deter innovation from occurring. The empirical analysis yields a negative correlation between innovation (measured through complexity/fitness approaches) and income inequality within European countries. We find evidence in support of high fitness reducing local inequality and high-income inequality reducing a country's fitness. The results hold when studying the gap between the 80^{th} and the 20^{th} percentile, and the 50^{th} and the 20^{th} percentile, showing that higher fitness occurs within a country with high institutional capacity, implying the local learning and job opportunities and reduces the local risk to negative shocks. Nonetheless, fitness is also associated with a growing gap between the 80^{th} and the 50^{th} percentile and the reverse relationship highlights that higher inequality between the 80^{th} and the 50^{th} income percentile is not necessarily a deterrent for higher fitness, but rather contributes to it. This inequality is not necessarily a deterrent for local innovation and may be a physiological feature of complex ecosystems even in presence of inclusive institutions and governments. Nonetheless, without further insights into social mobility and local opportunities, our conclusions of how negative an increase in inequality at the higher end of the income distribution may be, are only partial.

Further limitations are acknowledged. First, our findings are specific to the European context. Second, our understanding of inequality could be further disentangled by looking at inequality between occupations, skill sets and industries. This may shed additional light into who benefits and who is left behind. In addition, while the national focus is motivated by the role of national policies, our methodology does not capture to what extent the relationship is driven by within-region or between-region inequality. While inequality may be lower at national level, closer inspection may lead to find that large cities are the main beneficiaries of complexity while other places are left behind (Mewes and Broekel, 2021, Pintar and Scherngell, 2021, Van Dam and Frenken, 2021). Addressing these limitations would require detailed data but could add nuance to our understanding of where inequality is increasing and therefore inform a more nuanced policy response.

In terms of policy recommendations, this study finds that managing low levels of income inequality is important to achieving higher complexity. Our findings also support recommendations that countries should develop the capabilities to specialize in more complex economic activities (Hausmann et al., 2011; Balland et al., 2019; Hidalgo, 2021). This emerges as a viable path for inclusive and sustainable growth since the local capabilities will become self-reinforcing and reward broadly distributed (Balland et al., 2022). However, how to successfully innovate in more complex economies matters. While this is not the focus of the chapter, past research shows that focusing investments on strategic domains is insufficient if not translated into competitive advantage, which is in turn unlikely without the co-evolution of skill supply systems and institutional capacity (Hartmann et al., 2017). In a complex ecosystem it is crucial that training, reskilling and upskilling occur at the intersection of academia, firms and research.

Finally, recognizing what we still do not know in the complexity literature is important to highlight the limitations and costs of policy recommendations. For example, investing in complex technologies is inadequate in geographical places that do not have a well-established knowledge core. Examples are old industrial regions or places specialized in activities highly exposed to fast automation. Human capital development is surely insufficient as existing skills are unlikely to contribute to the local economy. It is also crucial for research to identify actors (regions, firms, labourers) that are not embedded in the complex ecosystem and how they may suffer by additional complexity. In an economy focused on global economic advantage, it is essential to understand and manage who is left-behind in the process. Indeed, the process of how to increase local knowledge complexity while maintaining healthy levels of income inequality becomes a context and geographically specific approach.

Overall, this chapter points to an important debate on how complexity helps us understand the nuances in the innovation-inequality relationship. Future research in this will become a crucial tool for policy makers to help ensure that inequality does not lead to inescapable challenges.

Chapter 3: Gender Diversity in Industry 4.0 Innovation; Presence and Effect

Disclaimer: This chapter is also a paper currently as a work in progress with Hamid Bekamiri; Assistant Professor at Aalborg University Business School in Denmark.

3.1. Abstract

This chapter delves into the underrepresentation of women in the Industry 4.0 digital revolution, emphasizing the importance of gender diversity in innovation. Industry 4.0 focuses on smart technologies and connected production systems and the inclusivity of the sector will certainly shape our future society, in context and in quality. Analyzing female scientists' contribution to Industry 4.0 patents, the chapter reveals a persistently low percentage of female presence, with slow signs of improvement. Using Natural Language Processing (NLP) techniques, the study measures the impact of gender representation on patent quality, finding that a higher percentage of female inventors correlates with increased novelty but lower impact and quality. The findings suggest the continued need for policies capable of attracting and maintaining gender diverse talents in addition to the need for further research to contextualize these results and highlight the nuanced role of gender diversity in innovation within Industry 4.0.

3.2. Introduction

In the midst of the Industry 4.0 digital revolution, where everything is getting smarter and more connected, there's a noticeable gap: fewer women are involved. This paper explores why this matters and why including more women isn't just about fairness—it's about unlocking new ideas and innovations for the future.

In terms of the role of women in scientific endeavors, we can recognize that we currently see a higher rate of female representation than ever before. And yet, the increase in representation is not enough and we are far, years and years away, from achieving gender parity (European Commission, 2021). It remains essential to understanding the role gender diversity plays in innovation activities specifically to highlight how female contributions should be encouraged and facilitated. Former studies show that innovation teams led by women are more likely to address otherwise overlooked women-specific issues more significantly (Koning et al., 2021; Nielsen et al., 2018) and that female absence within an industry leads to fewer quality, variety and quantity of products tailored for women (Einiö et al., 2019). In addition to the impact on the type of innovation being produced, other literature also argues that gender diversity can improve the quality of the innovation itself - regardless of who it is created for. As articulated by Page (2019), the "diversity bonus", which includes elements of team gender diversity, enhances the cognitive diversity of the team, leads to increased creativity and more innovative solutions in general (Nielsen et al., 2018). The benefits of such diversity are mostly relevant in non-routine and highly cognitive tasks emphasizing the need for complementarity in skills and variety in perspectives. While a great stream of literature effectively highlights how gender diversity increases innovation, there is still a need to understand and analyze, once diversity exists, what type of innovation it can contribute to.

Disentangling the role of women in innovation endeavors is specifically required in emerging industries that we expect to shape the future of the society we're creating. Industry 4.0 is currently an important and essential industry to consider. Industry 4.0 focuses on smart and internally connected technologies and production systems that are designed to sense, predict and interact with the physical world (UNCTAD, 2022). “Smart” refers to their access to real-time data and ability to make reactions and decisions accordingly which support efficient and effective processes in real-time. The internet of things, cloud computing and artificial intelligence are important technologies that have made the advancements of this industry possible (EPO, 2017). Industry 4.0 focus is increasingly used to create mutually beneficial relationships between technology and people across industries and use-cases. As with many previous technological and industrial revolutions, multiple social and economic issues will arise as the industry continues to grow and develop (OECD, 2017; European Commission, 2015).

Recognizing the essential role that females play in innovation projects and the growing role of Industry 4.0 in the current innovation ecosystem, this paper looks into the role that females play in Industry 4.0 innovation. How well are females represented within the industry? What impact does their representation have on the industry itself?

Looking at gender diversity in Industry 4.0 is important for a multitude of reasons. First, understanding gender diversity across all industries is important as it allows us to tailor policy recommendations on gender inclusion accordingly. To the best of our knowledge, no research has specifically investigated gender diversity within Industry 4.0 thus far. Second, it is important for market relevance. Women are key consumers and decision-makers, their opinion matters and should be considered when creating products for the general consumer. Often, a diverse workforce can better respond to the needs of the market by enhancing the relevance of products and services to specific consumers. Finally, understanding gender diversity within Industry 4.0 contributes to our understanding and contribution to broader sustainability goals, in terms of social cohesion and equal access to opportunities across the spectrum.

This paper begins by studying the contribution of female scientists to Industry 4.0 patents in general, analyzing their representation within the industry. We find, as multiple different articles and academic papers confirm (Nielsen et al., 2018), that the female presence in such patents remains at a staggeringly low percent, despite showing slow signs of increases. Within the past few years, these percentages have stagnated, showing that as team sizes per patent continue to increase, the female proportional representation does not. The paper then looks into the impact of gender representation on the quality of the patents. While gathering inspiration from traditional patent indicators, we employ more modern Natural Language Processing (NLP) techniques to measure innovation in unbiased and data-driven approaches. By utilizing NLP transformer models, we are able to proxy for the novelty, impact, and quality of the patent. Novelty is defined by backwards similarity; how different the patent is from previous ones. Impact is defined as forward similarity; how similar future patents are to it. Quality is defined as forward similarity scaled by backwards similarity. We find that the percentage of female inventors has a significant effect on all above indicators. The higher the percentage of female inventors, the higher the novelty of the patent. However, the higher the percentage of female inventors, the lower the impact and the lower the quality of the patent. Indeed, we find that females introduce novel perspectives and solutions to the projects they are involved in. Nonetheless, this does not typically translate to higher impact of the patents themselves. Reasons could be the high level of communication coordination required in heterogeneous teams, or may be linked to the type of projects that females tend to be involved in. Additional research would be required to contextualize all findings.

The paper is organized as follows. Section II summarizes the literature review on female involvement in innovation and the impact of gender diversity on innovation quality. Section III presents the research question. Section IV describes the context better by providing background information on Industry 4.0. Section V explains the methodology followed. Section VI presents the solutions while section VII discusses and concludes.

3.3. Literature Review

3. 3. a. Female Involvement in Innovation

Current research on gender diversity in innovation focuses on the concept of the "leaking pipeline". Notably, the concept itself is not new and has been discussed as far as 30 years ago (Alper, 1993) indicating the persistence yet important of the issue. While certain advancements in gender education equality have been achieved (EPO, 2022), the higher up we go within the career ladder, the larger the gap between male to female involvement becomes. Thus, the pipeline of the career ladder is "leaking women". Indeed, the EPO (2022) shows; female involvement decreases as we transition from PHD enrollment to STEM PHD graduates, to scientists within R&D departments and even more to lead scientists. This is displayed quite evidently in **Figure 3.1** (EPO, 2022). In all 9 European countries studied, the percentage of "Women Inventor Rates" (WIR) is significantly lower than women rates in PHDs, general employment or other specific employment fields.

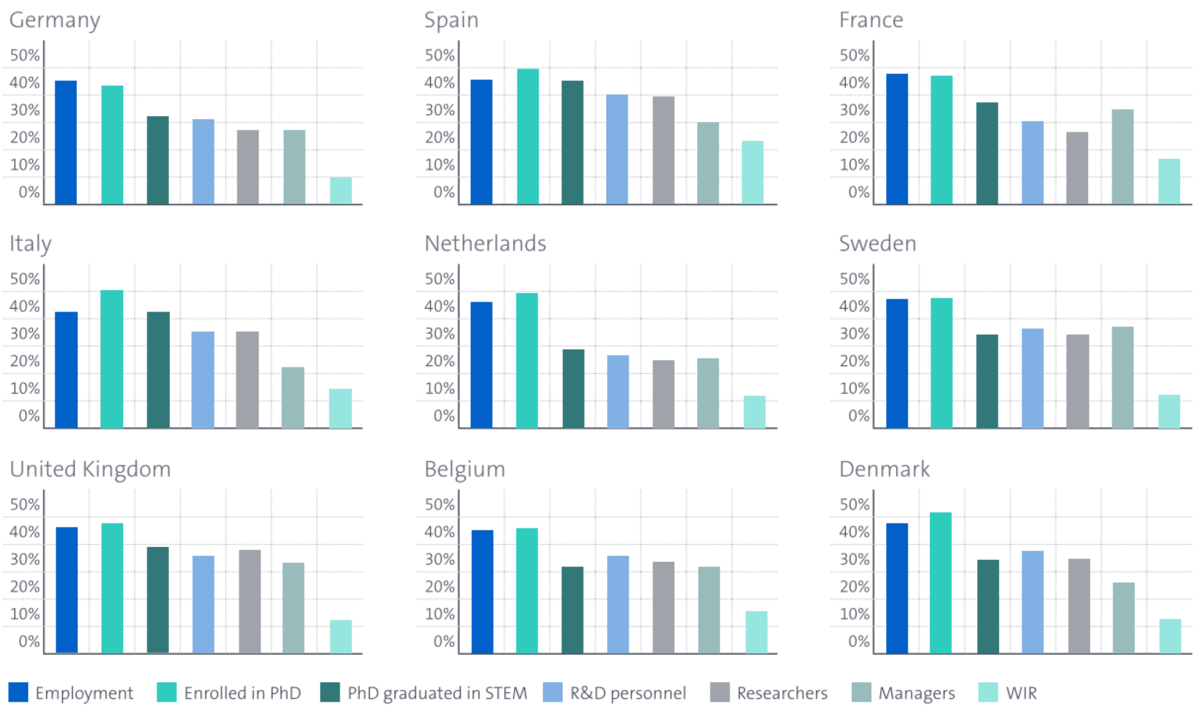


Figure 3.1: Comparison of WIP with Women's Share of Total Employment; 2010 - 2019 (Source: EPO, 2022)

Multiple reasons may be behind this. These include, but are not limited to, cultural expectations translating into gender biases, biological burden of the childbearing years, or the lack of female role models to advise and help in career progressions. Notably, while gender parity is a general issue, it is not evenly felt across disciplines and locations. The European Commission (2021, p. 22) found that while women graduates were over-represented in some fields, they were under-represented specifically in fields relating broadly to "ICT, Engineering, Manufacturing and Construction".

Knowing that the gender gap within ICT fields is even wider than the average specifically when studying the role of the inventor, it remains beneficial to zoom into the issue at hand.

3. 3. b. Does Diversity Matter for Innovation?

We can hypothesize that diversity matters for innovation in two different ways; in the types of innovation that is created and in the quality of innovation that is created. Our paper focuses more on the latter, but to truly understand the context and urgency of this issue, both will be discussed (albeit one more briefly than the other).

A study on US biomedical patents by Koning et al. (2021) uses text analysis to find that patents produced by women are more likely to focus on women-specific health problems that may otherwise be overlooked, underestimated, or less understood within the medical community. This relationship is even stronger when studying patents that are conducted by teams with women leaders. Einiö et al., (2019) find similar results, albeit more generally, by arguing that innovators are more likely to invent products useful for consumers that have similar gender, socio-economic status, age and thus needs to themselves. The authors argue that the under-representation of women amongst inventors decreases the type of products invented for women, leaves women with less product variety (with potentially lower quality) and results in a gender "cost of living" gap due to their limited options and the decreased competitiveness of the female-focused market. Nielsen et al., (2018) also discusses how throughout history, women's integration into industries with a traditional male majority has coincided with such industries expanding on their research agendas. This is true in fields such as history, medicine, and primatology. Nonetheless, the question of which comes first; "the openness of disciplines to new questions or the increase of women in these fields" (ibid, p. 728) remains unsolved. Nonetheless, we can see that the type of innovation which is beneficial for women suffers in both quantity and quality because of having less women inventors.

Other authors also argue that the quality of innovation, whether linked to female products or not, suffers from the lack of gender diversity within inventor teams (Nielson et al., 2017; Page, 2019). According to the diversity bonus (Page, 2019) principle, the impact of females on innovation comes from having "diversity" within your team. Diversity can come through different sources of identity diversity, which include gender, ethnicity, socio-economic status, and religion. Identities shape the various experiences individuals have and thus the type of knowledge individuals have exposure to and the ways they analyze such knowledge (Page, 2019). Various research shows that this type of cognitive diversity heightens team creativity and stimulates the search for novel solutions (Nielsen et al., 2018).

Østergaard et al., (2011) show that both gender and education diversity make the firm more creative by widening the company's knowledge base, increasing the interaction amongst various competences, and effectively broadening the search space for novel solutions. By doing so, this creates a greater possibility for new combinations of knowledge to emerge (Schumpeter, 1934), thus improving the probability of innovation occurring. Diverse inventor teams and unrepresented inventor profiles introduce inventors that think and analyze data differently than the average individual. Page (2019) highlights that the diversity bonus is mostly useful, in non-routine and cognitive tasks which include research tasks, invention, prediction, policy design, problem solving, and various other creative tasks. Such tasks require (or benefit from) a vast number of diverse skills and perspectives that do not necessarily have to be achieved in a linear manner and can be achieved through varying paths. In addition, it is highly unlikely that one individual on their own would possess all required skills, requiring a complementary partner or more. Therefore, the key to finding successful candidates for such a task would be to create a team of complementary cognitive diversity, in which the individuals themselves may be differently skilled but in a way that they complement one another. Thus, introducing diversity into a team helps achieve this by reducing the risk of groupthink (Janis, 1971).

This type of diversity is not easily or feasibly captured by empirical analysis. Academic tests would not be able to capture this type of distinction. Basically, because the analysis is not arguing that men or women are more intelligent or creative. But rather that their culturally different paths impact their minds, cognitive skills and perspective in varying skills that may provide similar outcomes but through varying paths. The optimal way to empirically support these arguments would be through providing empirical evidence of the diversity bonus in practice. Multiple streams of literature have investigated this relationship, for example studying the female involvement in companies' board of directors, female CEOs/CTOs (Dohse et al., 2019; Griffin et al., 2021; Wu et al.,2021 *amongst others*), and female role in scientific publications (Stvilia et al., 2011; Campbell et al., 2013; Joshi, 2014 *amongst others*). Nielsen et al., (2018) conduct a literature review of multiple studies that empirically test the impact of gender diversity in research teams, focusing on patenting activities. Focusing specifically on for-profit R&D settings, patenting and firm performance, they show evidence of a positive impact of gender diversity on innovation in Danish firms (Østergaard et al., 2011) and on radical innovation in Spanish firms (Diaz-Garcia et al., 2013). Turner (2009) does not take a geographically specific approach and yet finds that gender diversity positively influences both individual and collective team performance, albeit with modest statistical effects. Building up on the same dataset used in Diaz-Garcia et al., (2013), while focusing specifically on the manufacturing industry, (Fernández, 2015) find a positive relationship between gender diversity and service innovation which follows a U-Shaped model. Beyond a certain threshold the relationship changes from positive to negative. Theoretically, this is not surprising as having too many females in one team reduces the cognitive diversity and may produce too much of a homogenous team which is less conducive to innovation. By utilizing a detailed dataset on manufacturing firms in a coastal province in China, Xie et al. (2020) attempt to focus further on the mechanisms through which the diversity bonus occurs within R&D teams. Their quantitative model finds that gender diversity promotes the efficiency of innovation performance and that this is enhanced in situations when task complexity and market uncertainty is high. This logic is also supported by Page's (2019) argument about where gender diversity matters most. Xie et al., (2020)'s qualitative assessments show that this advantage occurs due to the various experiences and perspectives that females can contribute to R&D projects, in addition to the social benefits that enhance team communication across and within departments. Also using data about Chinese R&D activities, Zhang & Zong (2023) show that gender diversity in inventor teams enhances the quality, defined as forward citation count, of patents. The authors find that the positive diversity-innovation relationship is enhanced in regions where female educational levels are high and in industries where market competition and uncertainty is high. The above streams of literature show how diversity in teams introduces new perspectives and novel ideas, increases awareness, and improves the accuracy of problem solving (Østergaard and Timmermans, 2023).

Amongst this literature, there is a considerable gap in understanding and contextualizing what type of innovation gender diversity eventually contributes to. Contextualizing this can be influential in understanding when and how to push for further diversity incentives and the specific contexts in which they may be useful. In fact, Williams and O'Reilly (1998) support the significance of contextualizing innovation by arguing that a potential difficulty the literature has in studying the effects of diversity stems from the lack of separating the creativity phase from the implementation phase. The authors argue that diversity may improve the creation process but be less effective in the implementation phase. Since that paper, multiple others have been published which may have more successfully found positive or negative effects of diversity, but scrutinizing the relationship even further remains important and not as effectively discussed in the literature.

Moreover, the above papers leave room for further contributions in the field. First, the measures of innovation can be improved upon. Østergaard et al., 2011; Diaz-Garcia et al., 2013 and Fernández, 2015 measure innovation as the total number of patents per firm, or a self-declared measure of whether a company has introduced "new products" into the market (Østergaard et al., 2011; Diaz-Garcia et al., 2013; Fernández, 2015). These types of indicators risk the model being influenced by certain individual biases which do not necessarily reflect the market reaction. In addition, such data does not allow a distinction between two or more similar products introduced to market. In reality, a product may be novel but not successful. While the same applies to patents, we methodologically overcome this limitation by including both novelty against past patent and impact towards future ones as a measure of discussion. In addition, linking firm surveys to firm employment data may provide information on firm diversity, but that does not necessarily reflect the diversity of teams working on introducing specific innovations to the market. Xie et al., (2020) measure innovation and innovation efficiency by looking at the sales of new products compared to older ones and to R&D expenditure. Working with patent data on the patent level allows overcoming certain limitations as the data allows more accurate links between labor inputs (researchers) and their outputs (patents). Zhang & Zong (2023) utilize this power by measuring innovation through the number of IPC codes a patent belongs to. However, this indicator is weak in predicting heterogeneous quality between patents belonging to similar IPC classes. Previous work in this field has certainly suffered data limitation issues as it is difficult to find enough projects willing to share such detailed information and unbiased measurements of innovation that go beyond just the quantity of outputs. Hofstra et al. (2020) analyze PHD dissertations using a text model to measure novelty by identifying unique combinations of ideas. Their findings indicate that minority students, including female PHD candidates, introduce novel and diverse perspectives more frequently; however, the impact of their dissertations is often perceived as less influential compared to male counterparts. The study offers a measure of novelty without relying on survey biases and objectively compares ideas to those of the past. Indeed, the power of text analysis produced an underexplored method of scrutinizing innovation in a non-biased and data-driven way.

However, there are two strands that may contribute to disproving the hypothesis of the diversity bonus and the positive benefits of gender diversity to a team. First, some literature actually argues that diversity can be bad for innovation by creating higher levels of conflict. Perceptions of differences amongst social categories may cause individuals to see their teammates as either "similar" or "other" and thus creating communication, coordination and thus commitment difficulties (Jackson et al., 2003). Even in Nielsen et al.'s (2018) literature review, we find various studies that found no notable impact of gender diversity on innovation (Stvilia et al., 2011; Faems & Subramanian, 2013; Joshi, 2014; Lungeanu & Contractor, 2015). Notably a majority of these papers study innovation through the specific context of academic publishing.

Secondly, literature in cognitive psychology is not decisive whether cognitive differences indeed exist between males and females. While some studies argue the presence of certain differences (*for example,* Buss, 1998), others (specifically meta-analysis such as Hyde, 2005; Hyde, 2014; Zell et al., 2015) argue that overall, the magnitude of such differences either does not exist or tends to be very small. In addition, Hyde (2014) argues that in more equal societies (or industries or countries), as the division of labor by gender narrows down, psychological gender differences should decrease and instead, we expect to see more "gender similarities". The author explains how the theory of cognitive social learning expects that psychological gender differences tend to arise not due to some inherent skill differences, but rather because of gender differences in societal expectations, rewards and punishments and the human tendency of imitating role models from within the same gender. This latter argument though in fact does support our augment of the diversity bonus. If gender equality had been achieved in society as a whole or in R&D activities specifically, which it certainly has not (EPO, 2022; European Commission, 2021), then we may expect gender diverse teams to not benefit from the diversity bonus. However, at the current state of education, societal expectations and STEM working environments, we expect that the differences still exist and lead to cognitive differences relating to gender. In addition, whether these cognitive differences in fact exist, differences in perspectives within STEM innovation can lead to a diversity bonus by introducing variations in the topics discussed, the consumers targeted, and the problems attempted to solve.

3. 3. c. Industry 4.0

This paper contributes to the literature on the gender diversity bonus, while focusing on the case of Industry 4.0. Accordingly, it is important to discuss what the industry entails, and what distinguishes it from others. According to Lasi et al., (2014), Industry 4.0 flourished within a context of important political, social, and economic triggers. Higher competition within sectors necessitated short development cycles and the shift from a seller's into a buyer's market made the individualization of products and processes an asset for firms. Consumers began looking for more flexibility, decentralization for faster decision-making procedures and resource efficiency within their applications. Additionally, the increase in digitalization, mechanization, automation, and miniaturization (ibid, p.240) within daily routines increased the capacity of the industry's growth.

