Joseph Monroe

THE ROOTS OF INVENTION

EMPIRICAL STUDIES ON KNOWLEDGE RECOMBINATION

STOCKHOLM SCHOOL OF ECONOMICS

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What drives technological invention? This dissertation examines one core mechanism of invention, namely knowledge recombination, in shaping invention outcomes across three studies. The first study reveals that inventors' personality traits significantly affect their invention output, depending on their organizational knowledge context. The second study examines the use of inventions' previous versions or historical knowledge to develop future inventions. The third study examines entire technological domains and shows that contrary to previous findings, invention rates increase when knowledge becomes more interdependent. This thesis highlights the importance of understanding knowledge recombination and offers valuable insights for innovation management.

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Joseph Monroe

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Chapter 3, Section 3.4.3 & Tables 1-3

The results use 10-year, not 5-year, invention impact. The 5- and 10-year results reflect negligible differences. Section 3.4.3 states: "[…] To reduce bias towards older patents, i.e., patents having been at risk of being cited for more extended periods, studies often implement a fixed 5 or 10-year window for forward citations (e.g., Nemet & Johnson, 2012). In this study, we implement a 5-year time window but also perform robustness tests using alternative windows." 5-year impact was intended as the focal dependent variable, with 10-year impact as a robustness check.

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Foreword

This volume is the result of a research project carried out at the House of Innovation (Department of Entrepreneurship, Innovation, and Technology) at the Stockholm School of Economics (SSE). The volume is submitted as a doctoral thesis at SSE. SSE is grateful for the financial support provided by Handelsbanken, which has made it possible to carry out the project.

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Director of Research

Stockholm School of Economics

Magnus Mahring

Professor and Head of

the House of Innovation

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Doing a PhD is kind of like riding a wild Walrus: it sounds cool and mysterious until you're actually doing it. Then, it's just stressful. *"Why did I think this was a good idea?"* you ask. Good question. *"Who in their right mind would ride a wild Walrus?"*

Walruses have enormous tusks and can weigh over 1000 kilograms. You shouldn't try to ride one alone. Fortunately, you meet nice people during your ride, some of whom bake cookies. Others ride Walruses themselves, so you can swap riding tips. A treasured few will slap your Walrus's behind to make it buck harder, pushing you to explore new ideas, scream loudly, and truly ride the Walrus. Like rodeo clowns, they tease and pretend to be aloof – but are truly on guard, ready to defend you, the rider.

While a Walrus ride only lasts—on average—37 seconds, whereas a PhD grinds on for years. You fall off again and again. The people you meet whisper *"Don't give up … ride the Walrus!"* Over time, your butt hardens. Your hands callus from gripping blubber. The sharp tusks dull. Slowly, you become one with the Walrus.

Suddenly, you're a Walrus rider, ready to explore an ocean of ideas. You can read and understand scientific papers. You can write your own. You can present complex ideas. A scary fish comes near? No problem. You've got a Walrus.

To those who've supported me, thanks a bunch. More specifically …

People who were noticeably kind-hearted: Uyen "good morning!" Vu, Xiao "omg!" Lu, Ingrid Koivisto, Emelie Fröberg, Jennie Fahlstom, Mats Pettersson, Krystal Zhao-Jansson, Camille Korschun, Sina Behzadifard, Kathrin Reinsberger, Mickaël Buffart, Anna Essén, Michael Barret, Eivor Oborn, Hui Sun, Thomas Lavelle, Malin Krebs, Katharina "Kata" Schilli

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Anna Fahlgård Lahache: From North of the wall (Umeå). My sister from another mister. We've spent the whole PhD bothering each other across a cubicle wall. For five years, Anna's charm and humor warmed my soul.

Joseph Monroe
Stockholm, 1 October, 2023

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Chapter 1: Introduction

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SUMMARY

What drives technological invention? This dissertation examines one core mechanism of invention, namely knowledge recombination, in shaping invention outcomes across three studies. The first study reveals that inventors' personality traits significantly affect their invention output, depending on their organizational knowledge context. The second study examines the use of inventions' previous versions or historical knowledge to develop future inventions. The third study examines entire technological domains and shows that contrary to previous findings, invention rates increase when knowledge becomes more interdependent. This thesis highlights the importance of understanding knowledge recombination and offers valuable insights for innovation management.

1.1 Motivation

Invention is the act of creating a new method, idea, or product, whereas innovation is broader and includes applying inventions to create value, often by introducing them to the market (Schumpeter, 1942; Drucker, 1985). This thesis is about technological invention, i.e., the act of creating new technologies, and focuses on sustainable technology.

Invention is important. Many periods in history are separated by new technologies and inventions that changed the way we live (Nelson & Winter, 1982; Roberts, 2014).[1] For example, the clock and telephone enable us to coordinate across vast distances (Standage, 1998). In some ways, technological inventions co-evolve with overall human development (Kelly, 2010). Although inventions emerge from a process of human creativity, new inventions can change how we think (Cohen & Levinthal, 1990), such as how the printing press helped spread ideas across time and space (Friedman, 2002). Therefore, we should care about what drives the invention of new technology, especially as the pace of technological change has increased (Friedman, 2002; Kurzweil, 2006).

1.2 Literature background

In the early innovation scholarship, scholars at that time were more focused on the role of technology in general economic development (e.g., Nelson & Winter, 1982; Rosenberg, 1994). For example, Schumpeter (1942: p. 132) described the dynamic nature of innovation with respect to economics:

[1] Technological changes are often minor tweaks and incremental improvements rather than fundamentally paradigm-shifting inventions (Dosi, 1982).

"The function of entrepreneurs is to reform or revolutionize the pattern of production by exploiting an invention or, more generally, an untried technological possibility for producing a new commodity or producing an old one in a new way, by opening up a new source of supply of materials or a new outlet for products, by reorganizing an industry and so on."

Over time, scholars have progressively narrowed their study of invention to focus on mechanisms active in national economies (Trajtenberg, 1990; Rosenberg, 1979; Nelson & Winter, 1982), industries (Ulrich, 1995; Schilling & Steensma, 2001), and individual firms (Cohen & Levinthal, 1990; Von Hippel, 1990). As we dig down to the core of invention, we find that a process of *knowledge recombination*—as executed by inventors—is central to invention across levels of analysis.

1.2.1 Knowledge recombination

While heavily influenced by top-down mechanisms at higher, invention necessarily includes an individual-level process of finding and recombining existing knowledge (Felin & Hesterly, 2007; Arthur, 2007). By analogy, consider that evolution is affected by population-level dynamics and mechanisms, ecological mechanisms, and even the systems-level dynamics within an individual biological organism (Barghi et al., 2020). However, the fundamental mechanism of evolution is the DNA replication system, as executed by individual cells. The recombination of DNA by cells is necessary and foundational to all evolution. It is not that mechanisms at higher levels do not exist, but rather that they guide and shape DNA-based mechanisms.

Similarly, knowledge is the fundamental material used by individuals in invention. The core material used in an inventor's mind is not metal, silicon, or rubber—but knowledge (Kogut & Zander, 1992). Moreover, technologies are themselves not only physical mechanisms instantiated as tools you may use, but they are also forms of knowledge to be used in future knowledge recombination (Arthur, 2007). For this reason, technologies are also termed "knowledge components," where technologies are themselves ingredients in the recipe for new inventions (Tushman & Anderson, 1986; Cohen &

Levinthal, 1990).[2] Similarly, invention is a problem-solving search for new combinations of knowledge components that reflect solutions to invention problems.