A 2022 report from the consulting firm McKinsey[24] highlights the general shift in labor skills that Industry 4.0 requires: a lower demand for basic numeracy and literacy skills, physical and numerical skills but higher demand for more advanced coding and technological skills, complex cognitive skills, and social and emotional skills. Industry 4.0 problems are complex. Its solutions require personalization and fast development cycles. Thus, the role of the inventor group and their varying perspectives becomes essential in two ways. First, to be able to make sure that the group as a whole is able to provide, as much as possible, the necessary skills of creativity, problem solving and emotional intelligence. Second, ensuring that the group provides complementary yet distinct perspectives and social intelligence to ensure that personalization of products occurs in a seamless, inclusive, and non-bias way.

[24] https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-are-industry-4-0-the-fourth-industrial-revolution-and-4ir

3.4. Research Question

This paper studies the role that females and gender diversity plays within Industry 4.0 Patents. It studies the questions; How well are females represented in industry 4.0 innovation? How does their representation impact the type of innovation being produced?

First, we look at the distribution of gender diversity amongst the patents in general. This section provides the descriptive analysis of our contextual framework. As a next step, we study whether and how the "diversity bonus" manifests itself within the field. We study whether gender diversity in Industry 4.0 innovation contributes to more (or less) novelty in the innovation produced or more (or less) impact of the innovation.

We motivate our focus on Industry 4.0 technologies by the fact that the industry is both young and growing. It is no surprise that Industry 4.0 technologies of today will shape our future in substantial ways. Understanding the inclusivity of who gets to invent in this field is thus crucial. The rapidly developing and changing pace of this industry makes it that uncertainty is high and so is the need for creativity and a multitude of varying skills. However, it is important to note that we have no priors of whether the "diversity bonus" is higher or lower in this specific industry compared to others. This is both methodologically non-feasible[25] and beyond the scope of our research interest. Recognizing the limitations of the literature presented above, this paper contributes to the literature in two essential ways. First, we study gender diversity and the presence of (or lack thereof) of the diversity bonus in Industry 4.0 patenting activities. This is not discussed in the literature and may be influential in shaping gender inclusion policies within STEM. Our second contribution is methodological. By using patent data and tailoring NLP methodologies for our specific research question, we find ways to further contextualize the innovation we study by scrutinizing its novelty and impact components. This allows us to overcome data biases in previous measures of innovation, permits comparisons between two types of patents belonging to similar technology classes, and allows a more direct link between the team, its gender components and the outputs produced.

[25] This is owing to the fact that the methodology this paper employs is quantitatively demanding.

3.5. Methodology

3. 5. a. Data Collection, Female Identification

The first required task was collecting all possible patents belonging to Industry 4.0. While there is no well-established way in the literature to do that, we follow EPO (2017). The report provides a list of CPC Codes that represent Industry 4.0 patents. The authors of the report develop this cartography based on intellectual input from patent examiners at the EPO. Classification experts from all technical areas were asked in which CPC ranges they would assign Industry 4.0 patents. Their answers were collected and further verified through ad-hoc queries in which the full text patent was extracted and analyzed using text-mining techniques. When anomalies were identified, the patent classifications were re-assessed and corrected if necessary. We follow EPO (2017) by extracting all patent applications belonging to the identified CPC Codes for the 30-year range: 1988 - 2017.

EPO (2017) also organizes Industry 4.0 patents into three different sectors and various technology fields based on their use-case. The organization is based on the CPC Codes that the patents belong to, allowing us to recreate and follow the same assumptions. The schema is depicted in **Figure 3.2**. The three main sectors are Core Technologies, Enabling Technologies, and Application Domains. The core technologies include hardware, software and connectivity-based technologies that make transforming products into smart devices connected to the internet and real-time data possible. Enabling technologies include power supplies, user interfaces, artificial intelligence, security, and position determination technologies that were typically used with the core technologies to improve the use case of the products. The application domains represent the use cases where the potential of connected devices is exploited. For more practical examples of Industry 4.0 product use-cases, see appendix based on EPO (2017).

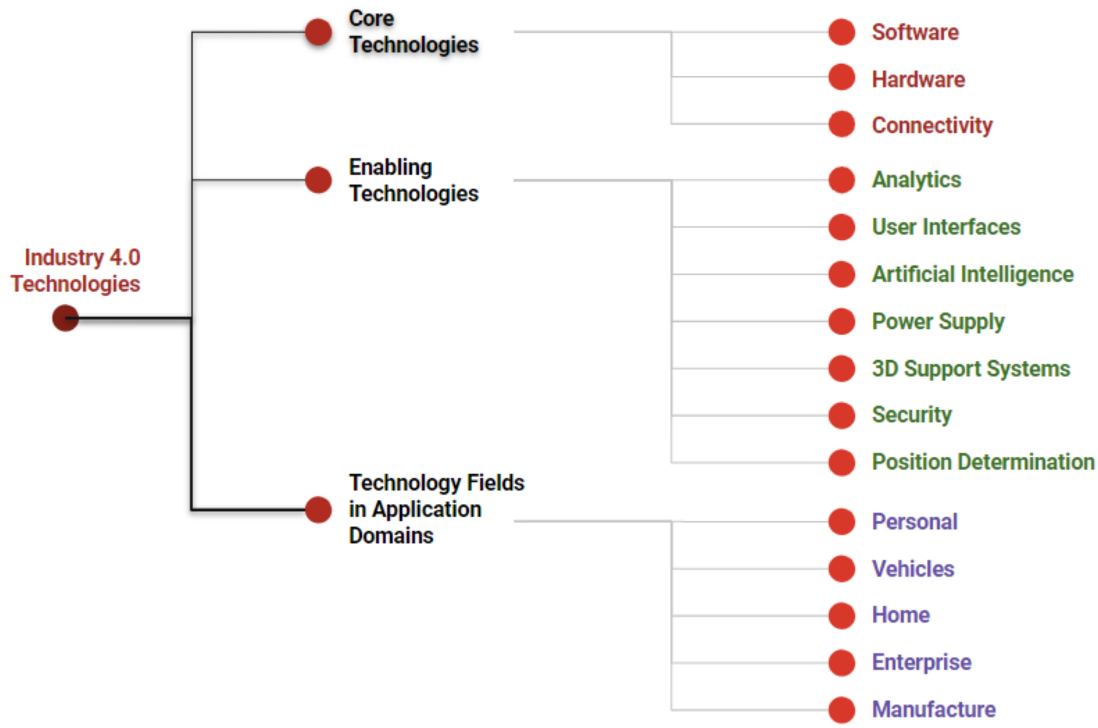


Figure 3.2: Industry 4.0 Sectors & Technology Fields
(Data sourced from EPO, 2017)

The next step would be identifying the gender distribution within the inventor teams. Where possible, we extracted the inventors identified for each patent application. We relied on a matching algorithm to identify a gender probably to each name country combination. For the name, country, gender data we relied on the World Gender Name Dictionary compiled by WIPO[26] (Martinez et al., 2021).

3. 5. b. Measuring Novelty & Impact

The final step is identifying the novelty and impact of our patents. To do that, we gather inspiration from a vast stream of literature that has attempted to create accurate indicators of these concepts both before (Verhoeven et al., 2016; Grimaldi & Cricelli, 2019) and after the possibilities of NLP techniques (Hain et al., 2022; Jeon et al., 2022). Previously used indicators of patent novelty[27] in the literature are typically based on either patent citations or patent classes. Novel Patents would

[26] https://www.wipo.int/edocs/pubdocs/en/wipo_pub_econstat_wp_64.pdf & https://github.com/IES-platform/r4r_gender
[27] For more detailed analysis see; Verhoeven et al., 2016; Grimaldi & Cricelli, 2019

be defined as those that cite patents belonging to different technological classes or combining previously non-combined technological classes. Such indicators perceive novel innovation as the ability to extract knowledge from “novel” sources, or to (re-)combine knowledge in useful yet not previously used ways. Such indicators were influential and useful due to their feasibility, the ease of data access in terms of citations and patent classes.

Nonetheless, such indicators are limited in their ability to assign value to patents, especially those that belong to similar classes. Indeed, the indicators are built upon and thus limited to predefined classes which may be too coarse or too broad depending on the use-case (Hain et al., 2022). In addition, the update of such classes may not happen as quickly and accurately as industry advancements. Based on how they are constructed, such indicators cannot successfully identify technological differences between patents belonging to the same technology classes. In fact, two “novel” patents recombining similar sources of knowledge do not necessarily equally succeed in the market, or produce lasting impacts. In response to these limitations and as a natural evolution of data availability and text processing capabilities in the past few years, new indicators have relied on Text Mining and NLP Techniques to measure Patent Novelty. Amongst those indicators, variations also exist (see Hain et al., 2022 for a detailed summary). Such indicators leverage methodologies such as Bag of Word Algorithms, Subject Object Action based methods, and more…

Kelly et al. (2021) is an influential paper in this regard, which has served as somewhat of a baseline for our model. The paper argues for a text-based measurement of patent quality based on the newness of concepts (based on document-word frequency) introduced in each patent and the impact they have on the occurrence of such concepts in future patents. They argue that this indicator is a good predictor of patent quality in the market and can predict future paper citations, thus acting as a more time-efficient measurement of patent quality. In this paper, we employ more modern NLP techniques; sentence-transformer models. This allows us to overcome the reliance on word-document frequency, considering that newness of words may simplify the complexity of the abstracts and concepts presented. Sentence-Transformer models allow us to represent text as numerical vectors, which in turns allows further mathematical calculations to be employed. The sentence transformer model we utilize is the PATENTSBERTa[28] (Bekamiri et al., 2021) which is a "Deep NLP based Hybrid Model". Using the PATENTSBERTa model allows us to leverage the efficiency of the well-known and utilized SBERT model (Reimers & Gurevych, 2019) which allows the creation of accurate embeddings without necessitating the creation of a language model from scratch. Nonetheless, the PATENTSBERTa model (Bekamiri et al., 2021) is additionally fine-tuned on 1 million patent claims. This step is necessary to introduce domain knowledge, allow the model to understand the specific language of patents and to improve the model's industry accuracy and performance. By doing so, the PATENTSBERTa model contributes both feasibility and the creation of specific embedding which accurately preserve the patent's technological properties (Bekamiri et al., 2021). The model is then capable of mapping sentences and paragraphs to a dense vector space made of 768 dimensions - a standard number of dimensions for these types of large language models.

We employ the model on our dataset of 1.3m abstracts belonging to Industry 4.0 patent inventions. Once we transform our patent abstracts into vectors, we compute a patent similarity matrix. By employing cosine similarity, we calculate a similarity score for each pair of patents. The semantic similarity 1.3m x 1.3m matrix, representing the similarity between each two patents together. Based on this similarity matrix, we further measure a *novelty* and an *impact* score.

The novelty score is derived from a modified version of the backward-looking similarity score; answering how similar is the patent in comparison to the patents occurring only <u>before</u> that specific publication date.

$$\text{Backward Similarity}_i = \sum_{j\,\epsilon \beta_i} \rho_{ij} \quad (1)$$

Where ρ_{ij} is the pairwise similarity of patents i and j, defined in equation (1), and β_i denotes the set of 'prior' patents filed prior to the filing of patent i.

To calculate the novelty indicator for a specific patent application, we sum all similarity scores from patents filed before the application's filing date as backward similarity. Backward similarity is inversely related to the definition of the novelty of the patent, meaning that an application with

[28] https://huggingface.co/AI-Growth-Lab/PatentSBERTa

fewer similar patents should have a higher novelty indicator score as shown in **Figure 3.3.** To establish a direct relationship and make this indicator more intuitive, we transformed it. This transformation is detailed in Formula 2. According to the formula, a decrease in the Backward similarity score of a patent leads to an increase in its novelty indicator score. This is based on the principle that patents more unique or distinct from previous ones are considered to have higher novelty.

$$novelty_{score(i)} = \frac{1}{1+backward\ similarity(i)} \quad (2)$$

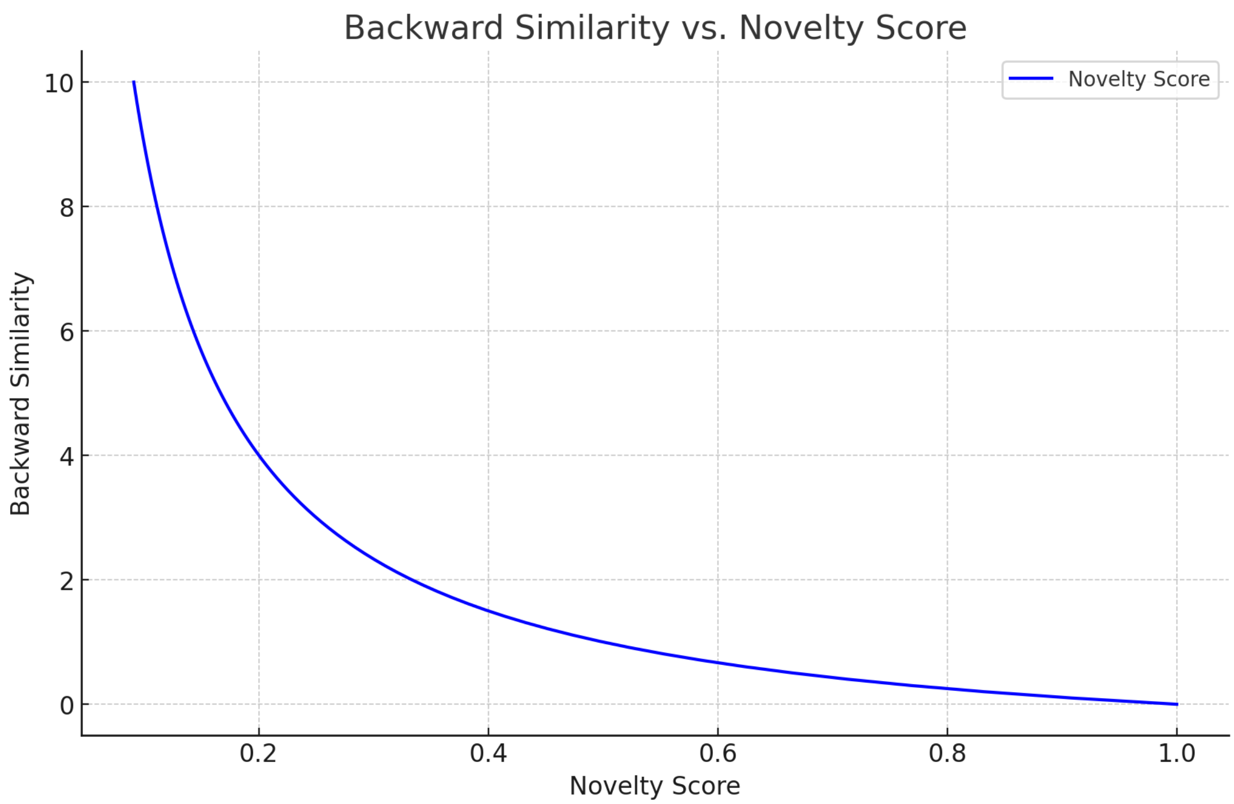


Figure 3.3: Inverse Relationship Between Novelty Score and Backward Similarity

The impact score is a forward-looking similarity score; answering how similar is the patent in comparison to the patents occurring only after that specific publication date.

$$\text{Forward Similarity}_i = \sum_{j\,\epsilon \mathrm{F}_i} \rho_{ij} \quad (3)$$

Where ρ_{ij} is the pairwise similarity of patents i and j, defined in equation (3), and F_i denotes the set of subsequent patents filed after to the filing of patent i.

The impact indicator is simply the Forward Similarity measure, as demonstrated in Formula 4.

$$impact_{score(i)} = Forward\ similarity_i \quad (4)$$

Finally, following Kelly et al. (2021) we also measure what they term as a "quality" score for each patent. The quality indicator interprets patents with high novelty and high impact as significant and is more likely to capture patents with "scientific breakthroughs" (p. 13) - those that are highly influential for future research and that deviate from the status quo. To measure our quality indicator, we use the impact_similarity score and scale it by its backward similarity (novelty_similarity). Thus, we get equation (5). All three indicators, *novelty*, *impact* and *quality* allow us to study and hypothesize the different mechanisms through which gender diversity influences the type of innovation being produced.

$$quality\_score_{(i)} = \frac{impact\_similarity_{(i)}}{novelty\_similarity_{(i)}} \quad (5)$$

3. 5. c. Econometric Model

When studying the impact that team composition has on the quality of the patent being produced, we control for the number of industries that the patent contributes to in a few ways; by looking at the number of CPC codes found in the patent, or the number of IPC codes, or (to account for our specific context) looking at the number of Industry 4.0 defined technology fields the patent contributes to.

We test our indicators against the percentage of females present in a team. We use this as our main variable of diversity. Since in this case we only have two characteristics contributing to gender diversity (male vs. female), then we believe that more complicated measurements of diversity are not necessary (e.g: HHI). Instead of the percentage of females in a team, we also look at the presence of at least one female in a team and its impact on performance. While this is an important and widely used indicator in the literature and can provide valuable insights into diversity dynamics, it's important to note that this only captures a part of the larger picture. True gender diversity and inclusion efforts aim to create environments where women are represented at all levels and across all teams within an organization, rather than relying on a token presence of one female team member.

We control for team size following certain results showing that patent quality to be correlated with team size since collaboration boosts the quality of output, its required speed and potentially the complexity of the problem at hand (Guimera et al., 2005). Controlling for national diversity, while important, was not feasible with the data we have. However, following Ferruci & Lessoni (2019), we control for age diversity within a team and include a proxy for average experience of the team. We do not have data on average inventor age, but we calculate a proxy based on the first time an inventor has contributed to any patent in the past. Age diversity is calculated as the standard deviation of inventors' age working on a specific patent. We hypothesize that age diversity can impact the quality of the patent by contributing to either positive variety in perspective or negative separations (ibid). We calculate team experience as the average age of inventors working on a specific patent. The quality of innovations is likely to increase within more experienced inventor teams that have a higher age average. This can be done by more experienced inventors being assigned to more important projects or by those inventors bringing in higher in-depth knowledge of the field, after accumulating years of experience (ibid; Schettino et al., 2013).

3. 5. d. Validation

To validate our NLP model, we use two different approaches. The PATENTSBERTa model is already validated in Bekamiri et al., (2021) by looking at how well the model predicts which technology classes each patent belongs to. We complement this validation with additional techniques valid for our use-case. First, we focus on validating the similarity matrix. Since other indicators are built upon the similarity matrix, then their validation should follow. Following Hain et al. (2022), we test the following assumptions: patents published the same year should be more similar (and thus have a higher similarity score) than those which are not, patents that share an inventor, cite similar patents, belong to the same technology field, belong to the same IPC/CPC codes should be more similar than those which do not. We run an OLS analysis testing the similarity scores against the respective conditions and find that all of them, except for the assumption of the same year, hold. The correlation results are found in Table 3.1. The results remain positive and significant if we control for more than one similarity criteria at the same time (not shown below).

	Similarity Score
Same Inventor Binary	0.0622 (0.013)***
Same Inventor Count	0.0296 (0.007)***
Same Citations Binary	0.0006 (4.76e-05)***
Same Citations Count	2.771e-05 (6.88e-06)***
Same Sub-Industry Binary	0.0002 (7.46e-06)***
Same Sub-Industry Count	0.0003 (9.43e-06)***
Same IPC Code 6-Digit Binary	0.0018 (7.24e-05)***
Same IPC Code 6-Digit Count	0.0016 (7.77e-05)***
Same IPC Code 4-Digit Binary	0.0022 (5.21e-05)***
Same IPC Code 4-Digit Count	0.0017 (4.65e-05)***
Same CPC Code Full Binary	0.0051 (0.000)***
Same CPC Code Full Count	0.0051 (0.000)***
Same CPC Code 6-Digit Binary	0.0018 (5.69e-05)***
Same CPC Code 6-Digit Full	0.015 (5.2e-05)***

Table 3.1: Validation Tests for Similarity Score
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Amongst all variables tested for, two patents having a similar inventor is the greatest determinant of patent similarity. This is also a good sign/validation of our model as logically writing styles can be quite personal and are different to change with time or be replicated by someone else.

In our second validation approach, we use citation analysis to assess the accuracy of the impact and novelty indicators. This step allows for a comprehensive evaluation of the indicators' effectiveness in identifying significant patents. We identified 4 million patents (this includes patents in our dataset and patents being cited in our dataset) as references. We then created a citation matrix, which is a table that shows which patents cite each other. To create the citation matrix, we checked to see if each reference was cited by any patent in the dataset. This resulted in a matrix with a size of 1.3 million rows (patents) and 4 million columns (references). We then used cosine similarity to compute the citation similarity between all pairs of patents based on the patents they cite. We also modeled the relationship between semantic similarity and citation similarity using regression analysis. The regression model was statistically significant, as seen below (Table 3.2). To summarize, our NLP similarity index (how similar two patents are to each other, in terms of writing) is positively and significantly correlated with the citation similarity index (how similar two patents are to each other, in terms of the patents they cite).

	Semantic Similarity
Citations Similarity	2.9862 (0.001)***
Constant	-1.4883 (0.001)***
#Observations	59577549
R-Squared	0.07

Table 3.2: Validation Tests; OLS Regression for Text Similarity and Citation Similarity Scores
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

3.6. Findings

3. 6. a. Female Involvement in Industry 4.0 Patents

First, we do a descriptive analysis on female involvement in Industry 4.0 technologies in general. While we have general data on female involvement in STEM and in Patents (*the most recent being* European Commission, 2021; Carpentier & Raffo, 2023), we lack specific data on female involvement in Industry 4.0 patents. To start with a general description of the Industry 4.0 field, **Figures 3.4a** and **3.4b** show the increase in number of patents throughout the years represented in our dataset, specifically with respect to all other patents and non-Industry 4.0 patents. We follow EPO (2017) in which they divide Industry 4.0 patents into 3 sectors depending on their use-case and value. The sectors and technology fields are displayed in **Figure 3.2** and explained in more detail in the appendix (Tables A3.1, A.3.2 and A.3.3) and the distribution of patent applications amongst these technology fields is shown in Figure A3.1.

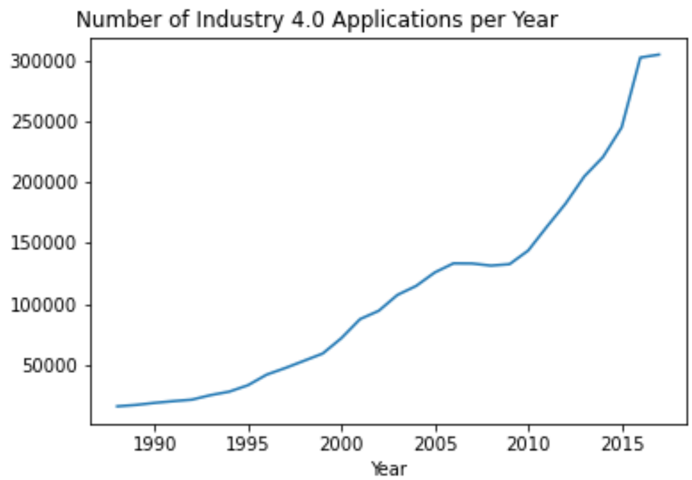


Figure 3.4a

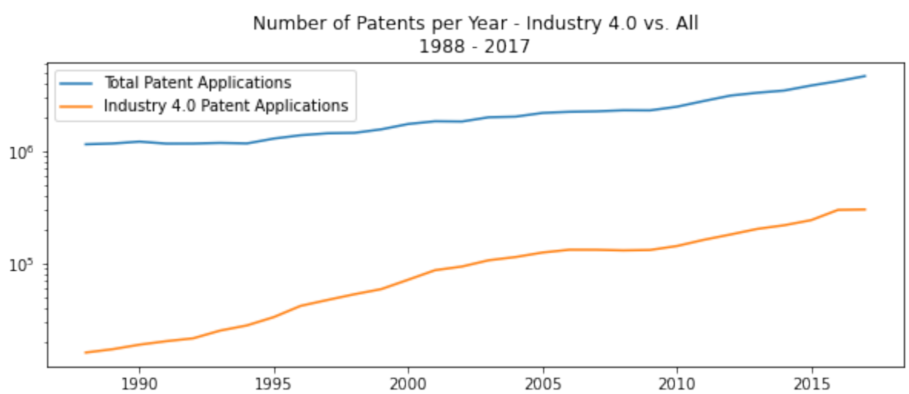


Figure 3.4b

Now, we shift focus to the role of female inventors in these patents. **Figure 3.5a** Shows the total number of patents with at least one female inventor per year represented in our dataset. Unsurprisingly this number has been increasing, owing (potentially) both to an increase in the number of Industry 4.0 patents per year and a slight increase in representation in the industry due to higher number of female graduates in STEM fields. We expect this increase to be mimicking the general increase in female involvement in innovation activities across sectors (as shown in European Commission, 2021) but we do not empirically prove that in this current paper. Next, **Figure 3.5b** looks at the average number of female inventors per application. We see a slow but consistent increase with time showing that general representation in the field is improving. Nonetheless, the average percentage of females represented in a patent is still a staggeringly low

12%. To understand why the average percentage has almost plateaued since 2014, we look at average team size in **Figure 3.6**. We can see that the team size per patent has been increasing which can be explained by the increased complexity of problems being tackled and the diversity of skills required (Page, 2019). Together, these figures show that while team size has indeed been increasing, we see an increase in the number of females represented but they still take up similar percentages within the teams. The increase in female representation as a share of group size has not kept up pace with the increase of group size.

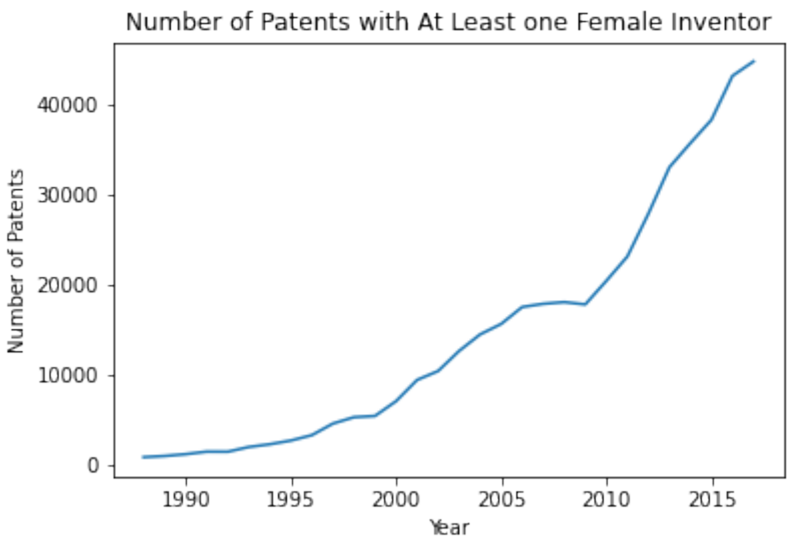


Figure 3.5a

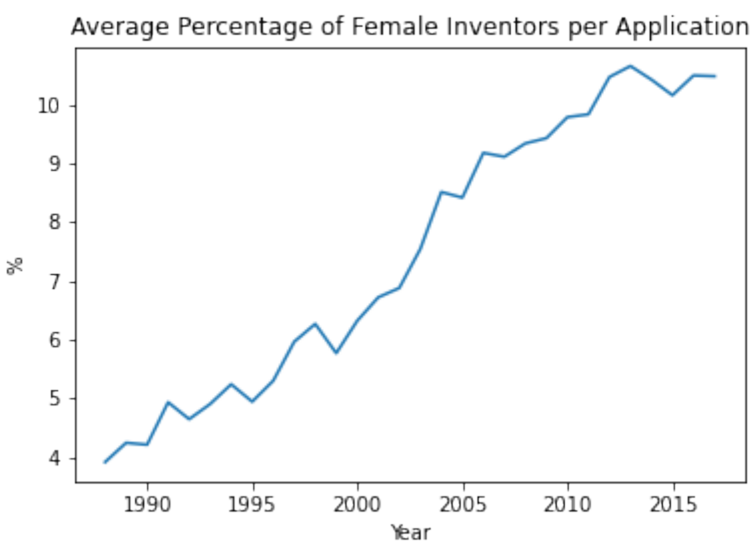


Figure 3.5b

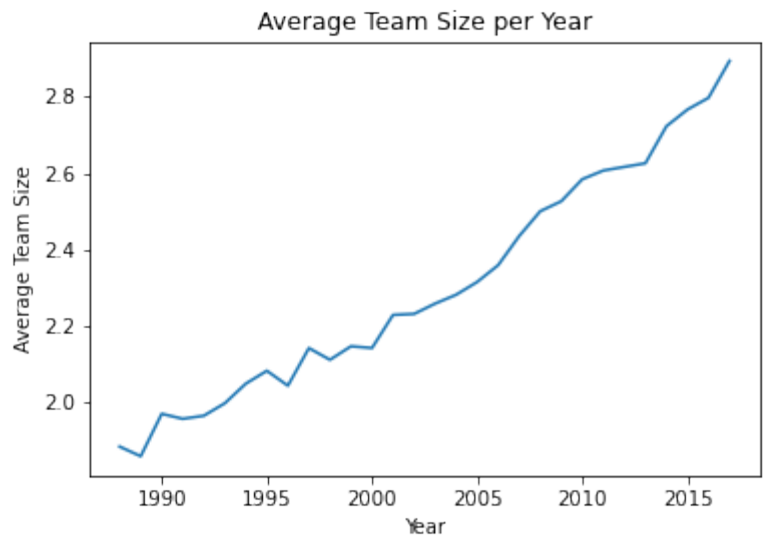


Figure 3.6

For a more thorough analysis, we look at average representation across the three main sectors and the various technology fields. **Figure 3.7** shows that the average percentage of females across sectors is quite similar. Still, slightly higher percentages are found in patents focused on "Core Technologies". In **Figures 3.8a & 3.8b**, we can see that females are most highly represented in "software" and "personal" technology fields at around 11% on average. While we have no prior expectations for females to be represented in software patents in comparison to others, we expect that the female perspective is surely important in the application of Industry 4.0 in personal use-cases where gender and gender understanding begins to matter. Vehicles, manufacturing, and analytics are the least represented industries with less than 7% of inventors being female.

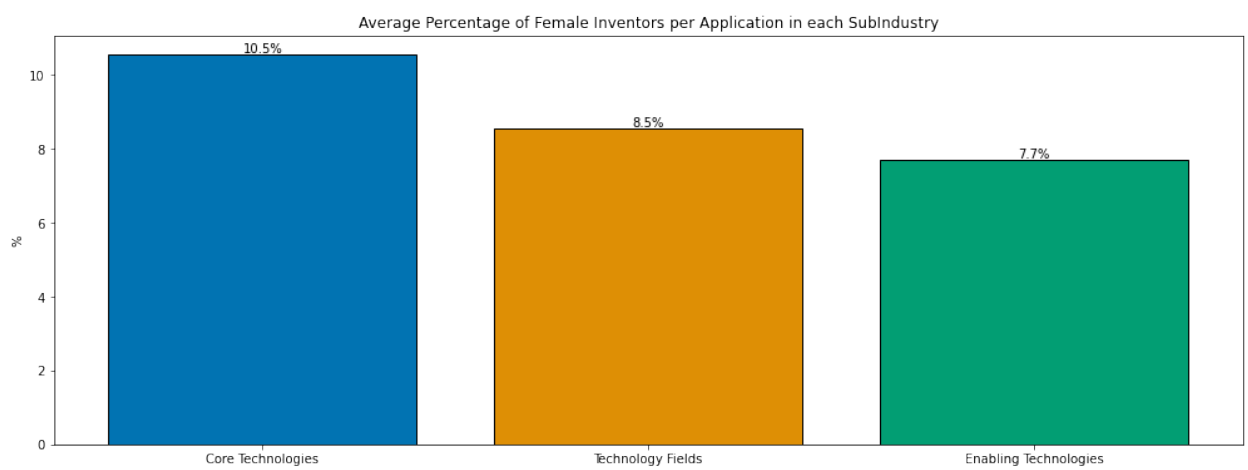


Figure 3.7

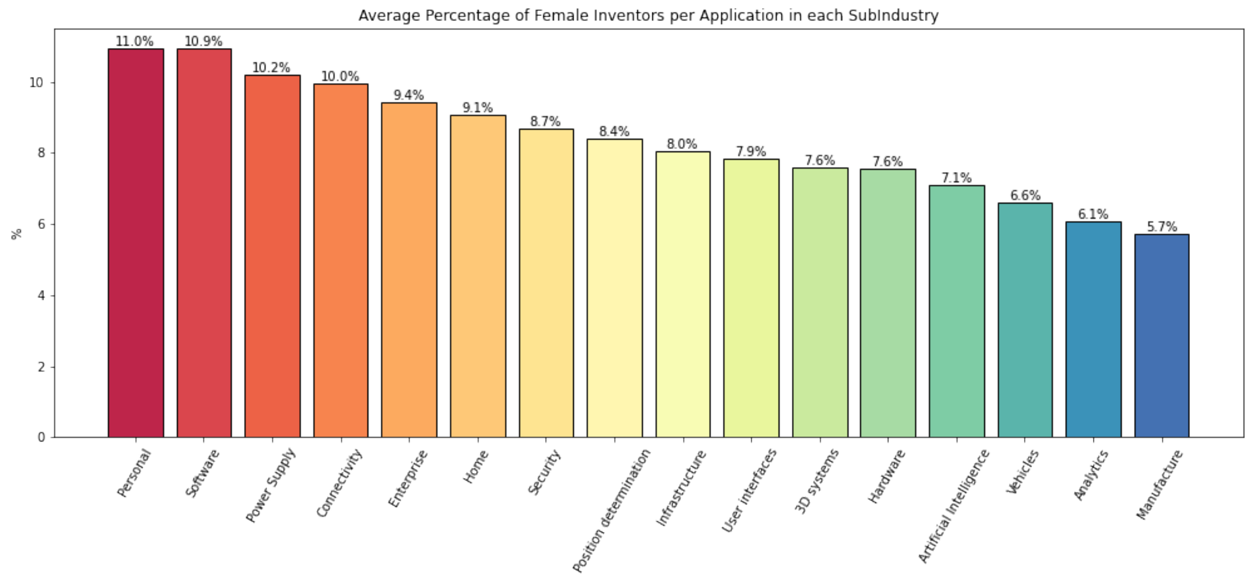


Figure 3.8a

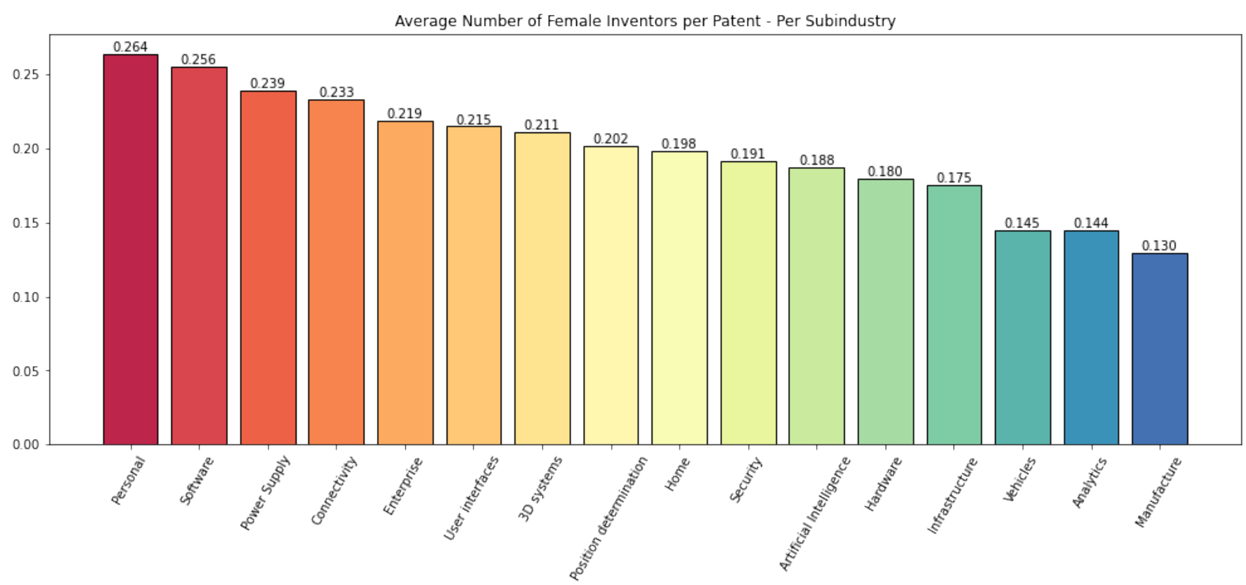


Figure 3.8b

3. 6. b. Results and Analysis

The result of our regressions (**Table 3.3**) demonstrates a positive and significant relationship between the percentage of females on a team and the novelty of the resulting patent. This supports the argument that as hypothesized, females in inventor teams introduce novelty into inventions by introducing new perspectives to problems. As previously described, relevant skills required within Industry 4.0 are various elements of social intelligence. We can hypothesize that gender diverse teams can achieve this. Alternatively, as more females are introduced into inventor teams, the pool of possible talent to choose from is increasing, which improves the chances of creating a team with distinct yet complementary skills. Following the diversity bonus, homogenous teams of all females and/or all males are less conducive to innovation than heterogeneous ones. However, additional regressions (**Table 3.4**) fail to show the existence of such an inflection point. A potential explanation of this could be due to the low number of females in the inventor teams, as shown above. Page (2019) expresses it nicely in his book by reminding us that when we empirically study the diversity bonus, we are trying to understand the world "as is". Potentially, with a higher involvement of females within the industry, the inflection point would be clearer. In reality, there are very few teams with a female majority to be able to rely on this evidence. In terms of the control variables, we find that patents that contribute to more than one industry are more novel. This is true when we account for various definitions of technology fields, following the EPO (2017) technology field definitions, CPC Codes, or IPC Codes. This is unsurprising as we expect these patents to rely on, and potentially recombine, more than one source of knowledge and thus have higher levels of novelty. We also find that higher average age increases the novelty of the patent by increasing the experience provided to the team and that the higher age diversity increases the novelty through providing both "fresh" and "experienced" perspectives. Also surprisingly, we find that when we control for the percentage of female-inventors, team size is no longer a significant determinant of the novelty of the patent. This indicates that increasing the size of the team is not as important as paying attention to who is added to the team and how they contribute to the diverse structure of the team. Additionally, when we look at team size impact more thoroughly, we see that beyond a certain point, increasing the team size may create additional communication burdens and thus reduce the novelty of the invention.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Novelty							
Percentage Female Inventors	0.000430***	0.000459***			0.000816***	0.000557***	0.000840***	0.000541***
	(0.000163)	(0.000163)			(0.000164)	(0.000163)	(0.000163)	(0.000163)
At Least one Female Inventor			0.0351***	0.00517***				
			(0.00984)	(0.000711)				
Team Size		0.00546***		0.0191*				
		(0.000698)		(0.0101)				
Number Subindustries					0.192***			
					(0.00310)			
Number of IPC Classes						0.0404***		
						(0.00175)		
Number of CPC 6-Dig Codes							0.425***	
							(0.00686)	
Number of CPC 4-Dig Codes								0.559***
								(0.0130)
Constant	1.931***	1.903***	1.929*	1.904**	1.463***	1.768***	1.416***	1.345***

			**	*				
	(0.0637)	(0.0638)	(0.0637)	(0.0638)	(0.0637)	(0.0640)	(0.0638)	(0.0650)
Observations	839,490	839,490	839,490	839,490	835,536	838,254	839,490	839,490
R-squared	0.013	0.013	0.013	0.013	0.017	0.015	0.020	0.016
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.3: Preliminary Regressions – Novelty x Gender Diversity
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
VARIABLES		Novelty		
Percentage Female Inventors	0.00111***	0.00352***	0.00361***	0.00316***
	(0.000181)	(0.000537)	(0.000535)	(0.000179)
(Percentage Female Inventors)^2		-4.50e-06	-5.58e-06	
		(6.29e-06)	(6.26e-06)	
Team Size	-0.00116*	0.000889	4.45e-05	0.000997
	(0.000684)	(0.000829)	(0.000687)	(0.000812)
(Team Size)^2		-9.57e-06***		-9.84e-06***
		(3.00e-06)		(3.00e-06)
Number Subindustries	0.190***	0.421***	0.421***	0.420***
	(0.00330)	(0.0139)	(0.0139)	(0.0139)
Average Experience	0.137***	0.124***	0.123***	0.124***
	(0.00368)	(0.00358)	(0.00358)	(0.00358)
Age Diversity	0.0632***	0.0414***	0.0418***	0.0415***
	(0.00354)	(0.00347)	(0.00346)	(0.00347)
Constant	1.718***	1.723***	1.727***	1.723***
	(0.0787)	(0.0769)	(0.0769)	(0.0769)
Observations	736,549	736,549	736,549	736,549
R-squared	0.031	0.062	0.062	0.062
Year FE	Yes	Yes	Yes	Yes
SubIndustry Dummies	No	Yes	Yes	Yes

Table 3.4: Full Regressions – Novelty x Gender Diversity
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

In Tables 3.3 & 3.5, we find that it is enough to have one female on inventor teams to see the diversity bonus, in terms of introducing novelty, come into play. We also find that this has nothing to do with simply introducing new members on the team, but again their contribution to diversity matters. When we interact the indicators of "team size" and our diversity indicators, we find, in Table 3.8, that as the team size increases, the importance of having a higher percentage of females on the team increases as well (thus the positive interaction term). We do not find the same effect when interacting "at least one female" with the team size. Thus, when team size increases, in order for the gender diversity bonus to stay intact, the percentage of females involved within the team needs to increase as well.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Novelty					
At Least one Female Inventor	0.0351***	0.0567***	0.0210**	0.0447***	0.0354***	0.0483***
	(0.00984)	(0.00986)	(0.00986)	(0.00982)	(0.00983)	(0.0104)
Team Size						-0.00185***
						(0.000695)
Number of Subindustries		0.192***				0.190***
		(0.00310)				(0.00330)
Number of IPC Classes			0.0402***			
			(0.00175)			
Number of CPC 6-Dig Codes				0.424***		
				(0.00686)		
Number of CPC 4-Dig Codes					0.559***	
					(0.0130)	
Average Experience						0.137***
						(0.00368)
Age Diversity						0.0629***
						(0.00354)
Constant	1.929***	1.460***	1.769***	1.415***	1.344***	1.722***
	(0.0637)	(0.0638)	(0.0640)	(0.0638)	(0.0650)	(0.0787)
Observations	839,490	835,536	838,254	839,490	839,490	736,557
R-squared	0.013	0.018	0.015	0.020	0.016	0.031
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.5: Full Regressions – Novelty x Gender Diversity; At Least One F
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Studying the relationship between gender diversity and impact (forward looking similarity) we find different results. As Table 3.6 shows, a higher number of females is negatively and significantly correlated with the impact of a patent. Here, the size of the team begins to matter more than the percentage of the females of the team. Increasing the size of the team is positively correlated with the impact of the patent. Our other variables of interest show that the higher the number of industries, the higher the age experience and the higher the age diversity within a team, the greater the impact of the patent. When accounting for the quadratic term of team size, we also find, similarly to above, that beyond a certain inflection point, a greater team size no longer produces the useful benefits. Table 3.7 shows that the effect of having one female on the team is also negative, especially when the team size variable is added. When we control technology fields, the effect of having one female on the team becomes insignificant

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Impact					
Percentage Female Inventors	-0.0114***	-0.0104***	-0.00888***	-0.00567**	-0.000930	-0.00204***
	(0.000629)	(0.000628)	(0.000768)	(0.00257)	(0.00261)	(0.000755)
(Percentage Female Inventors)^2				4.52e-05	-1.65e-05	
				(2.85e-05)	(2.92e-05)	
Team Size		0.191***	0.156***	0.203***	0.155***	0.202***
		(0.00622)	(0.00583)	(0.00560)	(0.00584)	(0.00549)
(Team Size)^2				-0.000544***		-0.000542***
				(7.86e-05)		(7.80e-05)
Number Subindustries			0.366***	0.884***	0.888***	0.886***
			(0.0133)	(0.0660)	(0.0660)	(0.0660)
Average Experience			0.433***	0.395***	0.378***	0.396***
			(0.0204)	(0.0201)	(0.0202)	(0.0201)
Age Diversity			0.340***	0.242***	0.266***	0.241***
			(0.0198)	(0.0193)	(0.0195)	(0.0192)
Constant	0.228***	-0.756***	-1.629***	-2.388***	-2.156***	-2.389***
	(0.00891)	(0.0364)	(0.0536)	(0.0681)	(0.0702)	(0.0680)
Observations	839,482	839,482	736,549	736,549	736,549	736,549
R-squared	0.011	0.016	0.022	0.040	0.039	0.040
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
SubIndustry Dummies	No	No	No	Yes	Yes	Yes

Table 3.6: Full Regressions – Impact x Gender Diversity
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Impact	(2) Impact	(3) Impact	(4) Impact	(5) Impact
At Least one Female Inventor	0.184***	-0.427***	0.0691	-0.401***	-0.1075
	(0.0471)	(0.0501)	(0.0508)	(0.0528)	(0.05199)
Number of Subindustries			0.395***	0.367***	0.893***
			(0.0134)	(0.0133)	(0.0661)
Average Experience			0.352***	0.432***	0.378***
			(0.0202)	(0.0204)	(0.0202)
Age Diversity			0.454***	0.343***	0.266***
			(0.0197)	(0.0198)	(0.0195)
Team Size		0.197***		0.162***	0.156***
		(0.00655)		(0.00610)	(0.00585)
Constant	0.163***	-0.787***	-0.754***	-1.654***	-2.170***
	(0.00967)	(0.0366)	(0.0355)	(0.0536)	(0.0699)
Observations	839,482	839,482	736,549	736,549	736,549
R-squared	0.011	0.016	0.019	0.022	0.039
Year FE	Yes	Yes	Yes	Yes	Yes
SubIndustry Dummies	No	No	No	No	Yes

Table 3.7: Full Regressions – Impact x Gender Diversity; At Least One F
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Novelty	(2) Novelty	(3) Impact	(4) Impact
Percentage Female Inventors	0.00227***		-0.00244**	
	(0.000237)		(0.00104)	
Team Size	-0.00266***	-0.00227**	0.152***	0.222***
	(0.000853)	(0.00115)	(0.00624)	(0.00551)
Team Size x Percentage Female	0.000254***		3.87e-05	
	(5.15e-05)		(0.000304)	
Number Subindustries	0.420***	0.420***	0.845***	0.840***
	(0.0139)	(0.0139)	(0.0642)	(0.0642)
Average Experience	0.123***	0.123***	0.363***	0.378***
	(0.00360)	(0.00360)	(0.0198)	(0.0197)
Age Diversity	0.0425***	0.0410***	0.261***	0.241***
	(0.00348)	(0.00349)	(0.0191)	(0.0188)
At Least one Female Inventor		0.168***		0.725***
		(0.0127)		(0.0671)
Team Size x One Female		-0.000815		-0.129***
		(0.00144)		(0.00880)
Constant	1.730***	1.725***	-2.132***	-2.494***
	(0.0772)	(0.0774)	(0.0704)	(0.0680)
Observations	729,268	729,268	729,268	729,268
R-squared	0.063	0.063	0.039	0.039
Year FE	Yes	Yes	Yes	Yes
SubIndustry Dummies	Yes	Yes	Yes	Yes

Table 3.8: Regressions with Interaction Terms
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1)	(2)	(3)	(4)
		Quality		
Percentage Female Inventors	-0.000688***	0.000989***	-0.000720**	-0.000548***
	(7.22e-05)	(0.000317)	(0.000325)	(8.91e-05)
Team Size	0.0126***		0.0126***	0.0130***
	(0.000464)		(0.000477)	(0.000511)
Number Subindustries	0.00853***	0.0104***	0.00852***	0.00845***
	(0.00273)	(0.00275)	(0.00275)	(0.00273)
Average Experience	0.00967***	0.00341	0.00967***	0.00970***
	(0.00213)	(0.00211)	(0.00213)	(0.00213)
Age Diversity	0.0174***	0.0259***	0.0174***	0.0173***
	(0.00206)	(0.00205)	(0.00207)	(0.00206)
(Percentage Female Inventors)^2		-2.17e-05***	4.04e-07	
		(3.43e-06)	(3.55e-06)	
Team Size x Percentage Female				-4.24e-05*
				(2.24e-05)
Constant	-0.0833***	-0.0103	-0.0832***	-0.0849***
	(0.00753)	(0.00708)	(0.00758)	(0.00747)
Observations	736,551	736,551	736,551	736,551
R-squared	0.171	0.169	0.171	0.171
Year FE	Yes	Yes	Yes	Yes

Table 3.9: Full Regressions – Quality x Gender Diversity
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

The interaction term between team size and percentage of females is not significant (Table 3.8). However, we also see that the interaction term changes the results in Table 3.8, Column 4. In this regression, we find that both team size and having one female on the team increases the impact of the patent. Nonetheless, the interaction term is negative, meaning that once we have at least one female on the team and diversity has been achieved, the benefits of larger teams begin to have decreasing returns in terms of impact.