This mechanism of invention is captured in a theory termed *knowledge recombination* (Schumpeter, 1934; Fleming, 2001; Arthur, 2009). Several relevant definitions of knowledge recombination exist. Nelson & Winter (1982: 130) provide a seminal definition of knowledge recombination: "consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence." Schillebeeckx et al. (2021: 840) specify these conceptual materials as "knowledge components that an inventor team uses as inspiration, or as source material, for a new invention." Raveendran, Silvestri, and Gulati (2020: 846) note that the systems theory (including recombination literature) perspective "... views knowledge as a distinct entity or static property of organizations." Therefore, understanding invention through a knowledge recombination lens requires examining how knowledge is used across levels of analysis.

1.2.2 Invention inputs and outputs

In the knowledge recombination research stream, scholars examine knowledge recombination inputs and outputs (Garud, Tuertscher & Van de Ven, 2013; Xiao, Makhija & Karim, 2022). The outputs of knowledge recombination are the resulting inventions, which vary in several important ways (Fleming, 2001; Trajtenberg, 1990). Some are more useful than others (i.e., utility) (Arthur, 2007; Arts & Veugelers, 2015). Some inventions are more technologically novel, meaning original and path-breaking, and advance the technological state-of-the-art (Verhoeven, Bakker, & Veugelers, 2016; Strumsky & Lobo, 2015). Some inventions have a higher impact and promote or inspire more follow-on inventions (Hall, Jaffe, & Trajtenberg, 2001). These characteristics are important to understanding inventions' effects. For example, both novelty and usefulness can inspire new insights to

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[2] See Appendix A for definitions of common terms.

influence the direction of an industry (Trajtenberg, Henderson & Jaffe, 1997; Kaplan & Vakili, 2015).[3]

While also affected by mechanisms at higher levels of analysis, invention outputs are heavily affected by the characteristics of input knowledge components (Fleming, 2001; Savino, Messeni Petruzzelli, & Albino, 2017). Some input components are newer or more familiar to a given entity—or to the world in general—and so may inspire fresh insights and new combinations (Arts & Veugelers, 2015). However, newer components also come with higher uncertainty and cognitive burden (Fleming & Sorenson, 2004). Conversely, existing and familiar components are lower costs and easier to use (Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001). Some components' use is context-dependent and so may have limited transferability (Laursen & Salter, 2006; Arts & Fleming, 2018). Given the importance of familiarity and context, components' effects on recombination vary with their use over time (Nerkar, 2003; Kok et al., 2019).

When components are used together in a group, group characteristics emerge (Kaplan & Vakili, 2015). Combining components from the same domain signifies deep local knowledge search, whereas combining components from across multiple domains implies distant search and broader exploration (Rosenkopf & Nerkar, 2001; Katila & Ahuja, 2002). Broad search is more difficult but also avoids intellectual lock-in, unveils fresh opportunities, and so is associated with more novel inventions (Leiponen & Helfat, 2010; Kneeland, Schilling, & Aharonson, 2020).

Structural links between components also significantly influence recombination outputs (Henderson & Clark, 1990). Components' function or use often depends on dependencies upon other components (Ulrich, 1995; Fleming & Sorenson, 2001), and so modularizing components brings greater recombination flexibility and other systemic advantages (Schilling, 2000; Baldwin & Clark, 2000). In networks, both strong ties facilitate

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[3] There are many such terms and dimensions along which to evaluate the outputs of knowledge recombination, and many related concepts exist and overlap, such as breakthrough, radical, and "really new" inventions (Dahlin & Behrens, 2005; Garcia & Calantone, 2002; Arts & Veugelers, 2015).

knowledge flows and trust while bridging ties access diverse knowledge (Yayavaram & Ahuja, 2008; Schillebeeckx et al., 2021). A central network position enhances performance, and high connection density accelerates knowledge transfer (Phelps, Heidl, & Wadhwa, 2012; Hur & Oh, 2021).

1.2.3 Domains and trajectories

These knowledge structures also take the form of technological trajectories and technological domains, which form important dimensions of the knowledge landscape (i.e., environment) used and navigated by inventors to conduct knowledge recombination.

In a technological trajectory, inventions historically emerge from prior inventions, depending on those antecedent inventions as knowledge components. Chains of sequentially dependent knowledge components form overall technological trajectories that capture the historical evolution of a technology (Dosi, 1982). In turn, a trajectory represents a sequentially interdependent group of technologies that progress over time, building upon each other's advancements (Arts et al., 2013).

Trajectories exhibit distinct patterns of inventive problem-solving and approaches to technological challenges (Arthur, 2007). Trajectories also vary in their definitional use, contingent on the degree of sequential interdependence. The extent of influence a knowledge component has on an invention determines its role as an antecedent in a trajectory. The degree of this influence determines whether or to what extent technologies belong to the same trajectory. Conversely, trajectories can influence each other and, much like branches of a phylogenetic tree, often evolve in parallel, fostering competition, spillovers, and invention (Furr & Snow, 2015). As trajectories evolve, the functional characteristics of the technologies within them change, as do their relationships with technologies from other trajectories.

Technological domains differ from trajectories. A "domain" refers to a functionally similar group of technologies at a specific point in time, such as computer or medical technology, to which various components belong (Carnabuci & Bruggeman, 2009; Carnabuci, 2010; Carnabuci, 2011; Nemet & Johnson, 2012). Whereas trajectories can be likened to rivers, which have a direction and sequence of flow, domains are more like bodies of water, which reflect a collection of water at a point in time. For instance, despite differing in their technological trajectories, mechanisms, and knowledge components, a carpenter's hammer and a jackhammer could both belong to the same domain due to their similar purpose or function. The scope of a domain depends on the user's description and interpretation of technological characteristics (Kovács, Carnabuci & Wezel, 2021). Some people may categorize all computer technology under a single domain, while others may divide it into several domains. Domains can also overlap: technologies can belong to multiple domains. The scope of a domain is not static and may change over time as the perceived similarity of technologies evolves. As the number of components increases in domains, so does the potential for recombination (Weitzman, 1998).

It is tempting to use trajectories to define domains like the classification of species in evolutionary phylogeny, where reproductive lineage supersedes phenotypic traits at a given time. However, species are reproductively isolated—DNA cannot recombine across species—whereas knowledge components can freely recombine across trajectories and domains. Hence, while trajectories trace the evolution of technologies over time, they do not rigidly categorize domains. Domains focus on the functional or use similarity of technologies, while trajectories emphasize the temporal evolution or lineage of technologies. Technologies belong to one or more domains and trajectories, albeit these concepts capture different aspects of technologies' characteristics.

1.3 Research question

1.3.1 Research gap

Although prior research examining the role of search landscapes has been foundational to the knowledge recombination process, the current conceptualization of these landscapes provides a limited lens on how inventors use knowledge components.

Prior research lacks in two respects. First, while knowledge recombination is a multi-level phenomenon involving inventors, firms, economies, and so on, the dynamic interplay between levels of analysis is often overlooked. In particular, the dynamic interplay between inventor characteristics and the structure of their knowledge environments is underrepresented in previous literature (Fleming & Sorenson, 2004; Gruber, Harhoff & Hoisl, 2013). Studies with a strong emphasis on static aspects of knowledge recombination, like the accessibility and availability of knowledge components, risk neglecting the inventor's active and nuanced role in their environment (Ahuja, 2000; Singh, 2005). This perspective could potentially oversimplify the process to a mechanistic combination of components at a single level of analysis.