Together the positive relationship between novelty-diversity and a negative one between impact-diversity can be analyzed as a reflection of Williams and O'Reilly's (1998) hypothesis; gender diversity can be positively impactful in the creation process, improving team creativity and openness to new ideas, but may be less impactful in the implementation process, highlighting the negative side-effects and high communication costs of heterogeneous groups (Jackson et al., 2003). Nonetheless, while our findings may contradict what the diversity bonus discusses, it is also important to contextualize what does this diversity bonus mean? If we hypothesize that gender diversity increases the novelty within innovation, then our initial regressions confirm this. However, if we hypothesize that gender diversity increases the impact (or usefulness - although these are not necessarily related), then our regressions fail to show this. Additional research is required to further contextualize our findings. It could also be that the type of projects in which females are involved in, are projects where their diversity and specificity of female opinions and expertise are required. For example, if we follow the assumption - already proved in some literature - that females are more involved in projects related to female-focused markets, it may also follow that these types of projects are too specific to have an impact on future ones.

Finally, we look at our quality indicator, and how gender diversity correlates with it. We find in Table 3.7 that a higher percentage of females involved in inventor teams decreases the quality of the patents produced. This mimics the findings of the forward-looking indicator. Therefore, while we see that gender diversity in teams is successful in introducing novelty into innovation, we find evidence that gender diversity in teams makes it more difficult to introduce impact. To truly contextualize how the diversity bonus manifests itself (or not) within Industry 4.0, additional qualitative research would be required. Research that may contribute to our understanding would need to more thoroughly inspect the type of patents that females are involved in, and the type of environments in which their perspectives are considered. Considering this caveat, this paper effectively highlights the low involvement of women in Industry 4.0 innovation.

3.7. Discussion and Conclusion

This paper looks at the role that gender diversity plays in Industry 4.0 patents. First, we show the low representation of females within the industry. Despite the fact that this number has been increasing throughout the years, the representation in terms of percentages has been stagnating since 2015. This implies that although the need for researchers is expanding and team sizes per problem are increasing, the percentage of females is not increasing fast enough to keep up pace. While the low representation is present across the various sectors and technology fields, we find that female representation is comparably highest in patents focused on software, connectivity, and personal use-products. Representation is lowest in patents focused on analytics, vehicles, and manufacturing.

To try to qualify the type of inventions females are involved in, we look at the novelty, impact, and quality of the patents. Our NLP model utilizes advanced data processing abilities and the PATENTSBERTa transformer model to transform each patent abstract into a numerical representation; a vector of 768 dimensions. Transformer models are famous and reliable in the NLP literature, but we also provide validation for our model. Our econometric analysis finds that in terms of patent novelty, gender diversity within a team is a positive and significant contribution and more-so than just the team size. However, gender diversity is not positively associated with either the forward-looking impact of the patent, nor the quality (impact scaled by the novelty). While the novelty-diversity relationship confirms some hypothesis introduced within the literature, the impact-diversity and quality-diversity relationship may reflect that this specific novelty isn't specifically leading into a future uptake of the novelty produced. While this finding is influential, it also particularly highlights the need for future research to qualify the type of novelty introduced through gender diversity and the lack of impact it leaves behind.

It's important to reiterate that in this paper, we study the reality of the industry as it is and not how it could be in the future (Page, 2019). The diversity bonus may become clearer as we achieve higher levels of gender representation within the industry, especially considering the current low levels of female representation and the specific Industry 4.0 challenges that greatly benefit from diversity in skills and points of view. Alternatively, the diversity bonus may even disappear as perhaps with less discrimination we lose the priors to expect gender differences to bring in unforeseen perspectives. Nonetheless, this paper allows us to understand the current state of the industry. One thing is clear, female representation within Industry 4.0 patents is low. This is bad for a multitude of reasons but mainly because we can see that we miss out on novel perspectives and particularly more female-focused novel perspectives with less females on board. As the literature highlights (Lasi et al., 2014) Industry 4.0 products focus on the personalization of products and processes and without diverse and inclusive perspectives being taken during the invention period, how can personalization practically occur? There is multiple evidence on the unfortunate, expensive and potentially dangerous circumstances occurring when the female perspective is not considered in product development (Perez, 2019). The novelty and newness of the innovation being produced would also benefit from the involvement of more gender diverse innovator groups. This is confirmed by our analysis and is potentially linked to the diverse perspectives, market knowledge and combination of social and cognitive skills that gender diverse teams can bring to the table. The negative relationship between female diversity and impact opens the pathways for further research but could be linked to the low number of female inventors or the specific projects that female inventors are involved in (products with specific objectives that do not lend themselves for future uptake). Additionally, further research can confirm the hypothesize, presented and further supported by the data in this paper, that diversity in teams improves the creativity of teams but harms the implementation of their projects.

As it stands, we can hypothesize that the novelty introduced in innovation, which is being detected by our model, is linked to the various perspectives and points of view that gender diverse teams introduce into research topics. Nonetheless, it remains an important question for future research to investigate what type of novelty is introduced into innovation due to gender diversity, and how that particularly differs from other sources of diversity. An obvious question arises is whether the novelty being detected in this setting is linked to the research topics that females are more often involved in; female-related products and female-related markets for example. While this is important and influential, another assessment should be made on whether gender diverse teams are indeed capable of introducing novelty to more general questions and if so; why or why not. Further qualifying the type of novelty introduced into innovation is important as it allows additional understanding of why and how gender diversity should be introduced on the firm and policy level. Such an analysis would require a more thorough analysis, combining a qualitative analysis and different text-analysis method capable of quantifying topics and their significance within patents.

3. 7. a. Policy Implications

This paper sheds light on the importance of conducting research on gender dynamics within Industry 4.0 innovation. Future research would surely be able to define policy interventions more properly, in addition to aligning them with the changing social and economic context. Nevertheless, it remains helpful to recognize the implications of our findings in their current format. Our findings, coupled with the growing importance and relevance of Industry 4.0 in daily lives and routines, stresses on the importance of fostering inclusivity within the invention process. For this to be practically achieved, tailored and specific interventions need to occur. We can clearly see that high levels of educational attainment in terms of STEM are not easily translating into females achieving representation in R&D careers. Obviously, the industry is "leaking" their presence and their potential. This could be happening based on either intentional or unintentional discrimination within the firms, lack of desire of females entering such industries, and potentially the cost of additional family responsibilities. Introducing novelty into an inventor team is a highly important asset. It allows firms to stand out from the competition and equips them with unique perspectives to complex issues. If we couple the low percentage of female inventors with their positive contribution to patent novelty, we see it is essential to be able to overcome some of the hurdles that are leaking females outside of the industry. The industry needs to find a way to make research careers a viable and desirable goal for female scientists, this can begin early on through improving access to practical STEM teachings and through interventions that allow more freedom for females while managing life responsibilities. Significantly, it is also essential to make sure that female researcher's integration within research teams embraces their differences and novel perspectives. Otherwise, females will be quickly over-embedded (Xie et al., 2020) within the system without utilizing their unique assets productively. Wenger (2000) argues that for the coexistence between diverse competencies to generate learning and creative innovation, the interplay between such actors needs to be present and strengthened through both institutional and informal frameworks.

Multiple policy avenues become important and necessary in improving gender equality within innovation ecosystems (Profeta, 2020; Foley and Cooper, 2021). Such avenues require multiple organizations to be involved; local governments for design and implementation, statistical offices for evidence-based support (Eden & Wagstaff, 2021), firms and the educational sector for cooperation and implementation. Whatever policy mix is implemented needs to be context and location specific. While we have limited our analysis on Industry 4.0 to capture characteristics specific to our context, the industry itself also consists of varying sectors and technology fields. Accordingly, intervention will not look the same across sectors. In addition, the interventions should also be adapted based on regional context and sensitivities. To illustrate, in sectors and locations with little female representation (for instance the analytics, vehicles and artificial intelligence technology fields), efforts should be placed on understanding and reforming the barriers to entry. Perhaps the fields of study required in such industries do not get enough female graduates. Perhaps the applicant rate of females for jobs in such industries is considerably low. Here, the policy interventions should be at the educational level, or public awareness perspective. If the educational graduates for such industries are not gender diverse, then intervention should ease access to training opportunities across genders. If the educational levels are not the issue, then awareness should be raised on the role that females can play in such industries and industry-wide policies need to be placed to be able to attract females. In other sectors and locations, perhaps females are indeed entering the field, applying in substantial amounts, but not capable of achieving higher positions within the research career ladder. In such cases, the industry should create gender-specific policies capable of incentivizing females in staying and guiding them in their career progressions until they are in positions of power whether their contributions to innovation novelty are substantial. In such industries, intervention would require both female-specific training and firm-level reform to ensure that transparent and fair career pathways are available, specifically ones that do not discriminate (whether intentionally or not) based on gender. For that to be achieved, focus groups on female needs need to be effectively conducted. In addition, potential solutions could be gender-balanced parental leave, and childcare support (Profeta, 2020). It is crucial to create policies capable of achieving gender-neutral flexibility allowing families to harmonize work and other life-commitments without costs paid unevenly by the different genders. This is pivotal to empower females in fostering sustainable careers and advancing gender equality in the workplace (Tomlinson et al., 2018; Foley and Cooper, 2021). And while few, there may be industries and locations in which females are well represented and capable of being retained until they gather leadership positions. Our current dataset does not offer such examples as there are no technology fields with a substantial female presence in patenting positions. Nonetheless, in such hypothetical cases, focus needs to be placed on achieving equality in the cultural, and social sense, both on the regional and firm level. This ensures that the valuable perspectives females contribute are genuinely heard and acknowledged, rather than merely serving as symbolic gestures for gender representation. Practically, this can be achieved by having women in decision-making positions (Profeta, 2020), ensuring equal pay and compensation, and conducting relevant focus groups.

3. 7. b. Limitations

Despite its contributions, the limitations of this paper make way for future work to build up on the ideas in this paper even further. First of all, two important types of diversity are not included in our analysis due to data limitations and feasibility: geographical diversity and functional diversity. While both lend way to analysis and literature which is beyond the scope of this study, understanding how all these different sources of diversity complement (or not) each other may be relevant in the innovation and management literature as well. This paper also does not look at how team performance changes over time and whether, beyond a certain point, the diversity bonus begins to decrease as teams become more accustomed to each other and members of the team become more cognitively similar rather than different. In addition, while much of the literature discussed (Østergaard et al., 2011; Nishii, 2013) highlights the important role that company culture plays in allowing diversity to contribute to innovative performance, our data also limits us from controlling for this. We also do not consider regional or national heterogeneity in comparing places with higher gender equality with others. Finally, while we support our use of patent data for this specific analysis, the analysis of this paper should be contextualized within the limitations of using patent data. Indeed, patents do not capture all types of innovation that may or may not be occurring within Industry 4.0, not all patents are of the same quality, and there may exist an uncaptured bias in terms of what type of companies patent vs. those who do not.

Chapter 4: Moving to Smart Specialization for sustainability: the implications on the design of monitoring indicators

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4.1. Abstract

Smart Specialization Policy, Europe's place-based innovation policy is transitioning into an innovation policy for sustainability inspired by academic debate and the urgency of societal challenges. The implications in terms of policy design remain underexplored. This chapter studies the policy implications of this transition on the design of monitoring indicators. First, a theoretical framework, based on the literature is created. Then, monitoring indicators used in the first policy phase are summarized into categories and themes through inductive and deductive document analysis. The indicators' strengths, and limitations are discussed. By highlighting how monitoring indicators need to adjust to the policy transition, this chapter contributes to the literature on innovation policy and Smart Specialization. It also provides guidance to policymakers by developing a framework on indicator design and providing practical recommendations on aspects that need to be considered, captured and analyzed through the indicators.

4.2. Introduction

Smart Specialization policy (RIS3), Europe's biggest innovation policy to date (Tödtling et al., 2021; McCann & Soete, 2020; Coenen & Morgan, 2019; Foray, 2018), has been implemented since 2014. It primarily focused on targeting innovation policy through stakeholder involvement and R&D specialization. During its second phase (2021-), the policy was positioned as targeting both innovation and sustainability. This was motivated by the global challenges societies experience, their persistent consequences and exposure. Examples of such challenges include any combination of environmental degradation, global warming, aging societies and pandemics. While globally shared (Tödtling et al., 2021), these challenges have different local implications (*examples in Table A1*). Nonetheless, their persistency has increased urgency among European regions that "business as usual" (European Commission 2013, p. 3) is failing. The quest to create and/or leverage policy for solutions has intensified accordingly. Thus comes the case of Smart Specialization. Ongoing policy and academic debates have encouraged using this policy to not only target innovation aims, but also sustainability concerns. From a policy perspective, RIS3 was initially designed to implement locally specific solutions by utilizing local assets and mobilizing stakeholder involvement. Such elements make the policy particularly beneficial in a context focused on global challenges with regionally specific consequences. Academically speaking, the idea of integrating sustainability concerns in innovation policy is also supported by multiple streams of literature on sustainability transitions, mission-oriented policies, and challenge-oriented innovation policy.

However, practitioners involved in implementing the first phase of Smart Specialization may not necessarily possess the skills required to transition the policy into innovation for sustainability. For a precise focus, we study the practical implications of the policy transition on the design of monitoring indicators. Monitoring is an essential element of every policy in general but has played an undeniable role in RIS3 due to its experimental nature. To maximize RIS3 policy learning, a solid locally-tailored monitoring framework which provides evidence-based input for assessments is required (Foray et al., 2012). Although indicators do not represent the entire monitoring process, they are an essential starting point which any further assessment is built upon.

This chapter thus asks: “How should the design of Monitoring Indicators in Smart Specialization adapt to be able to achieve the EU’s desired sustainability goals?”. While multiple models on monitoring sustainability exist (*for example,* Ness et al., 2010; Batalhoa et al., 2019, and others), they cannot and should not be directly implemented without context within the innovation framework. When aligning innovation with sustainability, it is important to not lose sight of what either policy is intended to achieve. Thus, this chapter takes a specific approach by studying what innovation policy can learn from its past experiences to better align its policy and monitoring frameworks within a sustainability focus.

To analyse our question, we set a conceptual foundation by summarizing the differences between traditional innovation policy and innovation policy for sustainability. Then, we study policy documents which outline Smart Specialization design, during its first phase. The documents represent 39 regions and 8 countries (visualized in **Figure 4.1**) around Europe. Based on a deductive and inductive analysis, the extracted monitoring indicators were clustered into 31 reoccurring categories and 7 general themes. We use these indicators to empirically understand indicator design during the first phase of RIS3, how this fits in with our theoretical framework, and what - if anything - needs to be corrected as the policy changes its focus. While certain aspects of monitoring design were possibly sufficient from an innovation perspective, we hypothesize changes need to occur as the policy transitions into sustainability goals. Our findings can shed light on which changes need to occur and how best to implement them.

This chapter contributes to the broad literature on innovation policy for sustainability (Mazzucato, 2018; Kattel & Mazzucato, 2018; Diercks et al., 2019; Arne et al., 2022) and to the specific literature on Smart Specialization policy (Gianelle & Kleibrink, 2015; Foray, 2018; Marinelli et al., 2019; Fuster Marti et al., 2020; Marinelli et al., 2021). To the former, it contributes by providing a practical lens on what innovation policy for sustainability’s main goals and deviations from innovation policy imply practically. While multiple papers set the theoretical framework on how different these policies are (Weber & Rohracher, 2012; Schot & Steinmueller, 2018; Mazzucato et al., 2020; McCann & Soete, 2020; Tödtling et al., 2021), a practical application is still missing. The chapter also contributes to the literature on Smart Specialization by zooming in on the design of monitoring indicators, and what the policy transition can teach us in that regard.

To provide both contributions, we rely on literature on monitoring innovation policy and monitoring Smart Specialization.

This chapter is organized as follows. Section 4.3 presents the literature review on innovation policy, innovation policy for sustainability and monitoring innovation policy and set the foundations for the differences between Smart Specialization Policy (RIS3) and Smart Specialization Strategies for Sustainability (S4). Section 4.4 clarified our research question after identifying the literature gaps. In section 4.5, we develop the aforementioned literature in a more detailed yet precise way to clarify how certain elements of it frame our understandings and expectations on how monitoring should transition in theory. In Section 4.6, we support our theoretical framing through an empirical analysis to provide recommendations rooted in practice. A document analysis allows us to empirically highlight how monitoring indicators were designed within RIS3. Monitoring indicators are collected, analysed, and discussed. We conclude in section 4.7 and 4.8 while discussing potential solutions for the design of monitoring indicators.

4.3. Literature Review

In this section, we revise literature on the use of innovation policy for sustainability, its origins and characteristics. This guides our conceptual framing. Then we discuss Smart Specialization policy literature, upon which our case-study is developed. Finally, we examine literature on monitoring Smart Specialization which guides our empirical analysis.

4. 3. a. Broader Literature on Innovation Policy & Sustainability

The idea of using innovation policy for sustainability transitions is based on various theoretical works. Within this literature is: the transition management (TM) literature (Rotmans et al., 2001; Kemp et al., 2007; Loorbach, 2010), mission-oriented innovation (Mazzucato, 2018; Mazzucato et al., 2018), transformative innovation policy literature (Schot and Steinmueller, 2018; Diercks et al., 2019) and challenge oriented regional innovation systems literature (Tödtling et al., 2021). Most relevant for this chapter, all the above streams of literature embrace a view of innovation where the direction of innovation begins to matter, thus “directionality”. In a general sense, innovation policy aims to accomplish "change". Directionality prioritizes the "sustainable direction" of change. Thus, innovation contributing to solutions of grand challenges is prioritized. TM literature (Rotmans at el., 2001) describes the practical management framework through which cycles of experimentation, trial and error, reflection, learning and adaptation result in innovation-led sustainability (Kemp & Loorbach, 2007). Mission Oriented Policy (Mazzucato, 2018) describes the mission-oriented framework, established through lessons learned from mission-policies (ibid). Missions begin with a clearly defined goal and compromise a portfolio of R&D projects, long-term investments among different sectors and actors and require joined up policy making (Mazzucato and Penna, 2016). The Challenge Oriented Regional Systems of Innovation (CoRIS) literature builds on the RIS literature and explains what is needed to achieve sustainability; a focus on directional innovation, involvement of new innovation actors (specifically civil society organizations) and increased consideration on regional capacity to not only generate innovation but receive it, apply it and upscale it within the region and beyond (Tödtling et al., 2021).

The literature has some limitations (Binz et al., 2020). For example, few study the direct role that regional policy plays in practically influencing such transformation processes (Arne et al., 2022). Indeed, the practical influence is even less probable if the policy itself does not adjust in design and in practice to fit into the sustainability perspective. The literature fails to address how such policy changes can and should occur.

4. 3. b. Smart Specialization Policy

Smart Specialization is a place-based approach to innovation policy stemming from acknowledging that regionally specific competitive forces and knowledge dynamics drive innovation (Asheim and Gertler, 2005). In 2014, the deployment of European Regional Development Funds was conditional on the existence of a Regional Smart Specialization Strategy. The policy logic (European Commission, 2012; Barca, 2009; Foray et al., 2009; Foray et al., 2012) focuses on locality, stakeholder involvement, and priority setting. For investments to migrate away from improbable "technology miracles" looking the same everywhere, an Entrepreneurial Discovery Process (EDP) is facilitated. Through the EDP, local stakeholders collaborate on identifying regionally specific strengths and weaknesses *(locality and stakeholder involvement)* (Rodriguez-Pose et al., 2014) and then recommend technological priorities where R&D funds will be concentrated *(priority setting)*. The process intends to specialize and diversify regional R&D focus. Unlike other typical R&D policy instruments (for example, tax cuts), there is more ambiguity about how successful an EDP can be; for example, how well-tailored and locally accurate the priorities will be, how will the local economy adapt, or how will the de-prioritized sectors respond (Foray, 2018). The uncertainty of the EDP process makes RIS3 an experimental policy which requires long-term policy learning systems in place. To leverage the role of policy learning, locally tailored monitoring processes capable of tracking successes and failures and correcting course accordingly are impactful (ibid, p. 829).

As the first phase of RIS3 ended (2014 - 2020), academic and policy debates increased urgency on leveraging the policy to focus on Grand Societal Challenges. RIS3 priorities are encouraged to align with the European Commission's new political dedication towards sustainability concerns, the European Green Deal and the Sustainable Development Goals[29] (SDGs) (McCann and Soete, 2020; Marinelli et al., 2021). As expressed in the European Green Deal Strategy[30]; "research and innovation can vitally hurry and manage the necessary transitions to achieve the desired goals". The RIS3 guide also highlights the importance of social regional innovation, declaring it can create new local opportunities and alter citizen perception which provides the public sector local support while targeting important challenges (Coenen & Morgan, 2020; European Commission, 2012).
For innovation to be meaningfully used in leveraging grand societal challenges, technological and business innovation are insufficient. A bigger policy approach that prioritizes fundamental systemic change beyond business and technological action is required (Geels 2002, 2004; Markard, Raven and Truffer, 2012). In addition, technological innovation becomes beneficial to the extent it can positively contribute to the grand challenges at hand. McCann and Soete (2020) argue that RIS3 mechanisms and experiences can be used to achieve such goals. The first phase of Smart Specialization has "accumulated experience" (ibid, p.8) for regional policy-makers allowing them to more easily encourage and mobilize stakeholder engagement, manage opposing interests

[29] https://sdgs.un.org/goals
[30] https://ec.europa.eu/info/research-and-innovation/strategy/strategy-2020-2024/environment-and-climate/european-green-deal_en

and coordinate entrepreneurship and regional policy efforts. Such assets, coupled with the direction of sustainability transitions, provide a huge policy potential to target growing challenges of today and tomorrow. The authors term the desired approach as "Smart Specialization Strategies for Sustainability" (p.11), hereby referred to as S4. *Table A4.2* shows examples of what priorities could look like through an S4 perspective; aligning priorities with Sustainability Challenges.

There remains considerable doubt, and literature gaps, as to what extent RIS3 can practically achieve such a transition (Warnke et al., 2016; Moulaert and MacCallum, 2019) and what that implies in terms of policy design.

4. 3. c. Monitoring Smart Specialization Policy

The previous two sections summarize the literature on innovation policy for sustainability and Smart Specialization, setting the tone for our general research motivation and aim. As mentioned, our study focuses on the design of monitoring indicators within the policy process. This section discusses the literature on monitoring RIS3 and how it guides the rest of our analysis.

The Latin term *"monit"* means instruct, guide, check for quality and keep under review[31]. The necessity of monitoring in public policy comes from recognizing that policymakers make mistakes (Kuznetsov & Sabel, 2017), do not have access to perfect knowledge and cannot foresee the local reaction or behaviours to even the most thoroughly studied policies. This logic necessitates an adaptable process of policy planning followed by responsive "error detection and error correction" (ibid, p. 53). For such a process to be successful, an institutionalized monitoring system is required. The system should effectively and efficiently enable evidence-based decisions while supporting continuous responsive policy reactions (Leeuw & Furubo, 2008).

The literature on monitoring RIS3 (Gianelle & Kleibrink, 2015; Fuster-Marti et al., 2020) is surprisingly scarce considering the general academic interest in RIS3 (Mora et al., 2019), and the

[31] https://www.etymonline.com/word/monitor

initial policy reports that anticipated monitoring as a fundamental part of the process (Kuznetsov & Sabel, 2017).

Among the few contributions, Gianelle & Kleibrink (2015) emphasize the significance of RIS3 monitoring by explaining its main functions. Monitoring is used to clarify the ` logic of intervention to the public and the stakeholders involved, to identify and communicate policy achievements, and to promote transparent and evidence-based communication among stakeholders to strengthen partnerships. Collecting and sharing data in a timely manner maintains accountability of the policymaker towards the stakeholders involved and towards citizens. This also allows policy actions and reactions in a timely and robust manner. The authors then design a logical framework explaining how a monitoring system should be designed, based on a logic of intervention and a connection between the required inputs and the desired outputs. Output indicators capture how policy actions impact the target population. Result indicators capture the overall socio-economic changes achieved. The monitoring system is designed based on a link between the policy action, the output and the result indicator.

McCann and Soete (2020), highlight that the transition to Smart Specialization for Sustainability should focus on the overall innovation system and not only on the R&I system, specifically from a monitoring and evaluation perspective. The authors recommend that a continuous policy-learning dynamic needs to be introduced with a particular focus to early detection of trade-offs between innovation, competitive advantage, sustainability, and inclusivity. More specifically, indicators should correspond to the specificity of the regional transition vision (ibid, p.30). Marinelli et al., (2021) highlight how within an S4 perspective, monitoring needs to transition away from the administrative requirements and focus on outcomes of learning. The long-term goal of sustainability policies encourages any failure to become a learning process particularly integral to the achievement of important technological breakthroughs (Mazzucato et al., 2020). To achieve that, it is essential for evaluation to be continuous and reflexive. Whether or not the achievement of intermediate milestones was achieved should be utilized to guide policy reactions accordingly (Kattel & Mazzucato, 2018).

4.4. Research Question

Motivated by the political push to align RIS3 with sustainability challenges and the lack of papers looking at the practical implications of the policy transition, this chapter studies what the shift in RIS3 means for policy design. After motivating the importance of monitoring within the policy process (Foray, 2018), our analysis focuses on the question: "How should the design of Monitoring Indicators in Smart Specialization adapt to be able to achieve the EU's desired sustainability goals?" Here, a point on the slight but important distinction between monitoring and evaluation needs to be made. Monitoring is about systematically collecting data to understand the policy process and its implications. Evaluation is about effectively and scientifically using this data to answer questions on policy success and its impacts (UNITAR, 2012). While this chapter focuses on the design of monitoring indicators, the line between monitoring and evaluation is blurry. Various responsibilities and expectations fall within both processes theoretically and practically. To sum up, without designing and collecting proper and useful indicators, any evaluation attempt will be flawed, and practically incomplete. At early stages of a policy implementation, designing effective monitoring indicators is essential as it sets the potential effectiveness of future policy evaluations and decisions.

While the chapter is based on a specific policy-context, it can contribute to a wider discussion on how, in practice, innovation policy transitions into a policy focused on sustainability.

4.5. Theoretical Framework

This section outlines our theoretical framework by summarizing the distinctions between RIS3 and S4 and what this implies for indicator design, specifically those relevant for our discussion. Insights are gathered from literature on monitoring innovation policy, and the differences between regional innovation systems and challenge-oriented innovation systems (Tödtling et al., 2021). From the first stream of literature, we learn that monitoring is expected to transition from conventional to diagnostic monitoring (Kuznetsov & Sabel, 2017) to incorporate more directionality and experimentation in the policy process. The second stream of literature highlights more specific nuances in both policy processes, which guide the identification of relevant indicators.

4. 5. a. Conventional and Diagnostic Monitoring

Conventional monitoring is implemented to determine *whether or not* a specific policy-goal was met and typically resembles auditing procedures. In EU regional funding, strict audit requirements are necessary to maintain accountability of programme and project managers. Yet, some scholars argue such requirements may be too bureaucratically burdensome and stifle innovation (Kleibrink et al., 2016; Mendez & Bachtler, 2011). Strict obligations overburden administrations, scare-off promising and creative applicants and protect risk-averse ones (Kleibrink et al., 2016). The need to evolve from an over-reliance on the limitations of conventional monitoring and auditing can be addressed by diagnostic monitoring (Kuznetsov & Sabel, 2017). Diagnostic monitoring focuses on determining whether a goal was met and *why or why not*. It does not assume that agents in a policy process possess perfect information and attempts to identify which capacities (training, support, infrastructure) – if any – need to be strengthened for policy success. Diagnostic monitoring might even identify whether policy targets were "mis-specified or require additional revision" (p. 61). Diagnostic monitoring is thus capable of managing risk and failure based on forecasts and provide error detection and error correction policy mechanisms as timely as possible (p. 66).

Conventional monitoring is beneficial as it plays a key part in incentivizing agents to meet project requirements and previously set policy expectations. It is ultimately "backwards looking" and tends to assign responsibility for revealed mistakes, keeping the agents accountable (Kuznetsov & Sabel, 2017). "Forward looking" approaches, on the other hand, are designed to identify key issues and avoidable implementation errors (ibid). While they may be more beneficial in the context of long-term and experimental policies, they do run the risk of highlighting and potentially dwelling on failures. If monitoring is only understood as a mechanism through which we can attribute faults, then designing indicators to capture failure is undesirable. Failure is arguably not tolerated in large organizations and in politically sensitive policy frameworks with so much financial responsibilities on the line. Thus, conventional monitoring is more common. Nonetheless, because of the long-term and complex nature of sustainability transitions, diagnostic monitoring is not only beneficial but even essential. Notably, both conventional and diagnostic monitoring can co-exist within the same policy framework and even empower each other (ibid). This is applicable to S4 policies and other policies trying to target grand challenges. To recap, *Table A4.3* summarises the essential differences between conventional and diagnostic monitoring and their implications in practice.

4. 5. b. From RIS3 to S4

There are also stark theoretical differences between innovation policy and innovation policy for sustainability that imply specific changes on what needs to be monitored. To uncover this rationale, we rely on the work of Tödtling et al. (2021) which identifies how regional systems of innovation (RIS) need to adjust to target societal challenges and become challenge-oriented RIS (CoRIS). *Table 4.1* summarises our discussion and highlights the differences between RIS and CoRIS framework. If we assume RIS represents the logic behind innovation policies and thus Smart Specialization, and CoRIS represents Smart Specialization for Sustainability, we can draw conclusions on what the theoretical literature implies changes in indicator design. This is indicated in the final column of *Table 4.1.*

First, in RIS, innovation focuses on business and technological innovation. In CoRIS, innovation includes business innovation but expands to different remits such as social innovation, eco-innovation and institutional innovation. CORIS considers innovation beneficial to the extent it contributes to improving a societal challenge and thus, achieving innovation beyond the business sector is crucial. To make this feasible, the CoRIS network should extend beyond the typical players of institutions, academic institutions and firms to include civil society actors and innovation consumers. In addition, RIS is typically focused on the supply-side of innovation with the bottom-line of innovation policies being whether or not new patents/products/services are created. In CoRIS, the demand-side of innovation should be highlighted and the impact of innovation would be incomplete without local generation, adoption, application and upscaling. It is thus imperative that innovation is useful in solving concrete problems (Tödtling, Trippl, and Frangenheim 2020). For example, innovation in the water industry in a region facing water shortages, or innovation in the food industry in regions highly reliant on tourism. Finally, an important distinction concerns the failures that each policy targets. The rationale behind innovation policy is to correct underinvestment in R&D and systemic failures relating to infrastructure, network, capabilities and institutions (Woolthuis et al., 2005; Weber & Rohracher, 2012). Sustainable innovation policies, on the other hand, respond to different sets of failures including but not limited to the aforementioned ones. According to Weber & Rohracher (2012), sustainable innovation policies respond to four additional systemic transformation failures, directionality failure, demand articulation failure, policy coordination failure and reflexivity failure.

Directionality failure is the inability to guide innovation towards a particular "grand challenge". In that sense, the definition of innovation becomes more critical and not all innovation is considered a success. Demand articulation failure is the lack of capacity to understand user needs, to focus only on the supply-side of innovation factors and pay limited attention to the demand, diffusion, and use of innovation. For example, the diffusion of products and knowledge and how it is used, manipulated or improved upon in the locality is emphasised (Tödtling et al., 2021). Policy coordination failure is the ability to coordinate between different policies targeting similar and complementary goals. Reflexivity failure is the inadequate monitoring and readjustment of the policy path and policy results towards transformational change.

RIS	**CoRIS**	**Implications on Indicators**
Technological and Business Innovation	Social Innovation, User Innovation and Institutional Innovation.	Indicators design should capture various types of innovation.
Goal is fostering economic competitiveness.	Innovation required as a response to specific societal needs.	Indicators should capture the contribution to sustainability and to over-coming grand-challenges.
The innovation ecosystem network includes; firms, institutions, and academic institutions.	The innovation ecosystem network should target increasing participation by including various kinds of innovation users and stakeholders	Indicators should be nuanced and further divided within social groups. Important to distinguish who is benefitting from innovation.
Innovation is always positive	Innovation may lead to unfavourable outcomes; inequality, destructive creation (Soete 2013), job-losses, environmental degradation	

	(Schot and Steinmueller 2018; Coad et al. 2021).	
Emphasis on supply-side innovation	Generation, adoption, application and upscaling side of innovation - how regions use and apply innovation to solve concrete problems on the ground. (Tödtling et al., 2020)	Indicators should overcome focus on the supply of innovation.
The rationale behind the policy is to correct failures concerned with the innovation ecosystem (Woolthuis et al., 2005): - Infrastructural failure - Network failure - Capabilities failure - Institutional failure	Rationale behind sustainable innovation policy includes the previously discussed types of failures but also (Weber and Rohracher, 2012): - Directionality failure - Demand articulation failure - Policy-coordination failure - Reflexivity failure	Indicators should capture the contributions towards the failures that the policy attempts to correct.

Table 4.1: Required Change in Theoretical Framework between RIS and CoRIS, and the implications on Indicator Design

Source: Author's compilation based on Tödtling et al., 2021

4.6. Methodology

4. 6. a. Empirical Framework

After setting the theoretical foundations of this chapter, we now clarify our empirical methodology. The JRC Smart Specialization Platform[32] provided access to regional documents on RIS3. The documents clarify the Smart Specialization Strategy. While not uniform, most documents have sections on: analysis of the regional context, the approach, the prioritized sectors, the action plan and the monitoring strategies. Although meant for design purposes, the documents give a general representation of the regional set-up of innovation policy and monitoring approaches. These documents are key to comprehending how monitoring is designed from a practitioner's point of view. Our theoretical framework allows us to understand innovation policy and how monitoring should be conducted. Coupled with a practical understanding, we can provide more meaningful and feasible recommendations. Combining our theoretical framework with this empirical sections

[32] https://s3platform.jrc.ec.europa.eu/

makes our analysis and recommendations rooted upon solid understanding of the policy design perspective.

133 regional RIS3 documents were found belonging to European regions/countries around Europe administering the Smart Specialization strategy[33]. After reading the documents and looking for specific sections related to monitoring or evaluation[34], we focus on 72 documents containing a dedicated section. Of those, 39 (30% of total) clearly outline the indicators used in the monitoring process. Those documents were deemed the most practically useful for our analysis. The geographical representation is illustrated in **Figure 4.1**. About 180 RIS3 strategies have been developed overall[35] meaning that our dataset captures 22% of the total. In addition, out of the 19 EU Member states participating in RIS3, we have at least 1 regional document for 8 of them (representing 42% of total). Finally, owing to the method of data collection, we confirm gathering all possible documents that have made public their initial design of monitoring indicators.

[33] Documents were found and extracted in May 2023. Document analysis took place between June and September 2023.

[34] Language differences and different words for monitoring were accounted for while looking for these sections.

[35] https://s3platform.jrc.ec.europa.eu/#:~:text=The%20Smart%20Stories%20provide%20a,implement%20their%20Smart%20Specialisation%20Strategies.&text=In%20total%2C%2019%20EU%20Member,non%2DEU%20Regions%20have%20registered.

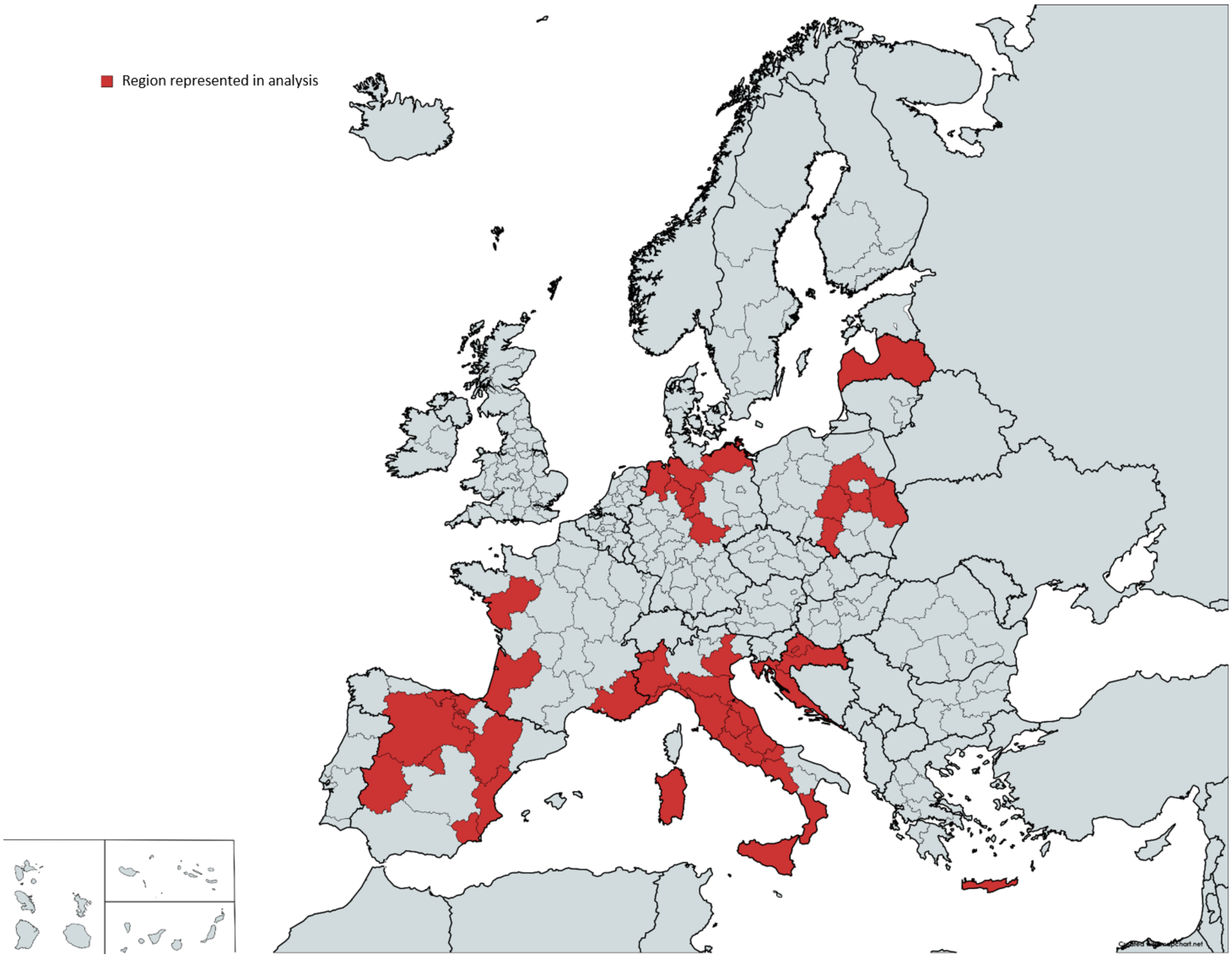

Figure 4.1: Regions Included in Analysis

The monitoring section in each document was extracted using PDF mining approaches and translated using Google[36] and DeepL[37]. To better understand the overall context, and make sure translations are accurate, the whole section, including the indicators used and their surrounding paragraphs, was fully translated.

We conduct a document analysis; a commonly used approach in qualitative research in which document data is extracted, examined and interpreted to elicit meaning and develop empirical knowledge of a certain phenomenon (Bowen, 2009). This approach efficiently and cost-effectively

[36] https://translate.google.com/

[37] https://www.deepl.com/translator

provides context-specific data to be used in both an inductive and deductive manner. In addition, documents provide access to data which lack obtrusiveness and reactivity – they are unaffected by the research process, are un-biased and factual (ibid, p.31). With more certainty, we can assume that the information provided is not incorrectly framed based on pressure to portray a job well done.

Indicators from the documents are collected and analysed together. After an initial read, we identify reoccurring words and synonyms. Based on an inductive process of grouping similar reoccurring words together, we do an initial clustering into meaningful categories. In the second step, categories are organized into general themes. This is done deductively based on how the categories, reoccurring words and data fit within our understanding of the literature and the RIS3 Policy Process, specifically within our theoretical framework illustrated in section IV. We eventually find that most themes are aligned with the failures that innovation policy focuses on correcting. **Figure 4.2.** represents a clarification of this process.

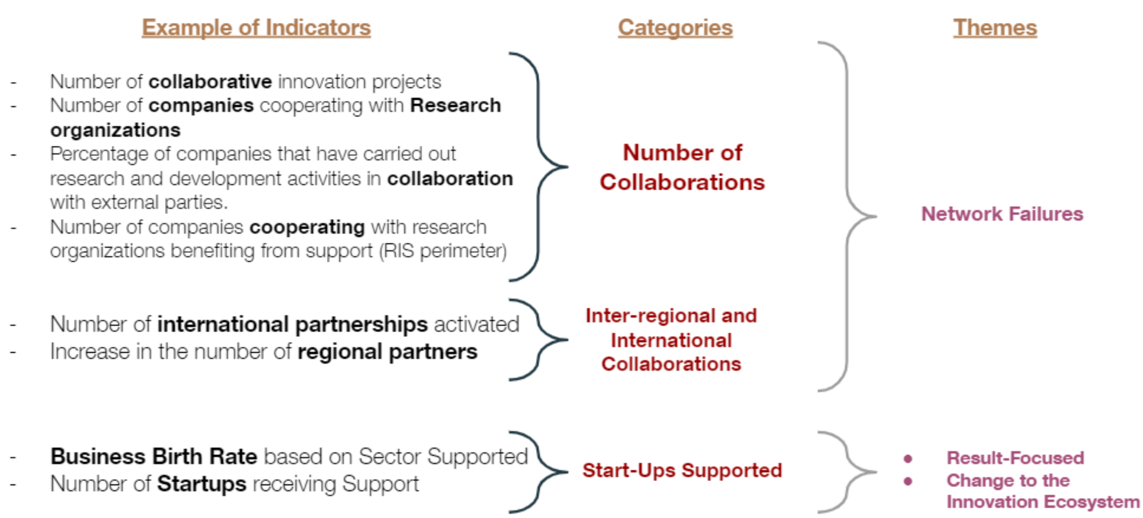

Figure 4.2: Organizing the Indicators into Themes & Categories – Examples

Despite the methodological strength of document analysis, certain limitations need to be highlights. In most document analysis projects, there is risk in accessing data which may not provide sufficient and thorough-enough details. In addition, since not all regions have made their indicators public, the data may suffer from biased selectivity (Bowen, 2009). Nonetheless, we believe the geographical coverage of the data enable meaningful analysis and a more thorough exploratory investigation of the indicators used. Other context-specific limitations also arise. Documents analysed were designed at early phases of RIS3. While monitoring systems should be designed early within the policy process, the possibility that indicators were updated as the policy implementation continued exists. Second, our document analysis specifically focuses on indicators used and does not capture the entire monitoring process. For example, we have no understanding on the stakeholders involved, how information captured is analysed and how policy reactions are taken. While indicator design is a starting point for any monitoring system and merits its own research, future studies may complement this one by looking at a more thorough case-study examples of how the entire monitoring system is implemented.

4. 6. b. Findings

On average, each policy document has 31.3 indicators varying between a maximum of 81 and a minimum of 6 indicators per document[38].

After collecting and reading through the indicators, we organize them into 31 reoccurring categories, and again into 7 general themes. Each indicator belongs to none, one or more than one category. Each category could belong to one or two themes as well.

The categories and corresponding themes are presented in *Tables 4.2a & 4.2b*.

[38] Graph A1 in the Appendix Section shows the distribution of the Indicators.

Result-Focused Indicators **(34.2% of total indicators belong to this category)**	**Under-Investment in R&D:** **(14.68%)**	**Changes to the Innovation Ecosystem:** **(11.07%)**
• New products produced • Start-ups supported • Partners Involved • Projects focused on process transformation • Tool development projects • Projects mobilizing regional assets • Scientific Publications • Patent Applications • Employment Created • Number of Social Innovation Projects • Export/Internationalization Initiatives • Specialization in Knowledge Intensive Operations	• Expenditure on R&D • Private investments matching funding • Research projects/researchers supported • R&D Personnel Supported	• Start-ups supported • Survival Rate of Funded Companies • Environmental Good-Practice Projects • Social Innovation Projects • Private investments matching funding

Table 4.2a: Reoccurring Themes & Categories

Infrastructure Failures: **(13.70%)**	**Network Failures:** **(25.92%)**	**Capabilities Failures:** **(21.33%)**	**Institutional Failures:** **(1.89%)**
• Digitalization Initiatives • Internet Usage Support • Private Investments supporting/matching funding • Infrastructure funding	*Local Networks:* • Partners in projects • Collaborative projects: Research – Corporate • Initiatives focused on knowledge sharing • Knowledge sharing through digital platforms • Academic Institutes Supported	• Training Expenditure: Doctoral Education Support/Continued Education/Skill Development • R&D Personnel Supported • Academic Institutes Involved	• Culture of Innovation

	• Academic Research projects and Personelle Supported • Cluster Formation *Non-Local Networks:* • Number of interregional and international projects • Internationalization (through exports) Initiatives	• Employment Created • High-Skill Employment Supported • Share of Employment Supported • Employment Created	

Table 4.2b: Reoccurring Themes & Categories

Percentages refer to the number of indicators belonging to this category out of the total number of indicators.

Figure 4.3 shows each indicator category and the percentage of indicators out of total belonging to each category. The most common indicators measure "Number of Partners Involved", "Digitalisation Initiatives", "Training Expenditure", and "Number of Collaborative Projects". These repetitions show the interest in measuring network effects of projects, and the expenditure spent on infrastructure (digitalization) and trainings. To make sure that these percentages are not only driven by projects that include many indicators in one document, we also look at how many times indicators were found across documents, regardless of how many times they showed up in total. This is visualized in **Figure 4.4.** This graph portrays the perceived importance of this specific category across different geographies and different cultures of understanding policy. The top indicators between both graphs do not vary much. Overall, we see a majority of documents have indicators which capture network effects of projects ("Number of Collaborative Projects", "Number of Partners Involved"), the expenditure spent on infrastructure (digitalization) and trainings and also the overall impacts on R&D initiatives (through measuring the expenditure, number of personnel, projects and research institutes supported). Both figures show that the indicators which are least repeated are those capturing cultural changes in the perception of innovation, projects focused on tool development and new employment opportunities created. To expand our understanding of the geographical distribution, *Table A4.3* shows the of the themes among the different regions.