Moreover, different inventors can perceive and utilize identical knowledge landscapes and components in different ways (Cassiman, Veugelers & Arts, 2018; Arts & Fleming, 2018). This variation accentuates the influence of individual cognitive traits in the invention process (Gruber et al., 2013; Arts & Veugelers, 2020). The ways inventors' cognitive traits influence the novel combination and utilization of knowledge components form a significant yet under-researched dimension of the inventive process.

Second, many studies on knowledge component architectures assume a static state of knowledge search landscapes, often examining a single instance of knowledge recombination or a single generation of technology (e.g., Fleming & Sorenson, 2001). This includes the character and accessibility of knowledge components as well as the search landscapes of inventors (Ahuja, 2000; Singh, 2005; Phelps et al., 2012). However, inventors dynamically influence these landscapes during knowledge recombination, and their combination of components into new structures can impact both current and future knowledge recombination. Inventors not only navigate knowledge landscapes but also actively shape them over time. The broader implications of these varied structural combinations, such as across multiple generations of technology or throughout entire technological domains, are yet to be fully understood (Adner & Kapoor, 2010). Over time, inventors may gradually develop "fertile ground" in an area to make further inventions easier. Conversely, they may harvest inventions from “barren ground due to how they use available knowledge structures.

These two points indicate that a deeper exploration of the dynamic relationship between knowledge recombination mechanisms across levels of analysis is warranted. This relationship can be succinctly characterized as the relationship between inventors’ approach to knowledge recombination and their evolving knowledge landscapes. This approach, mirroring Schumpeter's (1934) original insights on the dynamic interplay of the inventor and their environment, offers a crucial step towards a more holistic understanding of the invention process. Given that inventor-level knowledge recombination is necessarily a part of knowledge recombination mechanisms at every level of analysis, I broadly formulate my research question concerning individual inventors and their environments.

1.3.2 Research question

How do inventors interact
with evolving knowledge landscapes
to influence invention outcomes?

1.4 Methodology

Addressing this research gap is tricky for a few reasons. Firstly, examining inventors’ cognitive mechanisms in controlled environments may be desirable but unfeasible. While psychology research has extensively examined human creativity in controlled environments (Feist, 1998; Feist, 2019), the environments in which invention takes place are anything but controlled. Invention, in its natural environment, occurs in varied contexts, including those of competitive firm R&D, government labs, universities, and more informal settings, like household garages. More generally, invention takes place in the vast, chaotic environments of national economies, product markets, and labor markets (Nelson & Winter, 1982). The implicit self-selection, survival, and other biases and influences at play would be impossible to control for in a laboratory environment.

For example, consider examining differences in personality traits and invention performance. Personality traits have been shown to affect creativity differently in different activity domains, such as scientific and artistic creative domains (Feist, 2019). [4] Few studies have examined personality trait's effect on technological invention, for corporate inventors are both rare and busy inventing—not readily available in large numbers for laboratory experiments. Moreover, the technological context facing inventors changes over time, making it difficult to control.

1.4.1 General approach

Instead of using laboratory experiments to study knowledge recombination, we act like astronomers studying stars at a distance and using theory and reasoning to deduce what may be going on inside those stars. In our case, we are not looking at stars in the sky but inventions across domains of technology. Instead of a telescope, we will use patent data and statistics. In other words, my approach is to broadly use observational data and theoretical reasoning to better understand inventors' knowledge recombination.

Broad patterns of technological change occur across countries, decades, and industries and involve many levels of analysis. The benefit of my approach enables the possibility to explore broader patterns in knowledge

[4] Personality refers to consistent patterns of behavior, thinking, and emotions that tend to stay the same throughout a person's life (Roberts, 2009; Roberts & DelVecchio, 2000; Cobb-Clark & Schurer, 2012; Specht, Egloff & Schmukle, 2011). Psychologists have identified specific personality traits that represent these patterns, which cannot be easily changed by external factors like education or experience. Unlike many branches of psychology, which depend on abstract theories, standardized measures of personality traits are the result of nearly a century of rigorous econometric analysis of thousands of behavioral covariates and a multitude of varying psychometric inventories (Allport & Allport, 1921; Goldberg & McReynolds, 1971; McCrae & Costa, 1997; John & Srivastava, 1999; Feist, 2019). To measure these traits, psychologists use tests that assess a person's psychological characteristics (Cobb-Clark & Schurer, 2012; Soto & John, 2019).

recombination over long periods and using large amounts of data. These types of inquiries would be impossible with experiments, as we cannot experiment using the innumerable inventors operating over history. In contrast, observational studies can contribute to our understanding of knowledge recombination mechanisms across many levels of analysis—from the individual inventor to firms, through inventions' histories or trajectories, and finally to entire technological domains.

1.4.2 Data

The thesis research design will explore how inventors interact with evolving knowledge landscapes to influence invention outcomes. To empirically study these concepts, we utilize both survey and patent data.

A community of practice has emerged using patent data to embody and measure various facets of technological inventions and knowledge (Hall et al., 2001; Jaffe & Rassenfosse, 2017). As a tangible manifestation of the invention process and the knowledge involved in it, patents provide detailed technological descriptions, structured classifications of technological fields, citation data, and historical span (Griliches, 1990; Jaffe & Trajtenberg, 2002). Each patent serves as a concrete record of the recombination of existing knowledge reflected in previous patents into something novel and useful, inherently exemplifying the knowledge recombination process (Fleming, 2001).

Patents also detail the contextual elements tied to their development and application (Griliches, 1990; Trajtenberg, 1990). With regards to modeling technological trajectories, the intricate classification of patents, especially the citation data, forms a conduit for tracing the lineage of knowledge flows and the interweaving of diverse knowledge domains (Jaffe & Trajtenberg, 2002; Arts et al., 2013). This citation network is a roadmap of knowledge recombination, enabling researchers to track the evolution, interaction, and amalgamation of knowledge over time (Hall, Jaffe, & Trajtenberg, 2001). Consequently, the dynamics of knowledge recombination, a cornerstone of this research question, can be effectively disentangled and understood.

Moreover, the detailed technological descriptions and classifications furnished in patent documents offer insights into the types of knowledge being recombined and their specific technological contexts (Griliches, 1990). This data facilitates the assessment of the breadth and diversity of the knowledge being recombined, providing further elucidation of the knowledge recombination process. In essence, the granular, rich, and diverse information encapsulated within patent data makes it a robust, tangible, and practical tool to investigate the multifaceted, complex process of knowledge recombination.

To study such cognitive processes, it's vital to complement patent data with other data sources, such as surveys, to fully capture the complexities of knowledge recombination (Singh & Fleming, 2010). Targeting German inventors working in green, mechanical, and nanotechnologies, the survey data used in this research collects data on various aspects of inventors, including a personality test and information regarding their organizational and working contexts. This information aids in understanding inventors' cognitive traits, perspectives on knowledge access, and their inventive output given their organizational settings.