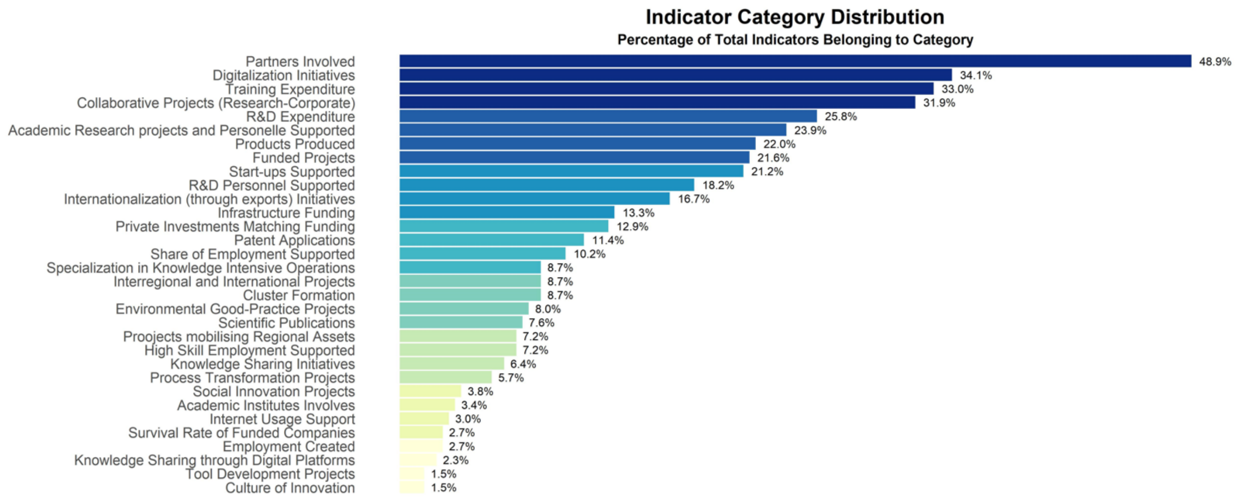

Figure 4.3: Indicator Category Distribution

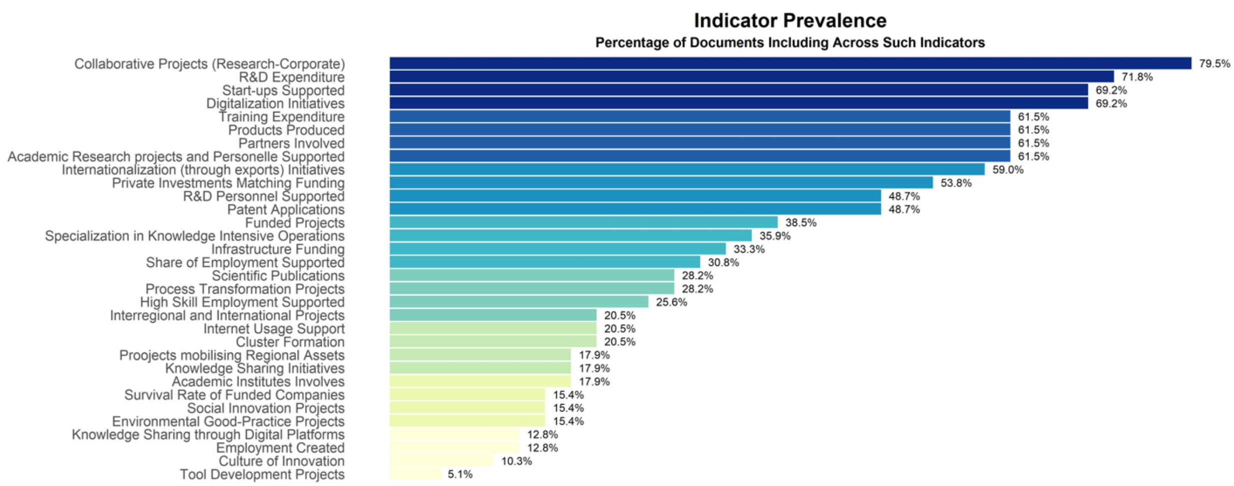

Figure 4.4: Indicator Prevalence

Delving deeper into reoccurring categories and themes, much can be learned. First, many indicators can be understood as basic indicator of outputs/results, such as the number of products produced, papers published and start-ups supported. The way these indicators are designed allow the policymakers to understand their "success" cases. While the indicators are capable of capturing whether a product is produced or a paper is published, no additional nuances can be extracted. Indeed, we do not know the instances of failures that occurred, why they did and who the instances of success benefit. 34.2% of all indicators, belong to this theme, making it the largest. Examples of indicators belonging to this category measure the number of projects supported (repeated in 38.5% of documents), the number of partners in projects (62%[39]), the number of products new to the company, market, or region (62%[39]), patent applications (49%[39]) and scientific publications (28%[39]). While these indicators are necessary to report and allow an understanding of where the funding is being distributed, they are, by their nature, meant to contribute to conventional monitoring (Kuznetsov & Sabel, 2017). They cannot contribute to a more nuanced understanding of the policy results. Despite their necessity, an over-reliance on them is dangerous as it does not allow to extract beneficial lessons learned. Second, these indicators capture the supply-side of innovation, by focusing on the extent to which projects are capable of producing outputs. Nonetheless, there is a lack of indicators measuring the demand side. For example, an aggregate number of products and publications produced does not shed light on the users of these products and local beneficiaries of the knowledge being generated. More complicated indicators are required for such purposes. We refer to the literature that highlights innovation policy's over-reliance on supply-side innovation as one of its main weaknesses (Tödtling et al., 2020) and confirm that this is mirrored through the design of monitoring indicators. In the context of challenge-oriented innovation policy, it becomes essential to capture elements of local demand, the diffusion of knowledge and the extent to which the local ecosystem responds and benefits from the publications and patents being produced. To iterate the focus on the supply of indicators, we highlight how very few indicators actually measure "Employment Created". While policy makers are too focused on what is being created, they tend to over-look who benefits from the additional jobs within the creation process. Finally, this set of indicators cannot capture "directionality", even if they do measure innovation. To give a specific example, while patent numbers may reflect one element of innovation, they do not measure the extent to which these patents require the use of toxic chemicals (Biggi et al., 2022), or the potential environmental implications of the products produced. An over-reliance on such simple indicators are insufficient, as an increase in the number of indicator does not necessary translate to an improvement in terms of sustainable innovation.

The other indicator themes (5 out of 7) highlight contributions towards solving market and structural system failures. In Tables 4.2a&4.2b, these themes are titled as: Under-Investment in R&D, Infrastructural, Network, Capabilities and Institutional Failures. Innovation policies, in general, are designed as a response to these aforementioned failures (Woolthuis et al., 2005; Weber

[39] Percentages refer to the number of documents out of the total in which these indicators are repeated.

& Rohracher, 2012). Such indicators are designed to capture the extent to which the policy is achieving its desired response.

Measuring the contribution towards market under-investment in R&D (14.68% of all indicators) is done through measuring the R&D expenditure on a local, regional or firm level (repeated in 72% of documents), also through measuring private investments which match public investments (54%[39]). The latter specifically highlights how the private sector is reacting to the local policies and sustaining the interest in innovation practices. A main role of innovation policy is correcting under-investment of the market in R&D projects (Jaffe et al., 2005). Studying how much the local market is responding to public funds by additionally contributing to funds themselves, allows identifying to what extent the policy is achieving correcting under investments and hypothesizing the potential longevity of such projects, with or without public support.

Another set of indicators (13.7% of all indicators) capture policy contribution towards infrastructural failures. Examples are measurements of digitalization in general (repeated in 69% of documents), the amount of internet usage locally (21%[39]), and the amount of funding primarily going for physical infrastructure development (33%[39]). Indicators belonging to the latter category measure funds to improve and modernize research facilities, business enterprises, technological equipment and internet infrastructure. Another interesting common indicator, already briefly discussed, was the amount of private investments complementary supporting public investments towards similar projects (54%[39]).

A larger set of indicators highlights contributions to network failures (25.92% of all indicators). Examples are the amount of collaborations between academic institutions and corporate entities (repeated in 80% of documents), cluster formation (20.5%[39]), and knowledge formation between different economic entities. To illustrate, indicators such as the number of products created in clusters and the number of companies entering clusters highlight their success rate and potential. Otherwise, indicators measuring initiatives contributing to knowledge sharing between different economic entities in general (18%[39]) and through digital platforms (12%[39]), help clarify to what extent the knowledge is being shared and utilized locally. Another indicator focuses on non-local network formation by measuring the projects creating collaborations between interregional and international partners (21%[39]). These sets of indicators show that policy-makers understand the role of innovation policy in contributing to forming and sustaining a strong innovation network and want to study to what extent that is being achieved. Indicators are designed to highlight how policies overcoming network failures and connecting essential parts of the innovation ecosystem deliver in practice. While not included, it is potentially helpful to recognize actors that are innovating outside of the R&D network, but not sufficiently collaborating with local stakeholders and whether repetitive collaborations are weakening knowledge formation and leading to knowledge-lock in (Boschma, 2005). This identifies what and where the potential bottlenecks to innovation may lie and acts as evidence for future policy refinements.

Capabilities failures (21.33% of all indicators) are captured through expenditure on local trainings (repeated in 62% of documents); either through skill development, funding of doctoral programs or through continued education training. This category also includes the amount of funding and/or initiatives which support R&D personnel (49%[39]), initiatives which support high-skill employment (26%[39]) and other employments depending on the sectors (31%[39]). The focus on skills, information and employment remains an essential element that should be captured when discussing sustainable transformation as skill availability, knowledge and the ability to change such knowledge into technology-based innovations are not uniformly distributed among people and regions.

Notably, the lowest number of indicators measure institutional failures. In fact, only one category could be attributed to that theme: indicators capturing how the projects developed are changing the local culture towards innovation. Such indicators are only found in 8% of the documents. Our analysis makes it clear the indicators are not designed to capture institutional failures. This is not surprising as the practical perception of monitoring may still be too focused on accountability and portraying success rather than the importance of extracting lessons. Normanton (as cited by Scott, 2018) defined accountability as the responsibility to "reveal and justify what one does". Many of the indicators presented above, potentially too many, capture accountability. However, a lack of indicators measuring institutional capacity leads to under-analysing and misrepresenting whether or not the policy's long-term impact (beyond financial responsibilities) is achieved throughout the process. Despite the vast literature on experimentation in policy settings, there is no clear understanding on how, in practice, the need for accountability can be reconciled with experimental policy making (Kanellou et al., 2019).

Finally, a small set of indicators capture the transformation of the innovation ecosystem overall. Two categories do so by capturing to what extent sustainable innovation is achieved, through social innovation projects (repeated in 15% of documents) or through projects contributing to good environmental practices (15%[39]). Notably, the indicators are simple, focused on measuring the number of successful outputs through an aggregate level. **Figures 4.3 and 4.4** show that these indicators are the lowest in percentage. Obviously, these specific indicators need to be increased if the general goal of the regional innovation strategy becomes focused on sustainability challenges. More complicated, yet meaningful, indicators need to be developed as well considering the long-term and complex path of sustainability transitions. Repeating simple outcome-indicators risks limiting the effectiveness of monitoring and evaluation practices.

Some less commonly observed indicators are worth highlighting as they represent good contributions to what indicators can and should capture. In one of the policy documents, indicators capture the number of users benefiting from the innovation. This is successful in overcoming the reliance of indicators on supply-side innovation and asks the question: “To what extent is demand fulfilled?”. Another policy document includes indicators which measure how different groups of society *(“for example: young people, unemployed, females”)* benefit from the products and services. This gives more nuance on whether innovation is always a “good” thing and how the answer depends on which portion of society we include. Both these indicators are indeed crucial in the case of challenge-oriented innovation policy.

4.7. Discussion

As Smart Specialization transitions into a policy aimed at alleviating grand societal challenges, substantial changes will occur within policy design and implementation. This chapter studies how the design of monitoring indicators within RIS3 should transition accordingly. Based on vast literature in the fields of innovation policy and sustainable innovation policy, we highlight how both policies differ in their approaches, rationale and aims. After setting the theoretical framing, we contextualize our practical starting point by studying how monitoring indicators were designed in the first phase of Smart Specialization. We rely on documents created by policymakers outlining the design of their RIS3 policies in general and their monitoring indicators specifically. Through an inductive and deductive document analysis, the indicators gathered are organized into meaningful categories and themes. The clusters show that indicators are designed to capture the policy's positive outcomes, and to measure the policy's contribution to market under-investment in R&D and to infrastructural, network and capabilities failures. This is in line with the academic literature outlining the failures to which innovation policy corresponds to (Woolthuis et al., 2005; Weber & Rohracher, 2012). implying that the indicators are motivated by the literature and/or designed in a way to highlight to what extent these failures are corrected by the policy implemented.

4. 7. a. Theoretical Contributions

The main indicator weaknesses identified in our analysis, within an S4 framework, are the over-reliance on simplified measures of success, the lack of measurement of directionality, lack of indicators capturing institutional and reflexivity failures and lack of measures accounting for supply-side innovation. Over-simplified measures of success do not tap into the potential of diagnostic monitoring for error detection and policy correction (Kuznetsov & Sabel, 2017). Both the experimental nature of RIS3 (Foray et al., 2012) and the long-term nature of sustainability challenges (Mazzucato et al., 2020) require an adaptable policy approach, allowing lessons from both success and failures. On the other hand, while lack of directionality and lack of focus on supply-side innovation tend to be commonly reoccurring in innovation policy (Tödtling et al., 2021), their shortcomings need to be avoided in the context of S4. Finally, reflexivity failures, as Weber & Rohracher (2012) highlight are a main reason for the need of S4 policies. Thus, indicators allowing policy makers to analyse them further are necessary.

Table A4.5 provides a summary and more thorough discussion of the weaknesses identified, with practical indicator examples and frameworks to overcome them. In brief, as the policy transitions into an innovation policy for sustainability, we find the indicators need to become more nuanced, provide more detail, and not be designed with the sole aim of measuring success. Indicators need to be designed to be able to detect potential policy failures need to be identified and guide further policy reactions.

4. 7. b. Practical Contributions

We provide recommendations based our theoretical discussion. First, to add nuance, indicators can be designed through a "Leave No One Behind Approach"[40] which creates indicators that can be disaggregated into different dimensions; age, gender, income class, educational level, ethnicity, migration and disability status. This detail necessarily captures who benefits from innovation and who doesn't. Second, for indicators to account for directionality, they need to be designed with a focus on how to capture sustainability. Indeed, it is no longer sufficient to only consider patents or products produced as result processes. More sophisticated indicators need to be employed. For example, indicators could capture the emission rate of products at various moments of the product design or product distribution, or how processes are efficiently reducing material and energy use, or the percentage of resources (funds, researchers, infrastructure) being spent on projects focused on climate change concerns or other grand challenges (Horbach, 2005). Indicators need to be locally tailored based on the goals set by each region, taking into consideration their challenges. Directionality can also be incorporated in already established indicators. For example, the networks that are focused on challenge-oriented projects, the presence of local capabilities and the extent to which they are utilized within this context. Third, creating indicators that measure both institutional and reflexivity failures is necessary to extract lessons on how the policy process itself can be improved. If this is not done, policymakers may miss out in identifying bottlenecks, mistakes or misassumptions.

How to incentivize policymakers to embrace capturing and learning from failure is a wider policy debate beyond the scope of our chapter. Here, we provide potentially useful indicators. For instance, it is important to measure to what extent the local priorities set are relevant with the local demands of the innovation network and the political sensitivity of the region. This could be done through surveys that expand on stakeholder participation (firms and/or citizens), or a thorough analysis of the calls for projects and the proposals being received. Another example is network analysis that captures the collaboration networks created by the projects funded and identifies key regional players that are excluded. This contributes to inclusive innovation networks. Another beneficial indicator is the extent to which the policy is able to coordinate data collected from different projects and stakeholders for more informed decision making. Finally, to capture supply-

[40] SDG Monitoring – Urban 2030 Team

side innovation, indicator design needs to account for who benefits from innovation and how (disaggregated by social groups), and the potential mechanisms through which innovation is being utilized; information sharing, potential for future collaborations and potential to contribute to solutions for wider societal challenges.

European Agencies such as the JRC, or the European Commission, play a role in guiding policy practitioners during the RIS3 transition. For example, during the first phase of Smart Specialization, the JRC provided workshop support and online course training for policymakers on monitoring[41]. Such support can be alleviated to achieve the new challenges at hand and could benefit from collaborating with projects such as the: "Regions 2030 – Monitoring the SDGs in the EU Regions[42]". This developing project focuses on increasing local ownership of SDGs at the regional level, openness, and transparency in the achievement of results. Such frameworks are necessary for S4 monitoring and need to be adjusted to focus on innovation in particular. More specifically, the design of monitoring indicators should be guided by how different they should be from the first phase, in line with the findings of this chapter. In addition, local partnerships including early collaborations with data practitioners should be encouraged to understand possibilities and limitations. Open Datasets of each region should be encouraged while taking into consideration privacy and security concerns. This boosts policy-learning throughout different local experiences. Examples of such datasets can already be found[43], but greater emphasis should be placed on those specifically highlighting the intersection of innovation policy and sustainability.

4. 7. c. Limitations & Future Research

While the recommendations here are motivated by our empirical approach, there are certainly caveats of how practical these recommendations are and limitations of our work. This chapter contributes to the topic of indicator design and so the discussion on implementation is beyond its scope. Nonetheless, a short summary of the caveats should be highlighted. To start, potentially the data required by indicators does not exist and infrastructure to capture it is not there yet. Still,

[41] https://s3platform.jrc.ec.europa.eu/monitoring-evaluation
[42] https://data.europa.eu/en/news-events/news/regions-2030-monitoring-sdgs-eu-regions
[43] *Example 1:* https://data.europa.eu/data/datasets?query=Sustainable%20development%20goals&locale=en&page=1
Example 2: https://s3platform.jrc.ec.europa.eu/monitoring

the data revolution is growing exponentially and while specific data may not exist yet, there is great potential for it to do eventually. For this to be feasible, collaborations between statistical offices and policy-makers are necessary and would be sped up by policy-makers knowing what type of indicators they are looking for and why such indicators are important. In addition, citizen participation and open-data platform can make the access to such data even more possible, and potentially available in a timely manner. Again, a collaboration between policy-makers and open-data practitioners is necessary. Another aspect to be considered is the time-frame. Whether or not indicators should be studied at a monthly, biyearly or yearly basis depends on each indicator and the logic of the rationale behind it. Finally, the idea of measuring failure is a highly political one, which does not come easily. Failure, in general, is difficult to accept and accommodate – especially in a public system responsible for taxpayers' money (Coenen, 2018). It is thus no surprise that policy-makers shy away from measuring it. Nonetheless, in a policy perspective dealing with grand challenges and in an experimentation setting, learning from failure continues to be essential (Rodrik, 2004). Arguably, the costs of such failures are certainly reduced once they are monitored and turned into lessons on how to fail smarter (ibid). Nonetheless, the highly politicized background of this is certainly a caveat of our discussion. The recommendations and discussion of our chapter remain beneficial while the design of the monitoring indicators is occurring and allow the opportunity to begin setting up the accurate and required infrastructure early on.

One of this chapter's limitations is the focus on monitoring indicators and not on the whole monitoring process (through the lens of stakeholders involved, procedures or frequency of evaluation). While using policy documents as a data source helps overcome locality and subjectivity issues that may be faced during case-studies or interviews, it limits the scope and source of the data used. Widening the scope, to the entire monitoring process or other elements of policy design and implementation is difficult through policy documents but presents an interesting avenue for future research through qualitative case studies. As regions start implementing their own S4 strategies, further case-studies on the policy transition can be developed and lessons learned extracted.

4.8. Conclusion

This chapter is motivated by a growing debate on using Smart Specialization to target grand societal challenges. What the transition from innovation policy to innovation policy in sustainability implies for policy design is underdeveloped in the literature, and our case-study can provide meaningful insights and recommendations for Smart Specialization and innovations studies and policy makers. The chapter specifically discusses implications on the design of monitoring indicators. We conclude our study by recommending that indicators be designed to capture more nuance and more detail about who is benefiting from the innovation, to capture the sustainable direction of change, to capture potential bottlenecks and institutional and reflexivity failures and to capture the supply-side of the innovation being developed. This is beneficial as it can guide policy-makers working on RIS3 and S4 regional policies as they design specific strategies to integrate sustainability within their innovation strategies. While this is specific to the context of Smart Specialization, we also believe that this chapter can contribute to a wider conversation on how innovation policy changes, in practical terms, when the concept of sustainability becomes a priority. To that end, policy-makers can benefit by early and ongoing collaborations with data experts and international organizers to design, implement and study meaningful indicators throughout the entire policy process. By doing so, the benefits of monitoring can truly be realized. An iterative experimental policy process can be created and updated accordingly as soon as imperfections are identified.

Chapter 5: Conclusion

As the first paragraph of this thesis stipulates, it is important to acknowledge that innovation will not stop, and it should not either. It still remains imperative that we understand how and when we can use innovation for sustainability purposes. This thesis investigates topics of innovation for equality, innovation for sustainability and inclusive innovation. By doing so, it studies, through various dimensions and scales, how innovation efforts and policies can be used for sustainability purposes.

Introducing sustainability within innovation is a critical consideration for policy makers, on the regional and national level. However, it is also important to recognize that sustainability is a business opportunity. Otherwise, a clash will be created between the goals of the policy community and the desire at the firm level of adhering with them. The perception that sustainability initiatives are costly to the firm requires awareness and mutual understanding between policymakers and businesses. Nidumolu et al., (2009) show, by studying sustainability initiatives over time for 30 large corporations, that sustainability yields both bottom-line and top-line initiatives. Environmental awareness and efforts lower company costs as they strategically reduce the inputs they use and increase revenues from products as the revenues themselves become of higher quality or create niches within the markets. These findings are also confirmed through a more recent (2022) analysis conducted by NOSCO consultancy firm[44]. Additionally, the latter report also shows that in our current generation, companies with better sustainability programs can hire better and retaining the loyalty and commitment of the workforce. All above authors argue that sustainability should be treated as innovation's new frontier. The conversations around these dynamics are not new and yet, as sustainability concerns become more pressing and efforts more stringent, the need for continuous analysis and awareness remains pressing to be able to bridge the gap between policy and firm needs.

[44] https://nos.co/the-role-of-innovation-in-reaching-sustainability-goals/

While each chapter of this thesis looks at sustainability within innovation at a different scale, and thus, contributes to different streams of literature, some common contributions arise as a collective of all three chapters, which will be reiterated here.

5.1. Theoretical Contributions

The stream of literature that this thesis contributes most widely to is that on innovation policy for sustainability. In the first chapter of this thesis, we utilize patent data and various measures of income inequality to shed light on the benefits and costs associated with knowledge diversification and thus contribute to the literature on inequality and complexity. The chapter finds that regions with a more complex knowledge core have lower levels of local inequality. Having access to a wider set of learning and job opportunities increases the bargaining and earning potential of the local labor force. A crucial implication of this research lies in identifying specific income distribution subsets that witness heightened inequality, enabling targeted policy interventions. Notably, heightened national knowledge complexity correlates with reduced income disparity between the 80th and 50th percentiles as well as the 80th and 20th percentiles. Conversely, this complexity is linked to increased income gaps between the 50th and 20th percentiles. Furthermore, the study underscores the intricate interplay between inequality and complexity, revealing that minimal inequality often coexists with higher levels of knowledge complexity and, specifically, that a larger inequality gap between the 50th and the 20th percentile is not necessarily a deterrent for higher complexity. Some form of inequality may be a natural consequence of complex ecosystems and understanding where exactly this inequality lies is essential to inform whether policy should correct the consequences of higher knowledge complexity and how.

In the second chapter, we contend that the evolution from general innovation policy to innovation policy for sustainability necessitates a theoretical understanding of the adaptation of policy design and implementation. This chapter focuses on elucidating this adaptation with a particular focus on the design of monitoring indicators. We provide a comprehensive framework, drawing on both literature and policy, to highlight the required changes in the design of these indicators. We find that the monitoring indicators used in the past examples of innovation policies (specifically in the context of Smart Specialization) overly rely on simplistic measures of success within these policies, which fail to track the direction of this success, its sustainability and inclusivity. The indicators, in general, do not consider, nor capture, policy or institutional failures or feedback. They additionally fail to capture whether the innovation results capture the supply-side demands of the innovation needs. These specific failures would weaken any innovation policy's ability of utilizing innovation for the sake of sustainability as well. Using overly simplified success measures risks that during the policy implementation, early mistakes will be missed and the chances for necessary policy adjustments overlooked. Given the long-term challenges of sustainability within innovation, we need flexible policies that learn from both successes and failures.

The final chapter contributes to the literature on the inclusivity of innovation and its impact. To the former, we find how Industry 4.0 patenting activities still suffer from a lack of gender inclusivity. Despite increasing levels and almost achieving gender parity in STEM education, studying the gender amongst Industry 4.0 inventors shows a staggeringly low levels of female inventors contributors. In addition, this percentage seems to be stagnating in the past few years. For the literature on how gender inclusivity impacts innovation, our research finds that more gender diverse teams introduce higher novelty into their research, but lower impact. While the results could be impacted by the already low levels of female representation in our dataset, the presence of these relationships remains significant and important to discuss. The current industry landscapes significantly highlight the missed opportunities by excluding diverse perspectives through gender diverse researchers. This is relevant in innovation studies in general, but also specifically in Industry 4.0 innovation as it relates to the sector's focus on personalization of products and services alongside the human experience.