Given the benefits and limitations in available data, I rely on four samples in this research:

- A survey of German green, mechanical, and nanotechnology inventors, which includes a personality test and items regarding inventors' organizational and working contexts.
- A sample of these inventors' patent portfolios.
- A sample of around 38,245 nuclear energy patents.
- A sample of 638 green energy domains (representing 36,506 domain-year observations and ~1.5 million green energy patents).

These samples boil down to two data sources, namely the German survey and the European Patent Office's *PATSTAT* database (2016 and 2019 versions). Notably, all three papers either include or focus on green technology. Green technology is a currently advancing field and, therefore, provides good examples of inventions to study. As a bonus, green technology is a *hot topic*. If we examined an older or stagnant field, our findings would be less generalizable to the current environment and would be less interesting to contemporary audiences.

1.4.3 Analysis

In this thesis, I will examine knowledge recombination across several levels of analysis: the inventor, firm, trajectory, and domain levels of analysis.

Paper one examines individual and firm-level aspects of knowledge recombination. At the level of the individual inventor, we will examine the relationship between inventors' personalities and their inventive output. We will then examine how firm-level knowledge environments moderate these personality-based relationships. Paper two examines trajectory-level relationships and how the use of knowledge components from a trajectory influences knowledge recombination. Finally, Paper three examines domain-level relationships, where the use of knowledge components can structure domain knowledge to make knowledge recombination more effective.

I will tie the research gap, levels of analysis, and data together to give you an overall picture by describing each of my research papers below. This will help map out my research contribution and demonstrate how my thesis fills the identified research gap.

Across the three papers that constitute this thesis, a variety of statistical strategies are employed to analyze the collected data. I will summarize what each paper studies and the statistical approaches used.

Paper One – Knowing Me, Knowing You: Personality traits shape invention output.

Literature on knowledge recombination has focused on inventors' access to knowledge components to be recombined as a key determinant of their inventive performance. Research from psychology has shown that openness and extraversion, two personality traits, increase performance in tasks akin to knowledge recombination. In this paper, we investigate how personality traits shape invention outcomes conditional on organizational knowledge context. We derive personality measures from a survey of 1,327 inventors and combine them with patent-based indicators of inventive performance. Our findings reveal how the relationship between personality and inventive output is moderated by knowledge context: the positive relationship between openness and invention output is stronger if organizational knowledge diversity is low. In contrast, extraversion negatively relates to invention output, but its effect is positively moderated by knowledge diversity.

In the empirical analysis, count-data regression models are utilized to model invention output, considering the expected count and fractional patent counts. This approach is favorable as it captures the skewed distribution and non-negativity of patent counts, resulting in more robust inferences (Cameron & Trivedi, 2001).

Paper Two – As Good as New: Historical trajectory integration affects invention impact.

In this study, we reconcile the literature on knowledge recombination and technological trajectories to develop a dimension of knowledge recombination we term trajectory integration. We explain how sequential knowledge components in a trajectory can be integrated to generate technological impact. Using data from the European Patent Office's PATSTAT database, we show that trajectory integration has a strong positive relationship with technological impact. Additionally, we find that trajectory integration positively moderates a well-known knowledge characteristic, technological distance, by helping distant knowledge to flow forward through the trajectory and into the focal knowledge domain. In sum, the findings both contribute to and link knowledge recombination and technological trajectories literature.

This paper uses the World Intellectual Property Office's (WIPO) International Patent Classification Code (IPC code) system to identify technological domains, including nuclear energy, and control for technological scope and diversity. The paper additionally uses negative binomial regression models to address overdispersion in the dependent variable (Fleming, 2001; Capaldo, Lavie & Messeni Petruzzelli, 2017; Barbieri et al., 2020).

Paper Three – On and On and On: Interdependence enables technological domain growth.

This study explores the impact of how interdependence knowledge within a specific technological field or domain influences the growth and innovation of that domain. We propose two ideas: (1) the more interconnected the knowledge within a domain, the faster the domain grows, and (2) a higher degree of interdependence within a domain pushes inventors to create more innovative solutions. Our analysis examines green technology patents filed between 1924 and 2012. The findings reveal that interdependence within a domain drives its growth but does not necessarily lead to increased novelty. This study contributes to our understanding of how the structure of knowledge within a domain affects the invention process, highlights the benefits of highly interdependent knowledge, and emphasizes the importance of considering the connections within domain knowledge when examining invention.

This paper employs negative binomial regressions to accommodate overdispersion in the count variables (Hilbe, 2011). These strategies together ensure that the research question is addressed comprehensively and accurately. This multifaceted approach underpins the research question at the core of this thesis, providing a tangible framework to navigate the inherent complexities of studying knowledge recombination and inventive processes.

1.5 Research contributions

Prior research on knowledge recombination ignored much of the "means" of knowledge recombination. In this thesis, I argue that extant literature would benefit from a deeper understanding of the interaction between inventors' cognitive characteristics and knowledge landscape structures, resulting in the thesis research question: "*How do different inventors interact with evolving knowledge landscapes to influence invention outcomes?*"

This thesis enhances our understanding of knowledge recombination by explicating the relationship between knowledge landscapes (in trajectories and domains), inventors' cognitive characteristics, and knowledge recombination outcomes. More specifically, this thesis:

- Better articulates knowledge recombination processes.
- Demonstrates how these recombination processes are context-specific.
- Demonstrates that collective knowledge structures are important for knowledge recombination.

1.5.1 Collective knowledge structures

It seems difficult to deny that technological invention almost always involves the recombination of technologies and knowledge. However, this seems to suggest that any new invention is sufficiently constituted as some simple recombination of its parts. That is, anything in an invention is simply a new combination of what was already there. Much of previous knowledge recombination studies treat knowledge components as independent units, which either affect recombination through their distinct individual features and contrasts between components in sets or groups, such as breadth or diversity (Pil & Cohen, 2006; Campagnolo & Camuffo, 2010; Savino et al., 2017). In this view, technologies are individual atomic functional units, and at any point in time, there is a given (large) number of available technologies that an inventor may combine to produce an invention. The way components are used when combined is irrelevant—it is only important which components are used. By analogy, there is no recipe for the ingredients but only a list of which ingredients are used and the features of those ingredients.

Another portion of previous research on component structures often focused on network architectures' effects on knowledge flows, which fundamentally regards the ease of access to or use of knowledge (e.g., Yayavaram & Ahuja, 2008; Phelps et al. 2012; Hur & Oh, 2021) or how these structures limit recombination in specific instances (Henderson & Clark, 1990; Fleming & Sorenson, 2001) thereby implying a preference for modularity (Schilling, 2000; Balwin & Clark, 2000).

Finally, another portion of previous research extols the virtues of low interdependence or high modularity, where any increase in knowledge component structures implicitly complicates or problematically complexifies recombination (e.g., Sanchez & Mahoney, 1996; Schilling, 2000; Campagnolo & Camuffo, 2010).

This thesis reframes the role of collective knowledge structures, which, when structured in some ways, reflect synergistic interactions among knowledge components. Evidence from both papers two and three demonstrates how trajectories and domain knowledge structures benefit knowledge recombination (Funk & Owen-Smith, 2017; Kalthaus, 2020).

Paper two elucidates how utilizing a trajectory can provide a conducive context for a deeper understanding and effective utilization of knowledge components. By aligning micro-level knowledge recombination with macro-level technological trajectories, it advocates for the value of intergenerational knowledge in enhancing comprehension of other components along a trajectory (Furr & Snow, 2015) and fostering new recombination opportunities (Malhotra et al., 2021).

Paper three extends this argument by emphasizing the importance of domain knowledge structures, particularly interdependence, as accelerators of domain growth and novelty. This novel perspective dovetails with existing research on the architectural structuring of knowledge components within various contexts, such as firms' knowledge bases (Raveendran et al., 2020; Zahra et al., 2020), social and knowledge networks (Phelps et al., 2012; Schillebeeckx et al., 2021), and interdependence relationships between components (Fleming & Sorensen, 2001; Murmann & Frenken, 2006). In demonstrating the benefits of high-performance technology domains, these findings promote a new examination of how domains may provide benefits to inventors (Fleming, 2007; Gruber et al., 2013), collaboration networks (Yayavaram & Ahuja, 2008; Schillebeeckx et al., 2021), and firms.

Moreover, the findings from these two papers present a counter-narrative to the notion that high interdependence is necessarily bad. The thesis explores interdependencies within collective knowledge, inviting a renewed exploration of interdependence mechanisms that have been previously investigated in various organizational contexts (Anderson et al., 2014), thereby encouraging a fresh interpretation of the impact of interdependence, particularly the potential advantages of high interdependence within collective knowledge structures might confer on firm performance (Siggelkow & Levinthal, 2003; Brahm et al., 2021).

1.5.2 Knowledge recombination process

This thesis deepens our theoretical articulation of knowledge recombination mechanisms using a behavioral strategy approach in paper one (e.g., Tandon & Toh, 2022). At the individual inventor level of analysis, innovation management literature has primarily focused on determinants such as knowledge sourcing (Dahlander et al., 2016; Laursen & Salter, 2006), socio-demographic factors (Gruber et al., 2013), and experience (Conti et al., 2014). Paper one posits the influence of inventors' psychological characteristics, specifically personality traits, on invention output, thereby refocusing our understanding on the cognitive, individual-level aspect of invention (Felin & Hesterly, 2007; Fleming, 2007; Ployhart & Moliterno, 2011). Moreover, paper one also highlights how the interplay between individual and organizational characteristics profoundly shapes knowledge-based processes (Eggers & Kaplan, 2013; Zahra et al., 2020). By introducing the personality traits of inventors as overlooked factors influencing invention output, this thesis complements existing innovation management literature examining knowledge recombination at the individual level.

This thesis delves into micro-level cognitive processes, emphasizing trajectory integration and domain knowledge interdependence's role in recombination processes. Paper two, emphasizing trajectory integration, underscores the temporal context faced by inventors (Nerkar, 2003; Kok et al., 2019), an area often eclipsed by the focus on depth, breadth, and diversity (Xiao et al., 2022). Additionally, paper two further explores the role and importance of trajectory integration as a process of knowledge consolidation using Funk & Owen-Smith's (2017) consolidation-disruption (CD) index, which represents and measures a technology's influence on prevailing trajectories. This measure, swinging between 1 (destabilizing) and -1 (consolidating), gauges the frequency with which a patent's citations influence later inventions. Post hoc analysis in paper three shows that while consolidation and disruption both significantly impact technological progress, their effects are nuanced and may diverge based on specific interaction circumstances. These two forces could spearhead technological progress through distinct pathways, emphasizing their unique contributions to the ever-evolving landscape of technological innovation.

Paper three underscores the influence of domain knowledge structures on recombination by highlighting the dynamic interplay of knowledge structure and search (Rahmandad, 2019; Ganco et al., 2020). In turn, this view challenges pre-existing notions of static knowledge landscapes, suggesting a far more fluid and dynamic terrain (Levinthal & March, 1981; Fleming, 2001; Fleming & Sorensen, 2001). Therefore, this thesis, rather than adhering strictly to prior research centered on cross-domain recombinatory search, underscores the intricate interplay of evolving knowledge structures in fostering invention (Fleming, 2001; Rosenkopf & Nerkar, 2001; Simon, 1955; Simon, 1956; Levinthal & March, 1981).

1.5.3 Context specificity

This thesis emphasizes the context-specificity of knowledge recombination processes, a critical finding that enhances our understanding of these processes' nuanced dynamics. Paper one foregrounds the role of organizational characteristics in shaping individual-level invention processes, demonstrating the profound impact of the environment on the outcomes of knowledge-based processes (Eggers & Kaplan, 2013; Eklund, 2022; Zahra et al., 2020). It posits that specific cognitive characteristics can render knowledge recombination highly context-specific for some inventors (Helfat & Peteraf, 2015; Judge & Zapata, 2015). For example, extraverted inventors' performance may improve in highly diverse knowledge environments, whereas open inventors' performance worsens.

The prevalent view in the existing literature attributes the difficulty of knowledge recombination to inherent properties of knowledge components, like distance (Rosenkopf & Nerkar, 2001) or interdependence (Fleming & Sorenson, 2001). This thesis suggests that the cognitive traits of inventors and the strategic assembly of related components along the same trajectory significantly affect the effectiveness of knowledge recombination. These findings underline that performance in knowledge recombination is not determined solely by available knowledge components but also by their contextual usage.

Paper three further underscores this context-specificity by illustrating how the growth of knowledge interdependence within a domain can sculpt the conditions for knowledge recombination within that domain. Paper three unravels the potential advantages of high interdependence, illuminating the mechanisms tying interdependence, domain growth, and novelty together. This novel perspective invites a re-evaluation of seminal works such as that of Fleming and Sorenson (2001), which presumes a static landscape for recombinatory search, where components' interdependence is constant across contexts, further highlighting the importance of context specificity in knowledge recombination.

These contributions collectively elucidate that strategic structuring of knowledge by inventors decisively impacts invention outcomes, as highlighted by the influence of inventor personality traits and trajectory integration. Crucially, the means of recombinatory search doesn't just direct search within search landscapes but also recursively transforms these landscapes.

1.6 Practitioner contributions

1.6.1 Inventors as strategic human resources

This thesis provides important implications for firm nonfinancial resource allocation (Coen & Maritan, 2011; Maritan & Lee, 2017) by highlighting the strategic significance of inventor allocation within organizations. This thesis reveals that individual personality traits impact organizations' inventive output. Therefore, these traits can be used in developing firm R&D strategies (Ployhart & Moliterno, 2011; Wang & Zatzick, 2019; Ray et al., 2021). The research further emphasizes the variable operation of human resources, contingent on their traits and the organizational knowledge context (Kristof, 1996; Zhou & Li, 2012; Arts & Fleming, 2018), necessitating context modification to optimize inventor performance (Witt et al., 2002; Morris et al., 2015). This underscores a deep interdependence between human, knowledge, and technological resources, with inventors playing a dual role as both resources and decision-makers in the use of knowledge components (Caner et al., 2017).

1.6.2 Harnessing knowledge recombination

The findings of this thesis can equip practitioners with a nuanced understanding of the knowledge recombination processes, which can be leveraged to enhance invention performance. Practitioners, particularly those leading R&D teams or innovation-focused departments, can consider these findings while strategizing knowledge recombination practices. This might involve placing a greater emphasis on aligning the cognitive traits of inventors with their roles and tasks (Arts & Veugelers, 2020) or more effectively structuring and sequencing knowledge components for recombination. For example, the assembly of related knowledge components could be strategized based on identified trajectories, enhancing the effectiveness of knowledge recombination. This approach emphasizes the value of strategizing the usage of knowledge components rather than focusing solely on their availability, potentially leading to better invention outputs and improved organizational performance.