5.2. Methodological Contributions

The third chapter of this thesis introduces an effective and data-driven way of measuring novelty and impact of a patent. This methodology is inspired by many attempts before it to use advancements in NLP research to create valid and robust indicators for patent quality (*amongst others* Hain et al., 2022; Jeon et al., 2022), this chapter stands out for its use of the most recent NLP methods of text embeddings, utilizes an NLP model which has already been fine-tuned to adapt to patent language and can effectively compare each patent with others without relying on estimation proxies. By doing so, we create three utilized indicators; the novelty of a patent (*how similar a patent is to those that occur before it*), the impact of a patent (*how similar the patents* *that occur after a specific patent are to it*) and the quality of a patent (*impact scaled by novelty*). These indicators are important as they overcome simplistic and industry-specific limitations in traditional patent indicators which tend to be slow in capturing technological developments and weakly capable of comparing patents produced within the same sub-sectors. Utilizing NLP transformers in the methods presented in our chapter contribute to implementing an efficient, objective and data-driven method in analyzing the added value of patents in comparison to other patents within the industry. While these indicators are used in a specific manner in our chapter, they provide meaningful contributions and use-cases throughout the innovation literature.

5.3. Policy Contributions

Since this thesis is situated within the policy focus on innovation for sustainability, most of its contributions lie within this subset.

In the first chapter, the findings of the chapter contribute to our understanding of how to achieve sustainable, inclusive and strategic growth on the national innovation level. The study highlights that managing low levels of income inequality could positively contribute to achieving higher complexity. Nonetheless, additional research would be necessary to understand how redistributive policies impact complexity directly and whether redistributive policies are themselves bad for growth or not (Berg et al., 2018). This study supports recommendations already initiated in other studies that countries should develop the capabilities to specialize in more complex economic activities (Hausmann et al., 2011; Balland et al., 2019; Hidalgo, 2021). However, we also confirm that specializing in more complex economic activities is itself a viable path for both inclusive and sustainable growth since the regional capabilities will become self-reinforcing and reward the actors embedded in the network (Balland et al., 2022). Doing so would require focusing investments in strategic research and knowledge domains, through both labour market training and the formal education ecosystem. In a complex ecosystem, reskilling, and upskilling of the labor force at the intersection of academia, the public and private sector becomes an essential and continuous demand. Integrating training within a regionally and technologically specific Smart Specialization framework, as discussed in Hazelkorn & Edwards (2019), improves local absorption capacity while maintaining the directionality of the innovation ecosystem. A framework committed to coordinating innovation approaches of private stakeholders and educational institutions through financial support and directed public investments in a context-specific manner is crucial to achieve the co-evolution of the institutional capacity alongside that of the national knowledge ecosystem.

In the second chapter, we highlight the missed opportunities of including more females in research positions specifically within patents, and even more so in leadership positions within these teams. Considering the finding that gender diversity contributes positively to the novelty of the patents produced, we emphasize the need for policy intervention to address the gender diversities within Industry 4.0. Policy actions should be implemented and prioritized in a context-specific manner which may include one of many, enhancing STEM education for females, reforming barriers to entry in male-dominated sectors, establishing transparent career pathways, and fostering gender-neutral flexibility in work-life arrangements. Collaborative efforts involving governments, educational institutions, and firms are essential to cultivate inclusivity, ensuring that females' unique contributions aren't merely symbolic but genuinely influential.

In the third chapter, we argue how policy efforts, in terms of design and implementation, need to adapt to the shift from innovation policy into innovation for sustainability. Our theoretical and policy-based analysis elucidates how this needs to happen from the point of view of monitoring indicators. We conclude with recommendations to design better indicators specifically for the policy of Smart Specialization for Sustainability and generally for any policy focused on place-based innovation for sustainability. First, the chapter highlights the need to develop indicators that are finely tuned across dimensions (age, gender, income class, etc..) to discern who truly benefits from innovation. Secondly, traditional metrics should be empowered through sustainability-focused measures. This involves assessing factors like emission rates, efficient resource utilization, and prioritizing challenges like climate change. Moreover, these indicators must be region-specific, aligning with localized goals, challenges, and capabilities, ensuring they encapsulate both directional and regional nuances. Addressing institutional and reflexivity failures is also pivotal, necessitating indicators that spotlight and rectify policy inefficiencies. Beyond these recommendations, there's a pressing need to encourage policymakers to cultivate a culture of learning from setbacks. This entails gauging the alignment of local priorities with innovation networks, promoting inclusive collaborations, and effectively coordinating diverse data streams for informed policymaking. In terms of contributions to the wider policy debate, this chapter should only be taken as an initial approach to the big question of how innovation policy needs to be adjusted. Studying the design of monitoring indicators was an essential starting point, but future research can and needs to build up on this and answer how the entire monitoring system, the entire phase of the Entrepreneurial Discovery Process, and the design and implementation of the policy need to adapt. As innovation policy increasingly centers around addressing sustainability challenges, there is a growing imperative to bolster the synergy between policy design, implementation and academia. This collaborative reinforcement is essential for effectively realizing the objectives in pursuit of sustainability goals.

5.4. Future Research

This thesis sets the starting point of multiple avenues of potential future research which will allow researchers and policy makers to more accurately understand the need, possibilities and complexities of utilizing innovation for sustainability goals. While multiple ideas may arise in response to the already developed thesis, I would be interested in aligning my research within the topics of policy adaptation between innovation and sustainability, the role of diversity on innovation implementation and the use of unconventional sources of data for innovation policy and innovation literature. For example, and as highlighted all throughout this thesis, there is a growing need for research to understand how innovation policy can and should be adapted to respond to sustainability transitions. While this thesis focuses on the role of monitoring, future research can study this topic in a general sense. For example, future research may utilize document and text analysis to study whether and how policy design has managed the policy transition so far and whether important implications of innovation literature are missing in practice. A lot can be learned about the context-specific and location-specific ability of policy to adapt to the emerging needs of sustainability. Secondly, the topic of inclusivity in the innovation ecosystem also leaves room for multiple future contributions in this field. A promising avenue lies in harnessing text mining methodologies to discern the qualitative impacts of different types of diversity on innovation. The empirical validation of such an analysis would necessitate contextual grounding through qualitative interviews. Moreover, delving into the intricate interplay between diversity and regional innovation could also be impactful. Although extant research within the migration literature underscores how migrants infuse diversity at the regional level, a gap exists in comprehending the nuanced impacts of minority involvement on the nature and trajectory of regional innovation. Lastly, as the innovation landscape continually evolves, there's an imperative to harness unconventional data sources to improve the implementation of innovation policy and the academic literature that is supporting and guiding this policy. For instance, methodologies like document analysis, policy text analysis, patent text analysis, spatial analytics, among others, can empower both innovation literature and policy frameworks, ensuring they remain pertinent and adaptive to contemporary challenges and opportunities.

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Appendix

Chapter 1

Source	Definition
Baregheh, Anahita; Rowley, Jennifer; Sambrook, Sally (4 September 2009). "Towards a multidisciplinary definition of innovation". Management Decision. 47 (8): 1323–1339. doi:10.1108/00251740910984578. ISSN 0025-1747.	Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate themselves successfully in their marketplace
Edison, H., Ali, N.B., & Torkar, R. (2014). Towards innovation measurement in the software industry. Journal of Systems and Software 86(5), 1390–407.	Innovation is production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and the establishment of new management systems. It is both a process and an outcome.
Rogers, Everett M. (2003). Diffusion of innovations (5th ed.). New York: Free Press. ISBN 0-7432-2209-1. OCLC 52030797.	An idea, practice, or object that is perceived as new by an individual or other unit of adoption
Hughes, D. J.; Lee, A.; Tian, A. W.; Newman, A.; Legood, A. (2018). "Leadership, creativity, and innovation: A critical review and practical recommendations" (PDF). The Leadership Quarterly. 29 (5): 549–569. doi:10.1016/j.leaqua.2018.03.001. hdl:10871/32289. S2CID 149671044. Archived (PDF) from the original on 24 December 2019.	Workplace creativity concerns the cognitive and behavioral processes applied when attempting to generate novel ideas. Workplace innovation concerns the processes applied when attempting to implement new ideas. Specifically, innovation involves some combination of problem/opportunity identification, the introduction, adoption or modification of new ideas germane to organizational needs, the promotion of these ideas, and the practical implementation of these ideas.
Drucker, Peter F. (August 2002). "The Discipline of Innovation". Harvard Business Review. Retrieved 13 October 2013.	Innovation is the specific function of entrepreneurship, whether in an existing business, a public service institution, or a new venture started by a lone individual in the family kitchen. It is the means by which the

	entrepreneur either creates new wealth-producing resources or endows existing resources with enhanced potential for creating wealth
Chen, J., Zhaohui, Z. and Xie, H.Y. (2004), "Measuring intellectual capital: a new model and empirical study", Journal of Intellectual Capital, Vol. 5 No. 1, pp. 195-212.	Innovation refers to the introduction of a new combination of the essential factors of production into the production system. It involves the new product, the new technology, the new market, the new material and the new combination. Innovation capital is the competence of organizing and implementing R&D, unremittingly bringing forth the new technology and the new product to meet the demands of customers. With the increasing importance of knowledge, innovation capital has become the core of IC providing a powerful drive for a company's continuous development. Innovation capital can be classified into three parts: innovational achievements, innovational mechanism and innovational culture
Zahra, S.A. and Covin, J.G. (1994), "The financial implications of fit between competitive strategy and innovation types and sources", The Journal of High Technology Management Research, Vol. 5 No. 2, pp. 183-211.	Innovation is widely considered as the lifeblood of corporate survival and growth
Bessant, J., Lamming, R., Noke, H. and Phillips, W. (2005), "Managing innovation beyond the steady state", Technovation, Vol. 25 No. 12, pp. 1366-76	Innovation represents the core renewal process in any organization. Unless it changes what it offers the world and the way in which it creates and delivers those offerings it risks its survival and growth prospects
Thompson, V.A. (1965), "Bureaucracy and innovation", Administrative Science Quarterly, Vol. 10, pp. 1-20.	Innovation is the generation, acceptance and implementation of new ideas, processes products or services
West, M.A. and Anderson, N.R. (1996), "Innovation in top management teams", Journal of Applied Psychology, Vol. 81, pp. 680-93.	Innovation can be defined as the effective application of processes and products new to the organization and designed to benefit it and its stakeholders
Kimberly, J.R. (1981), "Managerial innovation", in Nystrom, P.C. and Starbuck,	There are three stages of innovation: innovation as a process, innovation as a

W.H. (Eds), Hand Book of Organization Design, Oxford University Press, Oxford.	discrete item including, products, programs or services; and innovation as an attribute of organizations
Damanpour, F. and Schneider, M. (2006), "Phases of the adoption of innovation in organizations: effects of environment, organization and top managers", British Journal of Management, Vol. 17 No. 3, pp. 215-36.	Innovation is conceived as a means of changing an organization, either as a response to changes in the external environment or as a pre-emptive action to influence the environment. Hence, innovation is here broadly defined to encompass a range of types, including new product or service, new process technology, new organization structure or administrative systems, or new plans or program pertaining to organization members.
Plessis, M.D. (2007), "The role of knowledge management in innovation", Journal of Knowledge Management, Vol. 11 No. 4, pp. 20-9.	Innovation as the creation of new knowledge and ideas to facilitate new business outcomes, aimed at improving internal business processes and structures and to create market driven products and services. Innovation encompasses both radical and incremental innovation
Dosi, G. (1990), "Finance, innovation and industrial change", Journal of Economic Behavior & Organization, Vol. 13 No. 3, pp. 299-319.	Innovation concerns processes of learning and discovery about new products, new production processes and new forms of economic organization, about which, ex ante, economic actors often possess only rather unstructured beliefs on some unexploited opportunities, and which, ex post, are generally checked and selected, in non centrally planned economies, by some competitive interactions, of whatever form in product market
Becker, S.W. and Whisler, T.L. (1967), "The innovative organization: a selective review of current theory and research", The Journal of Business, Vol. 40 No. 4, pp. 462-9.	Innovation is a process that follows invention, being separated from invention in time. Invention is the creative act, while innovation is the first or early employment of an idea by one organization or a set of organizations with similar goals
Baregheh, A., Rowley, J., & Sambrook, S. (2009). Towards a multidisciplinary definition of innovation. Management decision, 47(8), 1323-1339.	Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, service or processes, in order to advance, compete and differentiate

	themselves successfully in their marketplace.
Baumol, W. J. (2002). The free-market innovation machine: Analyzing the growth miracle of capitalism. Princeton university press.	the recognition of opportunities for profitable change and the pursuit of those opportunities all the way through to their adoption in practice
Innovation Unit (2004) What is Innovation? [Online], London, Department of Trade and Industry. Available at www.innovationforgrowth.co.uk/ whatisinnovation.pdf (Accessed 14 February 2014).	the successful exploitation of new ideas
Freeman, C. and Soete, L. (1997) The Economics of Industrial Innovation, 2nd edn, London, Pinter.	A process of matching technical possibilities to market opportunities, through activities including experimental development and design, trial production and marketing.
Drucker, P. (1985) Innovation and Entrepreneurship, New York, Harper and Row.	A specific tool of entrepreneurs, the means by which they exploit change as an opportunity for a different business or service. It is capable of being presented as a discipline, capable of being learned, capable of being practiced.
Tidd, J. and Bessant, J. (2009) Managing Innovation: Integrating Technological, Market and Organizational Change, 4th edn, Chichester, John Wiley & Sons Ltd.	A process of turning opportunity into new ideas and of putting these into widely used practice.
Schumpeter, J. (1939) Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process, New York, McGraw Hill.	the introduction of a new good or a new quality of a good
Feldman, M. P. (2016). Geography of innovation. The Palgrave Encyclopedia of Strategic Management, Palgrave Macmillan, London.	Innovation is the ability to blend different types of knowledge into something new, different and often unexpected. Like art, innovation is a creative expression. However, unlike art, the measure of innovation is not in the eye of the beholder, but in acceptance within the marketplace that brings commercial rewards to the innovating entities and returns to society in terms of economic prosperity and growth.
Freeman, C. (1987). Technical innovation,	The innovation system literature claims that

diffusion, and long cycles of economic development. In The Long-Wave Debate: Selected Papers from an IIASA (International Institute for Applied Systems Analysis) International Meeting on Long-Term Fluctuations in Economic Growth: Their Causes and Consequences, Held in Weimar, GDR, June 10–14, 1985 (pp. 295-309). Berlin, Heidelberg: Springer Berlin Heidelberg.	the innovation process should be seen as the outcome of interaction between actors within firms, between firms, and between firms and other organizations like universities, educational facilities, financial organizations and government agencies (Freeman, 1987). So, being innovative is not just a 12 matter of having access to related variety or to local or non-local knowledge, but whether interaction takes place at all these levels.
Schumpeter, J. A., & Opie, R. (1934). The theory of economic development: an inquiry into profits, capital, credit, interest, and the business cycle. Harvard University Press.	Innovation is the practical implementation of ideas that result in the introduction of new goods or services or improvement in offering goods or services
ISO 56000:2020(en)Innovation management — Fundamentals and vocabulary. ISO. 2020.	a new or changed entity realizing or redistributing value
Acs, Z. J., & Audretsch, D. B. (1988). Innovation in large and small firms: an empirical analysis. The American economic review, 678-690.	Innovation is a process that begins with an invention, proceeds with the development of the inventions, and results in the introduction of a new product, process or service to the market-place
Damanpour, F. (1992). Organizational size and innovation. Organization studies, 13(3), 375-402.	Innovation is defined as the adoption of an idea or behaviour whether a system, policy, program, device, process, product or service that is new to the adopting organisation.
De Jong, J. P., & Kemp, R. (2003). Determinants of co-workers' innovative behaviour: An investigation into knowledge intensive services. International Journal of Innovation Management, 7(02), 189-212.	Innovation behaviour can be defined as all individual actions directed at the generation, introduction and application of beneficial novelty at any organisation level
Fruhling, A. L., & Siau, K. (2007). Assessing organizational innovation capability and its effect on e-commerce initiatives. Journal of Computer Information Systems, 47(4), 91-103.	Innovation is an idea, practice or object that is perceived as new to an individual or another unit of adoption.
Geiger, S. W., & Cashen, L. H. (2002). A multidimensional examination of slack and its impact on innovation. Journal of Managerial issues, 68-84.	Innovation refers to the creation of new product within the firm
Hage, J. T. (1999). Organizational innovation	Organisational innovation has been

and organizational change. Annual review of sociology, 25(1), 597-622.	consistently defined as the adoption of an idea of behaviour that is new to the organisation. The innovation can either be a new product, a new service, a new technology, or a new administrative practice.’
Palmberg, C., 2004]. The sources of innovations—looking beyond technological opportunities. Economics of Innovation & New Technology 13 (2), 1.	Innovation is defined as a technologically new or significantly enhanced product compared to the firm’s previous product which has been commercialised on the market.
Dibrell, C., Davis, P. S., & Craig, J. (2008). Fueling innovation through information technology in SMEs. Journal of small business management, 46(2), 203-218.	‘Innovations vary in complexity and can range from minor changes to existing products, processes, or services to breakthrough products, and processes or services that introduce first-time features or exceptional performance.’
Crossan, M. M., & Apaydin, M. (2010). A multi-dimensional framework of organizational innovation: A systematic review of the literature. Journal of management studies, 47(6), 1154-1191.	Innovation is: production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and establishment of new management systems. It is both a process and an outcome.

Table A1.1: Various Definitions of Innovation within the Literature

Chapter 2

Components of Technological Complexity

To motivate our use of Technological Complexity as a proxy of knowledge diversity, we analyse the various components that contribute to higher levels of economic complexity in each country. In our equation, countries with high levels of complexity show a considerable RCA in technologies of low ubiquity. For that purpose, we focus on the RCA of each country per each technology class and the ubiquity of each technology class overall. Although the measure of complexity begins from these initial measures, it becomes more complicated in further iterations. However, these initial measures provide a simple and yet meaningful context to understand our measure.

First, table A1 shows that the five countries with the highest patenting intensity across our time-frame. As expected, those countries are amongst the top 10 complex countries but are not necessarily the most complex. Another measure which could be beneficial is the average rate of RCA; how many times on average does a country show an RCA in a technology class. Table A2 shows that although Italy & Spain do not have the highest patenting intensity (in terms of number of patents), they have the highest average rate of RCA amongst all European countries. While some countries may have higher complexity measures due to specializing (RCA > 1) in ubiquitous technologies, the high levels of complexity in both Italy & Spain seem to be driven from a high rate in RCAs with technologies which have both less than average ubiquity and average ubiquity. Both Austria and Germany have almost 40% of their patents in operations, transportation and mechanical engineering. Otherwise, Germany has a high patent count percentage in the fields of electricity and physics. Despite having less overall patent families than Germany, Austria's high complexity index is driven by specialization in sub-fields which are more ubiquitous. This is evident when looking at the average rate of RCA in sub-technologies in Austria vs. Germany.

Country
Germany
France
United Kingdom
Italy
Netherlands

Table A2.1: Countries with Highest Patenting Count

Country	**Average rate of RCA**
Italy	0.48
Spain	0.46
Austria	0.45
Switzerland	0.43
United Kingdom	0.41

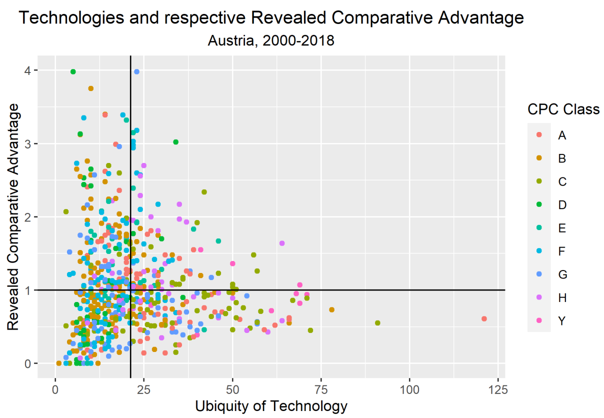
Table A2.2: Countries with highest RCA rate

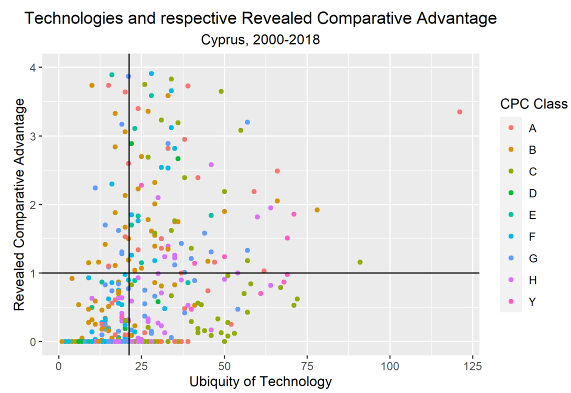
To further elaborate the point, in table A3, the technology classes are divided into four different quantiles based on their ubiquity measures. Within each quantile, we find the average rate of RCA of each country. Highlighted in green are countries which have a higher than 50% average rate of RCA than the remaining countries in this specific quantile, while highlighted in blue are countries which have a higher than the 90th percentile of rate of RCA than the remaining countries. A clear distinction can be made here between the countries with the highest complexity measures; Italy, Spain, Austria and Germany. While Germany shows a substantially higher than average rate of RCA in the first two quantiles (even higher than the 90th percentile), Italy, Spain and Austria show a higher than average rate of RCA in the first two quantiles but also in the third one. It is worth noting here that from the current way complexity is defined, a high rate of RCA in the 4th and 5th quantile is expected to drive the complexity measure downwards. However, the right balance is key here. Therefore, we can understand that the high measures of complexity in Italy, Spain and Austria is driven by a wider range of ubiquity in the technology classes they have RCA in, while the high measures of complexity in Germany (and Sweden, for example) is driven by a higher rate of RCA in the technological classes which less than average ubiquity.

Country	**Ubiquity Quantile 1**	**Ubiquity Quantile 2**	**Ubiquity Quantile 3**	**Ubiquity Quantile 4**	**Ubiquity Quantile 5**
Italy	0.39	0.44	0.55	0.57	0.47
Spain	0.31	0.47	0.48	0.50	0.59
Austria	0.40	0.45	0.55	0.56	0.32
Switzerland	0.34	0.41	0.42	0.47	0.52
United Kingdom	0.24	0.35	0.42	0.52	0.58
Germany	0.55	0.50	0.43	0.33	0.16
France	0.27	0.39	0.36	0.41	0.41
Sweden	0.23	0.30	0.34	0.31	0.32
Denmark	0.10	0.20	0.27	0.38	0.50
Overall Country 10%	0.34	0.44	0.47	0.50	0.69
Overall Country Average	0.17	0.27	0.33	0.40	0.47

Table A2.3: Average RCA per Country per each Ubiquity Quantile

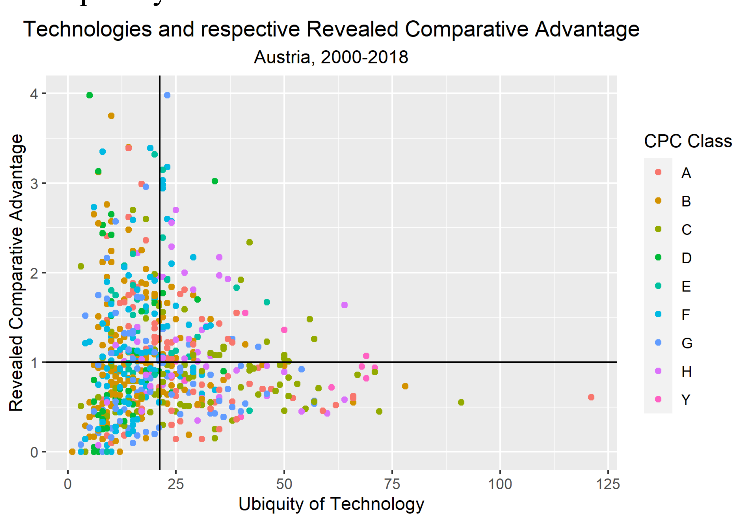
The figures below show differences in the distribution of RCA between a country with high levels of complexity (Austria) and a country with low levels of complexity (Cyprus). Here, RCA is compared as a non-binary value, but the horizontal axis shows that RCA = 1 measure. Above this axis are the technological classes in which each country has RCA in, and below are the technological classes in which each country does not have an RCA in. The vertical axis shows the average ubiquity of all technological classes. Technological classes on the left-hand side of this measure have less than average ubiquity, while technological classes that on the right hand side of this measure have higher than average ubiquity.