1.6.3 Contextual Factors and Invention Performance

The context-specific nature of knowledge recombination processes is a key insight from this thesis that can significantly influence invention performance. This research underscores how knowledge interdependence can broadly shape the individual-level process of invention. While firms may wish to decrease component interdependence to enable easier modular combinations, these benefits may be short-term. In the long run, modular architectures may reduce more general or radical innovation, entailing long-term threats to firm strategy. Therefore, the findings in this thesis may guide practitioners, particularly those in managerial or strategic roles, in creating better long-term knowledge development strategies.

Additionally, strategies to optimize the interaction between individual and organizational characteristics could include fostering an environment that encourages open communication, collaboration, and knowledge sharing to fully leverage the cognitive traits of inventors. For example, a highly open inventor might be provided with a supportive environment that helps them navigate the complexity of recombining knowledge components rooted in different fields of technology. By doing so, organizations can nurture an environment that not only supports innovative endeavors but also enhances productivity and overall performance. The insights from this research can thus be instrumental in informing strategies to drive and sustain innovation in an organizational context.

1.7 Limitations

This thesis has several limitations to be addressed in future research.

1.7.1 Observational studies

A core limitation of this thesis lies in its entirely observational nature, as none of the papers conducts controlled randomized experiments to generate empirical findings. While a variety of controls, robustness checks, and post hoc analyses are employed to support the findings, they fundamentally remain observational. This makes the work highly exploratory, suited to large-scale observational data such as patent data, but less capable of providing causal explanations of observed phenomena. This limitation is not unique to this thesis, as many innovation management studies utilize patent data while taking a largely observational approach combined with extensive theorizing to examine mechanisms behind invention (Fleming, 2001; Verhoeven et al., 2016; Savino et al., 2017; Xiao et al., 2022).

1.7.2 Collaborative cognitive processes

Another limitation stems from the difficulty in fully accounting for the collaborative dynamics and cognitive processes inherent in invention. Inventions often result from team efforts, and dynamics within these teams can significantly influence the knowledge recombination process (Morgeson et al., 2005; Somech & Drach-Zahavy, 2013; Melero & Palomeras, 2015; Aggarwal & Woolley, 2019). Given the constraints of the survey design used in paper one, it was not possible to fully characterize the personality traits and search behavior of all co-inventors, potentially limiting the understanding of team-level knowledge recombination (Morgeson et al., 2005; Somech & Drach-Zahavy, 2013). Moreover, the cognitive processes that guide how knowledge components are used in recombination are not unpacked (Felin & Hesterly, 2007). This lack of insight into the endogenous cognitive processes within inventors' minds and the team-level aggregation of personality traits suggests the need for future work to explore these areas more deeply, potentially through more complex research designs and the integration of cognitive models from psychology.

1.7.3 Industry Specificity

Another set of limitations relates to the industry-specific nature of the studies—which all concern green technology. While paper one also touches upon mechanical and nanotechnology, the overall emphasis on green technology is apparent. As a result, the generalizability of the findings is limited when applied to other industries (e.g., Rosenkopf & Nerkar, 2001; Murmann, 2006; Persoon et al., 2020). Given that the mechanisms theorized herein are more general in nature, extrapolating the application of these mechanisms will require case-by-case consideration by researchers.

1.7.4 Assumptions about Knowledge Recombination with Patent Data

Additionally, I make strong assumptions about how knowledge components are recombined based on patent data (Arts et al., 2013). This includes the assumption that patent citations reflect knowledge flows that operate as the core mechanism of knowledge recombination, which might not always be accurate. For instance, Fleming and Sorenson (2001) devised a model of interdependence derived from evolutionary theory, utilizing patent data to identify interdependence relationships. They employ the co-occurrence of IPC codes to determine the ease with which patents can be recombined, subsequently calculating interdependence based on the inverse of these IPC codes' ease of recombination. Similarly, how I operationalize variables might not entirely align with the theoretical conceptualizations of my proposed mechanisms.

However, the value of patent data should not be underestimated. Beyond serving as a collection of inventions, patent data offers comprehensive access to vital information, capturing extensive and cross-comparable details of scientific and technological advancements that might remain obscured in other forms of data. The datasets available in patent repositories are both vast and meticulously curated, providing a remarkably complete, coherent, and comparable set of data. Moreover, this network structure of patent databases (in their citation data) makes them invaluable for tracing overarching trends in knowledge evolution, giving us insights into how inventions, domains, and technology industries have transformed, innovated, and interacted over time. The chronological nature of patent records can act as a roadmap, highlighting the lineage and progression of ideas and inventions—knowledge structures that have been essential for my research.

1.7.5 Future research

Developing empirical studies of knowledge recombination in a more robust fashion—that accommodates the complexities of interdependent social mechanisms and joint cognition amongst inventors—would benefit from a more refined underlying theory of knowledge recombination. At present, much of knowledge recombination implicitly relies on the existing theory of bounded rationality (Newell & Simon, 1972; Fleming, 2001; Puranam et al., 2015). However, bounded rationality continues to encounter theoretical limitations in explaining problem-solving (Gigerenzer, 2021).

To better explain invention's psychological mechanisms, future research could additionally address the observational-related limitation of the subject studies by adopting experimental methodologies, such as natural experiments (e.g., Arts & Fleming, 2018), to explicate more nuanced mechanisms and generate more rigorous findings.

Future research could address the limitation of focusing on sustainable technology. by considering a broader range of industries. To remedy the limitations inherent in the use of sustainable energy domains, future research may wish to rely more heavily on natural language processing to enable a more nuanced operationalization of technological distance and relatedness, novelty, and knowledge recombination dynamics.

1.8 Conclusion

New technological inventions are incredibly important to human progress and well-being, firm competitive advantage, and a significant source of long-term economic growth. In understanding the source of inventions, my three thesis papers address three separate levels of analysis but combine to address knowledge recombination mechanisms. These papers provide useful insights into knowledge recombination, including the role of personality traits as cognitive characteristics of inventors (thereby speaking to the "means" of recombinatory search) as well as the role of knowledge structures in trajectory and domains (thereby speaking to the search space or "ends" of recombinatory search). By understanding the sources and drivers of knowledge recombination performance, we can develop tools to improve our ability to invent new technology. Implications include considerations for human resource allocation for R&D and mechanisms to inform R&D strategy.

Chapter 2

Knowing me knowing you:

How personality traits shape invention

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ABSTRACT

Literature on knowledge recombination has focused on inventors' access to knowledge components to be recombined as a key determinant of their inventive performance. Research from psychology has shown that openness and extraversion, two personality traits, increase performance in tasks akin to knowledge recombination. We investigate how personality traits shape invention outcomes conditional on organizational knowledge context. We derive personality measures from a survey of 1,327 inventors and combine them with patent-based indicators of inventive performance. Our findings reveal how the relationship between personality and inventive output is moderated by knowledge context: the positive relationship between openness and invention output is stronger if organizational knowledge diversity is low. In contrast, extraversion negatively relates to invention output, but its effect is positively moderated by knowledge diversity.