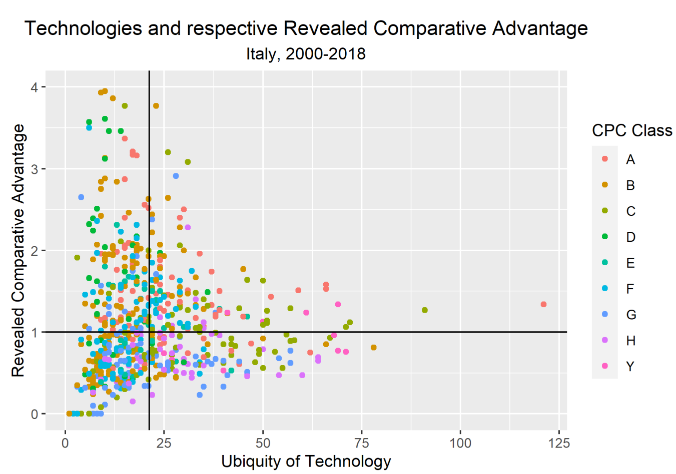


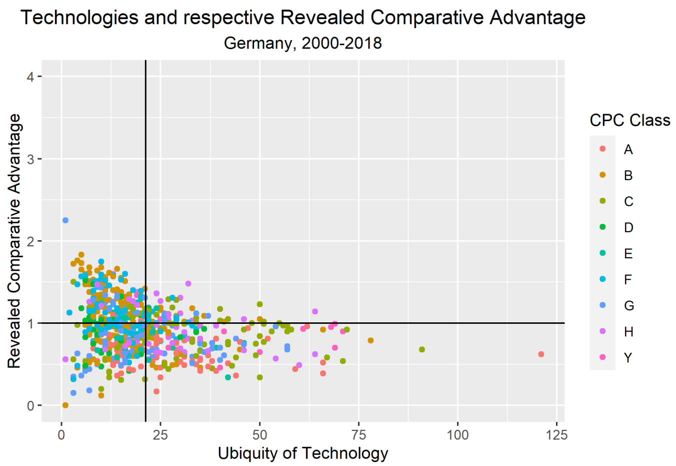


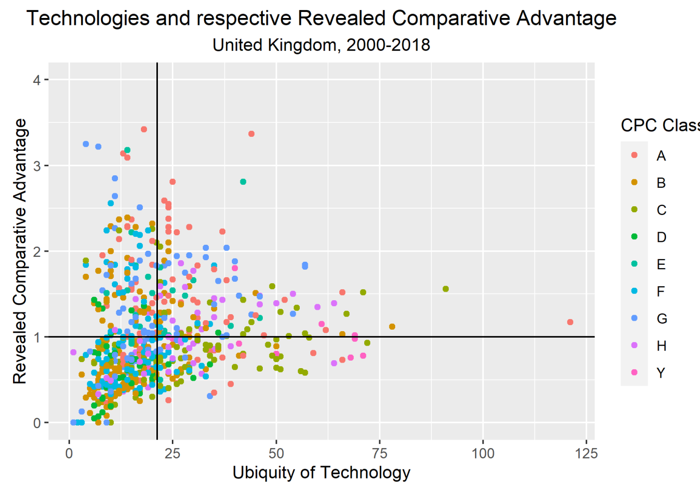
Figures A2.1 & A2.2

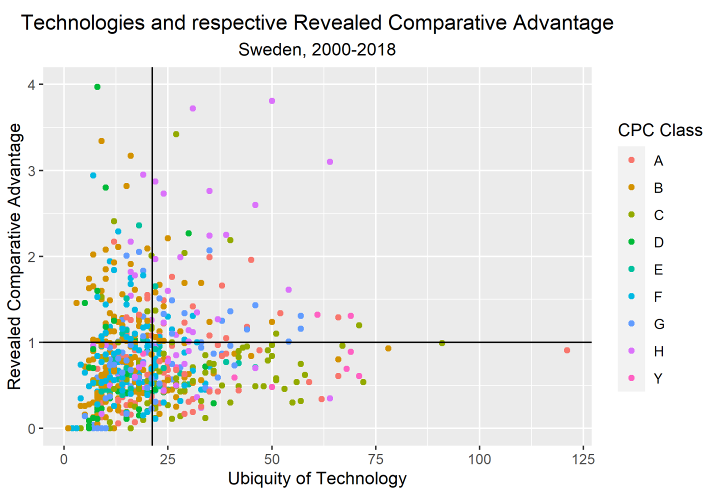
In the below, we see the distribution of each country's RCA in different countries with high complexity.






Technologies and respective Revealed Comparative Advantage
Germany, 2000-2018
Revealed Comparative Advantage
Ubiquity of Technology
CPC Class
A
B
C
D
E
F
G
H
Y
0
1
2
3
4
0
25
50
75
100
125


Technologies and respective Revealed Comparative Advantage
United Kingdom, 2000-2018
Revealed Comparative Advantage
Ubiquity of Technology
CPC Class
A
B
C
D
E
F
G
H
Y
0
1
2
3
4
0
25
50
75
100
125


Technologies and respective Revealed Comparative Advantage
Sweden, 2000-2018
Revealed Comparative Advantage
Ubiquity of Technology
CPC Class
A
B
C
D
E
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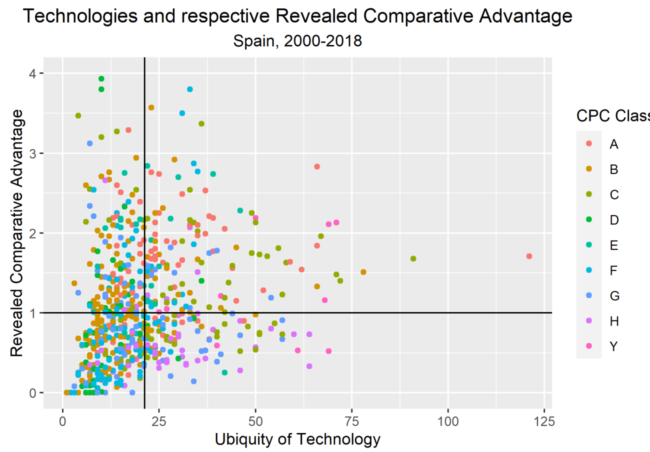
G
H
Y
0
1
2
3
4
0
25
50
75
100
125



Figures A2.3 – 2.8

Main Variables			
Equation (1)			
Variable	*Measurement*	*Source of Raw Data*	*Unit of Measurement*
Knowledge Complexity	Measured through R Econ Geo Package	PAT STAT	Standardized to EU Average
GINI	Gini Coefficient of Equivalised Disposable Income, Measured Through EU SILC	Eurostat	Standardized from 0 to 100
80^{th} vs. 50^{th} Income Percentile	Measured Through EU SILC		Ratio
80^{th} vs. 20^{th} Income Percentile			Ratio
50^{th} vs. 20^{th} Income Percentile			Ratio
Social Expenditure	Expenditure on social protection benefits measured through administrative data, national accounts and suveys/census data		Euro per Inhabitant
R&D Expenditure	R&D spending		Euro per Inhabitant

Migration	Calculated as population changes minus births plus deaths divided by population		Percentage of Population
Foreign Employment	Employment rates for citizens of foreign nationality		Percentage
Equation (2)			
Educational Attainment	Population by educational attainment level: Tertiary Education	Eurostat	Percentage
Adult Training	Share of people aged 25 to 64 who stated that they received formal or non-formal education and training.	Eurostat/EU Labour Force Survey	Share
Days to Open Business	Time required to start a business	World Bank/Doing Business Project	Days
Employment Rate	Employment rate of Labour Force	Eurostat	Percentage

Table A2.4: Variables Used and Data Sources

Variable	Information
GINI Coefficient of Equivalised Disposable Income	- **Total Disposable Income** of a household (HH): Personal Income Received by each HH Member + Income Received at HH Level + Income from Investments + Social transfers received - Disposable income is income remaining after deduction of taxes and social security charges - **"Equivalised" Income:** The equivalised income attributed to each member of the household is calculated by dividing the total disposable income of the household by the equivalisation factor. Equivalisation factors can be determined in various ways. Eurostat applies an equivalisation factor calculated according to the OECD-modified scale first proposed in 1994 - which gives a weight of 1.0 to the first person aged 14 or more, a weight of 0.5 to other persons aged 14 or more and a weight of 0.3 to persons aged 0-13.
s80_s20: Income quantile ratio	- Share of 80th percentile vs. share of 20th percentile for total disposable income - *Same definitions as above hold for total disposable income and equivalised income*
s80_s50: Income quantile ratio	- Share of 80th percentile vs. share of 50th percentile for total disposable income - *Same definitions as above hold for total disposable income and equivalised income*
S50_s20: Income quantile ratio	- Share of 50th percentile vs. share of 20th percentile for total disposable income - *Same definitions as above hold for total disposable income and equivalised income*
Knowledge Complexity	- Based on the Hidalgo and Hausmann (2007) methodology of the product space, which was later extended by multiple authors such as Boschma et al. (2015), Rigby (2015) and Balland and Rigby (2017) into the knowledge space, complexity is measured using patent data on patent families. Patent families are classified by three metrics utilized in our methodology; technology field, geography and timing.

	Technology field: Patent data are classified into different CPC-4-dig code technology fields based on the frequency of the knowledge claims that they made within each CPC class. *Geography:* The geography of the invention if traced by the location of the patent inventor or patent co-inventors. Individual patents are weighted from 0 to 1 according to the share of their co-inventors located within a specific country. *Timing:* Following the literature, we use the earliest filing date of the patent rather than the grant date in order to be as precise as possible with the time that knowledge is produced and to reduce bias due to the time-lags in patent examination. - Complexity is measured using PATSTAT data. The methodology first measures the complexity of all countries in order not to bias the measurements towards only European countries. Then the measures for the European countries included in our dataset are taken and normalized against the European average

Table A5: Additional Details on Variables Used

VARIABLES	(1) GINI	(2) GINI	(3) GINI
Fitness	**-0.949****	**-0.949****	**-0.951****
	(0.405)	**(0.406)**	**(0.403)**
R&D Spending	0.000972	0.000966	0.000951
	(0.00150)	(0.00150)	(0.00149)
Migration	0.127	0.127	0.160
	(0.309)	(0.307)	(0.315)
Foreign Employment	-0.0222	-0.0223	-0.0256
	(0.0270)	(0.0286)	(0.0268)
Tertiary Education	-0.0142	-0.0138	-0.0146
	(0.0513)	(0.0505)	(0.0502)
Dummy for Year = 2008	-0.0450		
	(0.220)		
Dummy for Year = 2009		-0.0263	
		(0.301)	
Dummy for Year = 2010			-0.349
			(0.249)
Constant	30.50***	30.49***	30.73***
	(1.953)	(1.969)	(1.970)
Observations	408	408	408
R-squared	0.040	0.040	0.044
Number of country_code	30	30	30
Country & Time Fixed Effects	Yes	Yes	Yes
Robust S.E.	Yes	Yes	Yes
Fitness Time Lag	3 Years	3 Years	3 Years

Table A2.6: Panel Regressions with Country Fixed Effects & Control for Financial Crisis Period

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) GINI	(2) GINI	(3) GINI	(4) GINI
Fitness	**-0.831****	**-0.836****	**-0.658***	**-0.658***
	(0.368)	**(0.382)**	**(0.377)**	**(0.377)**
R&D Spending	-0.000493	-0.000371	0.000381	0.000381
	(0.00108)	(0.00107)	(0.00128)	(0.00128)
Migration	0.111	0.119	0.144	0.144
	(0.242)	(0.242)	(0.256)	(0.256)
Foreign Employment	-0.0245	-0.0249	-0.0280	-0.0280
	(0.0267)	(0.0264)	(0.0275)	(0.0275)
Tertiary Education	-0.0853	-0.0846	-0.0681	-0.0681
	(0.0735)	(0.0733)	(0.0715)	(0.0715)
Dummy for EU-15 Countries	0.650			
	(1.398)			
Dummy for EA-12 Countries		0.735		
		(1.377)		
Dummy for GDP > 50% of EU Average			-2.240	
			(1.888)	
Dummy for Manufacturing GVA > 50% of EU Average				-2.240
				(1.888)
Constant	32.97***	32.99***	34.06***	34.06***
	(1.925)	(1.858)	(2.208)	(2.208)
Observations	408	408	408	408
Number of country_code	30	30	30	30
Time Fixed Effects	Yes	Yes	Yes	Yes
Robust S.E.	Yes	Yes	Yes	Yes
Fitness Time Lag	3 Years	3 Years	3 Years	3 Years

Table A7: Panel Regressions with Additional Country Controls
Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Does Complexity (4-year MA) Granger Cause GINI?					
Number of Lags Used:	**1**	**2**	**Number chosen such that AIC is minimized**	**BIC minimized**	**HQIC minimized**
Assumption 1: T is large relative to N (T tends to infinity as N tends to infinity)	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***
Assumption 2: Fixed T Dimension	p = 0.005***	p = 0.0024***	p = 0.0024***	p = 0.0024***	p = 0.0024***
Does Complexity (5-year MA) Granger Cause GINI?					
Assumption 1:	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***
Assumption 2:	p = 0.001***	p = 0.0051***	p = 0.0051***	p = 0.0051***	p = 0.0051***
Does GINI Granger Cause Complexity (4-year MA)?					
Assumption 1:	p = 0.000***	p = 0.0092***	p = 0.000***	p = 0.000***	p = 0.000***
Assumption 2:	p = 0.0029***	p = 0.3041	p = 0.0029***	p = 0.0029***	p = 0.0029***
Does GINI Granger Cause Complexity 4(5-year MA)?					
Assumption 1:	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***	p = 0.000***
Assumption 2:	p = 0.0003***	p = 0.0401**	p = 0.0003***	p = 0.0003***	p = 0.0003***

Table A8: Granger Causality Panel Test
*** p<0.01, ** p<0.05, * p<0.1

Simultaneous Equations Model Identification

For the SEM to be identified, it needs to meet the following identification condition: the number of excluded exogenous variables should be greater than or equal to the number of included endogenous variables.

$$m_i \leq (K - k_i)$$

m_i is the number of endogenous variables of the model, K is the sum of all exogenous variables used in all equations and k_i is the number of excluded exogenous variables. In our cases, the two dependent variables, Inequality and Complexity, are endogenous, in addition to Foreign Employment and R&D Spending. We used the lagged term of each variable as exogenous instruments. In the SEM models, we first specify the equation without introducing lags to Complexity and Inequality. This accounts for the simultaneity of the equations. We then introduce the 3-year lagged variables of complexity and inequality as exogenous instruments to account for the time frame needed for the theoretical model to take place.

Chapter 3

Field	Definition	Example
Hardware	Basic hardware, technologies	Sensors, advanced memories, processors, adaptive displays
Software	Basic software, technologies	Intelligent cloud storage and computing structures, adaptive databases, mobile operating systems, virtualization
Connectivity	Basic connectivity systems	Network protocols for massively connected devices, adaptive wireless data systems

Table A.3.1: Overview of Technology Fields in Core Technologies
Source: EPO (2017)

Field	Definition	Example
Analytics	Enabling the Diagnostic systems for massive data interpretation of information	Diagnostic systems for massive data
User interfaces	Enabling the display and input of information	Virtual reality, information display in eyewear
Three-dimensional support systems	Enabling the realization of physical or simulated 3D systems	3D printers and scanners for parts manufacture, automated 3D design and simulation
Artificial intelligence	Enabling Machine Understanding	Machine Learning, Neural Networks
Position determination	Enabling the determination of the position of objects	
Power Supply	Enabling intelligent power handling	
Security	Enabling the security of data or physical objects	

Table A.3.2: Overview of Technology Fields in Enabling Technologies
Source: EPO (2017)

Field	Definition	Example
Personal	Applications pertaining to the individual	Personal health monitoring devices, smart wearables, entertainment devices
Home	Applications for the home environment	Smart homes, alarm systems, intelligent lighting and heating, consumer robotics
Vehicles	Applications for moving vehicles	Autonomous driving, vehicle fleet navigation devices
Enterprise	Applications for business enterprise	Intelligent retail and healthcare systems, autonomous office systems, smart offices, agriculture
Manufacture	Applications for industrial manufacture	Smart factories, intelligent robotics, energy saving
Infra structure	Applications for infrastructure	Intelligent energy distribution networks, intelligent transport networks, intelligent lighting and heating systems

Table A.3.3: Overview of Technology Fields in Application Domains
Source: EPO (2017)

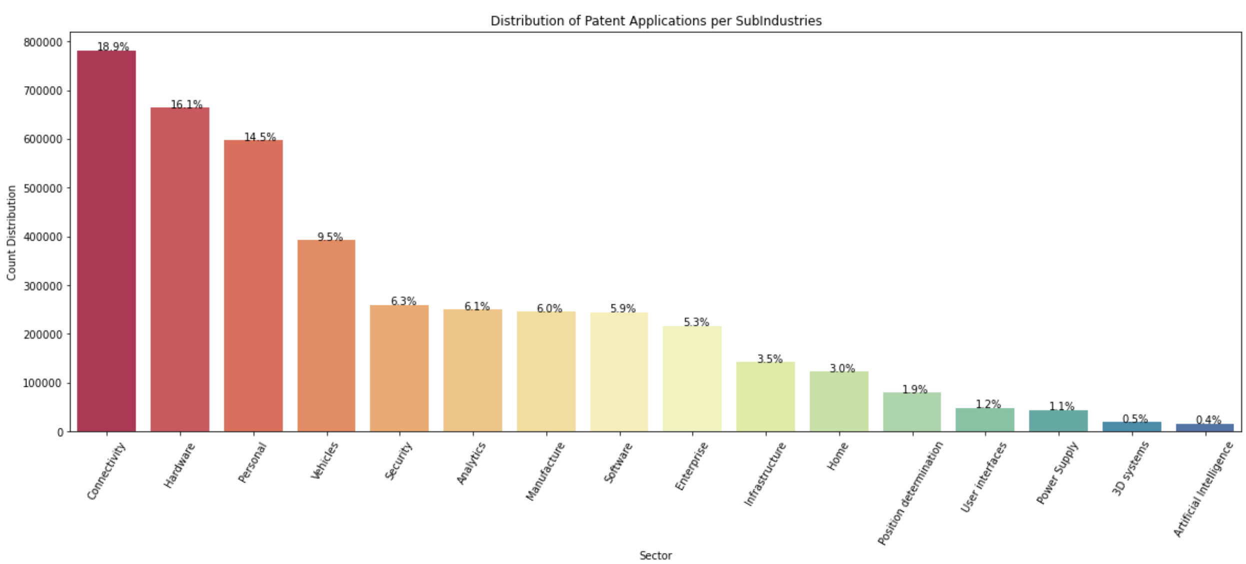


Figure A.3.1

Chapter 4

Grand Societal Challenge	Examples of Local Implications
Climate Change	Hurricanes, Tornadoes, Droughts, Floods
Demographic Changes	Ageing Societies in Japan and Europe, Increase in the ratio of dependents to working people
Pandemics	COVID19
Access to Energy, Water and Food	
Health and Well-Being Concerns	
Inequality	Political Tension, Local Mistrust
Difficulties in Achieving Sustainable Growth	

Table A4.1: Examples of Grand Societal Challenges and their Local Implications

Smart Specialization Priority	Mechanisms	Examples	SDGs Targeted
Circular Economy	• Management of Industrial Side Streams • Efficient Industrial Practices • Incorporating management principals of circular economy into all business activities	• Catalonia, Spain • Lapland, Finland	• **SDG 9**. Industry, Innovation and Infrastructure • **SDG 11**. Sustainable cities and communities • **SDG 12**. Responsible consumption and production • **SDG 13**. Climate action
Water Management	• Projects dedicated to water management, treatment, reduction and reuse	• Northern Netherlands Region • South Finland Region • Puglia, Italy	• **SDG 6.** Clean water and sanitation • **SDG 11**. Sustainable cities and communities
Low Carbon Economy	• Increasing material efficiency • Increasing clean energy adoption	• South Finland	• **SDG 7.** Affordable and clean energy • **SDG 11.** Sustainable cities and communities • **SDG 12.** Responsible consumption and production • **SDG 13.** Climate action

Table A4.2: Examples of Smart Specialization for Sustainability Priorities

Source: Authors Compilation based on Information from JRC RIS3 Platform - This table was inspired by practical examples already defined in previous RIS3 experiences[45]

[45] Information extracted from: https://s3platform.jrc.ec.europa.eu/

Conventional Monitoring	Diagnostic Monitoring	RIS3 to S4
• Used for auditing • Used to determine whether a goal was met • Assumes agents in a policy design and implementation know how to achieve success and have the capacity for it	• Used for problem solving purposes • Used to determine why goals were met or not • Assume agents in the policy design do not possess perfect capacity to achieve success • The initial response to under-performance is problem analysis and remedies to correct	Diagnosic monitoring (Kuznetsov & Sabel, 2017) is necessary due to the long-term and experimental nature of the policies: • Why goals were met or not • Whether agents lack the capacity or resources to achieve the target • Whether the target was mis-specified

Table A4.3: Change between Conventional and Diagnostic Monitoring

Source: Author's compilation based on Kuznetsov & Sabel, 2017

Indicator Category	Italy - Abruzzo	Italy - Calabria	Italy - Campania	Italy - Emilia Romanga	Italy - Lazio	Italy - Liguria	Italy - Marche	Italy - Molise	Italy - Piedmont	Italy - Sardenga	Italy - Sicily	Italy - Tuscany	Italy - Umbria	Italy - VDA	Italy - Veneto	Italy - Venezia
Capabilities Failures	1	4	5	0	3	2	1	2	2	4	2	3	2	4	1	2
Change to the Innovation Ecosystem	1	1	3	1	2	3	3	2	4	3	2	2	2	2	1	3
Infrastructure Failures	2	3	1	3	3	2	2	1	2	1	1	3	3	3	1	1
Institutional Failures	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Network Failures	4	2	5	1	1	2	2	3	4	4	3	3	3	3	3	3
Result Indicator	3	4	7	2	4	6	4	4	4	6	4	4	5	6	3	4
Under-Investment in R&D	0	3	3	1	1	2	1	2	1	2	0	1	2	3	2	1

Indicator Category	Capabilities Failures	Change to the Innovation Ecosystem	Infrastructure Failures	Institutional Failures	Network Failures	Result Indicator	Under-Investment in R&D
Spain - Murcia	1	1	2	0	4	3	1
Spain - Valencia	2	1	2	0	1	3	1
Spain - Aragona	3	1	2	1	3	4	2
Spain - Cantabria	3	3	2	1	3	3	2
Spain – Castilla y Leon	2	1	4	0	1	1	3
Spain - Euskadie	2	0	0	0	1	4	3
Spain - Extremedura	3	2	3	0	6	4	2
Spain - La rioja	5	0	1	1	4	5	3
Spain - Madrid	3	1	2	0	4	6	3
France - Aquitaine	1	2	1	0	2	7	0
France - Pays de la Loire	2	0	2	0	1	0	3
France - Lorraine	1	1	1	0	4	2	1
France - Cote D'Azur	5	2	3	0	3	5	2
Germany - Thuringen	1	1	2	0	2	4	2
Germany - Mecklenburg	3	2	1	0	0	3	2
Germany - Lower Saxony	5	2	1	0	3	4	3

Table A4.4: Geographical Distribution – Number of Themes Found in Each Policy Document

Indicator Category	Poland - Slaskie	Poland - Lodzkie	Poland - Lubeskie	Poland - Mazowza	Crete	Croatia	Latvia
Capabilities Failures	5	3	3	2	1	3	4
Change to the Innovation Ecosystem	1	1	0	3	3	3	0
Infrastructure Failures	1	0	0	2	2	3	0
Institutional Failures	1	1	0	1	0	1	0
Network Failures	4	4	3	4	1	4	1
Result Indicator	9	4	4	4	3	5	2
Under-Investment in R&D	2	2	2	1	1	3	2

Table A4.4: Geographical Distribution – Number of Themes Found in Each Policy Document