2.1 Introduction

Technological inventions leading to innovations have long been recognized as drivers of organizations' value creation and competitive advantage (Schumpeter, 1934; Nelson & Winter, 1982). To create new technology, organizations depend on inventors who search for and recombine knowledge resources (Zwick et al., 2016). Thus, organizations seeking to optimize invention output must understand how inventor characteristics relate to inventive output and how these relationships vary depending on the inventors' organizational context (Eggers & Kaplan, 2013; Ployhart & Moliterno, 2011; Zahra, Neubaum & Hayton, 2020).

Despite the extensive literature on knowledge recombination, the relationship between inventors' individual personalities, the set of traits that reflect stable patterns of cognition and behavior, and their success in different organizational knowledge contexts remains underexplored. This is surprising given that certain personality traits, i.e., *openness* and *extraversion*[5], consistently predict creative achievement in laboratory experiments (Batey & Furnham, 2006; Feist, 1998; Feist, 2019).[6] As work environments often entail a helpful or harmful person-context fit that affects individual performance (Eggers & Kaplan, 2013; Felin, Foss & Ployhart, 2015), an overarching framework also needs to consider how the organizational context moderates the personality effects on invention performance.

We study how inventors' personalities shape their invention output in different organizational contexts using a behavioral strategy approach that

[5] Two constituents of the widely established Five-Factor Model (FFM) (Goldberg, & McReynolds, 1971; McCrae & Costa, 1997).

[6] Psychological research has found that personality affects general, artistic, and scientific creativity (e.g., Feist, 1998; Batey & Furnham, 2006; Sawyer, 2011; Kandler et al., 2016; Feist, 2019). It has, however, not been explored how these insights apply to the more structured task of technological invention in the context of corporate R&D. The few existing studies relating personality to invention output are based on a small sample of inventors or generally compare inventors to the broader population (e.g., Colangelo et al., 1992; Henderson, 2004; Sim et al., 2007; Mieg et al., 2012; Zwick et al., 2016). Conversely, large-scale studies on inventor characteristics and invention output focus on demographic characteristics such as skills, education, and experience (Gruber, Harhoff & Hoisl, 2013; Zwick et al., 2016)—but have not linked psychological measures of personality to performance indicators.

combines a strategic management perspective with insights from psychology (Powell, Lovallo & Fox 2011; Sibony, Lovallo & Powell, 2017). To theorize how personality relates to inventive performance in different contexts, we use the established framework of knowledge recombination (Xiao et al., 2022). We argue that openness mainly affects the type of knowledge elements available to inventors for recombination. Specifically, openness increases the number and diversity of knowledge components inventors search and consider for knowledge recombination (*what*). Extraversion mainly affects the efficiency of the recombination of available knowledge elements (*how*). Extraverts are characterized by higher sociability and confidence and are thus more likely to obtain contextual information that facilitates recombination.

To explore the moderating effect of organizational context, we focus on *organizational knowledge diversification (OKD)*, namely the degree to which the knowledge resources held by an organization are dispersed across different technological areas (Laursen & Salter, 2006; Nagle & Teodoridis, 2019). On one hand, OKD increases the number of potential combinations and accordingly the potential for invention. On the other hand, OKD complexifies the search space for inventors to explore. We argue that, because openness increases inventors' tendency for novel exploration and OKD increases search complexity, open inventors may be overburdened by disproportionate growth in search complexity. Thus, we hypothesize that OKD negatively moderates openness' effect on invention output. In contrast, extraverts' sociability facilitates obtaining additional information from social interaction, such as feedback and advice on which combinations are most promising or likely to fail. This information can guide extraverts through OKD's complexity to benefit from OKD's increased recombination potential. Thus, we hypothesize that OKD positively moderates extraversion's effect on invention output.

To test our hypotheses, we rely on a unique dataset from a large-scale survey of industrial inventors (Zwick et al., 2016). Our data contain responses from 1,327 inventors on their demographics, and organizational variables, including OKD and measures of FFM personality traits. Matching the survey data to the inventors' patenting histories at the European Patent Office (EPO) allows us to construct a dataset that includes measures of invention output. We operationalize invention output as the (job-tenure adjusted) number of patents an inventor filed.[7] Finally, we measure OKD as one minus the concentration of an organization's patent portfolio across different technology fields.[8]

In line with our hypotheses, we find that openness positively impacts invention output, and this impact is reduced with increasing OKD. Contrary to our hypotheses, extraversion negatively relates to invention output. However, extraversion's effect is context-dependent: Extraversion has a negative effect in low OKD contexts while a positive effect can be observed in high OKD contexts—the average effect is weakly negative. Our findings are confirmed by robustness checks such alternative estimation strategies, samples, and variable specifications.

Our study makes several contributions. First, we contribute to knowledge recombination literature by emphasizing personality as a neglected antecedent of inventive performance. Doing so, we emphasize how the individual-level process of invention is shaped by surrounding organizational characteristics in which knowledge-based processes take place (Eggers & Kaplan, 2013). Second, we contribute to the emerging stream of behavioral strategy in strategic management by theorizing how psychological characteristics, namely inventors' personality traits, determine invention output (e.g., Tandon & Toh, 2022). Third, we inform resource allocation literature (Coen & Maritan, 2011; Maritan & Lee, 2017) by focusing on a key resource driving an organization's invention output – human capital (Wang & Zatzick, 2019; Ray, Nyberg & Maltarich, 2021). Our results suggest that the human resource dimension of organizations' invention strategies should consider inventors' personality traits. Thus, our findings may influence organization-specific strategies with respect to innovation.

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[7] For patents with multiple inventors, we use a fractional count. E.g., if a patent had four inventors, it would count as 0.25 towards each inventor's invention output.
[8] We calculate the concentration of the patent portfolio using the Herfindahl-Hirschman Index.

2.2 Theoretical background

2.2.1 A behavioral approach

Innovation scholars have conceptualized invention as the successful search for new combinations of knowledge components (Fleming, 2001; Xiao et al., 2022), which include "any fundamental bits of knowledge or matter that inventors might use to build inventions" (Fleming & Sorenson, 2004: 910). At its core, knowledge recombination is a cognitive, individual-level phenomenon (Felin & Hesterly, 2007; Fleming, 2007) where inventors engage in an iterative, reflexive problem-solving process (Arthur, 2007; Arthur, 2009). In conceptualizing knowledge recombination, we follow existing work that linked the underlying cognitive process to a pair of scissors[9]: One blade represents the cognitive knowledge recombination capability of an inventor (i.e., *how* knowledge recombination takes place) while the other blade represents the knowledge resources available to an inventor (i.e., *what* knowledge components are searched and recombined) (Newell & Simon, 1972; Puranam et al., 2015). Inventors use these two blades to explore the combinatorial space resulting from the possible combinations of available knowledge components and are successful if they discover novel recombination which fulfills a specific purpose (Arthur, 2007).

Behavioral strategy research focuses on individual-level psychological differences, such as different biases in individuals' decision-making processes, to explain heterogeneity in individual performance (Kahneman & Lovallo, 1993; Lovallo & Sibony, 2018; Powell et al., 2011).[10] Similarly, individual-level characteristics reflect differences in the use of cognitive resources, namely individuals' knowledge, experience, intelligence, skills,

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[9] "Human rational behavior (and the rational behavior of all physical symbol systems) is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990, p. 7).

[10] For example, individual-level psychological concepts have been used to inform research on organization-level decision processes (Lovallo & Sibony, 2018; Felin, Foss & Ployhart, 2015) biases in capital allocation (Bardolet, Fox & Lovallo, 2011).

competence, and attention (Li et al., 2013; Helfat & Peteraf, 2015) and thus individual cognitive differences, such as differences in motivation, can explain differences in knowledge recombination performance (Sauermann & Cohen 2010; Arts & Veugelers, 2020)

2.2.2 Openness, extraversion, and inventive output

Personality regards patterns of behavior, cognition, and emotional affect that are highly stable throughout a lifetime (Roberts, 2009; Roberts & DelVecchio, 2000; Cobb-Clark & Schurer, 2012). Psychologists have clustered and decomposed these patterns into well-defined personality traits (John & Srivastava, 1999). These traits reflect tendencies not being captured by externally mutable measures, such as level of education or experience, and must be measured using psychometric testing (Soto & John, 2019). While vigorous debates have addressed the number of dimensions that constitute personality,[11] the most prevalent—both in terms of use and empirical support—is undoubtedly the Five-Factor Model (FFM) and its variant, the "Big Five" model (John, Naumann & Soto, 2008). The FFM consists of the traits openness, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae & Costa, 1997). It has found widespread use across psychology and related fields, including management and economics (Ployhart & Moliterno, 2011; Kerr, Kerr & Xu, 2018). As FFM studies have found that extraversion and openness strongly predict cognitive creativity in various contexts (Batey & Furnham, 2006; Furnham et al., 2008; Feist, 2019), we focus on these two traits in our theoretical development.[12]

[11] Standardized measures of personality traits are the result of a century of rigorous econometric analysis of thousands of behavioral covariates and a multitude of varying psychometric inventories (Allport & Allport, 1921; Goldberg & McReynolds, 1971; McCrae & Costa, 1997; John & Srivastava, 1999; Feist, 2019).
[12] We account for the other personality traits by adding them as controls to our regression analyses.

2.2.3 Hypothesis one: openness

Openness refers to "individual differences in the tendency to be open to new aesthetic, cultural, or intellectual experiences" (APA Dictionary, 2020). Open individuals tend to be curious, inquisitive, and imaginative (McCrae, 1987). They prefer novelty, broad interests, and depth and originality in their mental and intellectual life (Batey & Furnham, 2006; Nusbaum & Silvia, 2011). Thus, openness denotes a combination of *curiosity*, a *preference for novel experience*, and *imaginativeness* (Connelly, Ones & Chernyshenko, 2014; Silvia & Christensen, 2020; Ng et al., 2021).

Given these characteristics, we argue that openness primarily benefits the "*what*" of knowledge recombination, or the blade of the cognitive scissors that represents knowledge resources available for recombination.[13] As open inventors are more curious—with a preference for novelty—they are more likely to search across a variety of novel knowledge sources to consider more novel components (Heinström, 2003; Heinström, 2010; Kaufman et al., 2016). Moreover, open inventors are imaginative and more likely to "explore abstractly […] altering current categories and reconceptualizing or renovelizing" (DeYoung, Peterson & Higgins, 2002, p. 536). Thus, open inventors are likely to consider more novel components and new ways of using them and, how to conceptualize components more abstractly—all of which increase their recombination potential. Therefore, we argue that openness predicts increased invention output. Taken together, we formulate,

Hypothesis 1: An inventor's degree of openness is positively related to invention output.

[13] We acknowledge that both openness and extraversion will affect both blades of knowledge recombination. However, we believe that these effects will be asymmetric, such that openness *primarily* affects the "what" and extraversion *primarily* affects the "how" of knowledge recombination.

2.2.4 Hypothesis two: extraversion

Extraversion is characterized by "an orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience" (APA Dictionary, 2020). Extraversion thus reflects a tendency to be sociable, confident, dominant, expressive, and communicative (Lucas et al., 2000; Furnham et al., 2008). Extraverts tend to enjoy stimulating social activities, be leader-oriented in group settings, have a large network, and have distinctive social skills (McCrae & Costa 1997). At its core, extraversion denotes a combination of *sociability* and *confidence* (Lucas et al., 2000).

Given these characteristics, we argue that extraversion primarily benefits the "*how*" of knowledge recombination, meaning the blade of the cognitive scissors that represents the combination ability of the inventor. As extraverted inventors are more sociable, they are more likely to talk to others, share problems, ask for feedback, and receive support to filter and evaluate available knowledge (Lucas et al., 2000; Witt et al., 2002). Findings from behavioral strategy suggest that social discourse can improve risk assessment and mitigate cognitive biases (Kahneman, Lovallo & Sibony, 2011; Sibony, Lovallo & Powell, 2017). As the confidence and interest to engage in social conversations may enable better access to experts' knowledge (Schmickl & Kieser, 2008) and tacit problem-solving skills (Von Hippel, 1994), extraverts may foster distributed problem-solving processing among colleagues and lead to higher productivity (Dunbar, 1995; Cross & Cummings, 2004). Thus, extraverts' social tendencies may boost their problem-solving ability.

Moreover, recent research has shown that the extent to which an organization's internal networks are connected and centralized can affect recombination processes (Eklund, 2022). Extraverts tend to create extensive social networks (Paruchuri & Awate, 2017; Aggarwal & Woolley, 2019). Whereas inventors' socialization and reliance on their networks reflects an important part of inventors' human capital (Ray et al., 2021), ability to receive and transfer advice (Brennecke & Rank, 2017), and creative performance (Fleming, Mingo & Chen, 2007; Deichmann & Jensen, 2018; Kauppila, Bizzi & Obstfeld, 2018), extraverts' expanded social networks are likely to increase access to advice and feedback. Due to improved sociability, where social feedback helps to direct inventors' attention towards approaches that are more likely to yield inventions, extraverts benefit from improved ability in *how* to use knowledge components available. In summary, we formulate,

Hypothesis 2: An inventor's degree of extraversion is positively related to invention output.

2.2.5 The moderating role of organizational knowledge

There are many mechanisms and environmental factors across many levels of analysis that affect knowledge recombination (Savino et al., 2017; Xiao et al., 2022). Of these many mechanisms, some will interact across levels. In particular, differences in traits of openness and extraversion at the individual cognitive level of analysis may entail different interaction effects with their knowledge context at the organizational level of analysis and in different ways. However, the way openness affects inventors' knowledge recombination will differ from the way extraversion affects inventors' interaction with their knowledge contexts.

Differences in organizational knowledge contexts can entail a beneficial, neutral, or problematic person-organization fit for an inventor (Eklund, 2022; Schillebeeckx et al., 2021; Zahra et al., 2020; Ployhart & Moliterno, 2011; Sibony, Lovallo & Powell, 2017; Tandon & Toh, 2022), especially depending on individuals' psychological characteristics (Kristof, 1996; Judge & Zapata, 2015; Hennessey & Amabile, 2010; Kandler et al., 2016). Where organizations differ in the quantity and diversity of their knowledge components (Miller, 2006; Melero & Palomeras, 2015; Paruchuri & Awate, 2017; Teodoridis, Bikard, & Vakili, 2019), OKD is the degree to which an organization's knowledge components are evenly distributed across many different technological domains, as opposed to being concentrated within a few similar domains (Trajtenberg, Henderson, & Jaffe, 1997). Existing literature provides evidence that OKD has opposing effects on invention output (Lettl, Rost & Von Wartburg, 2009; Kaplan & Vakili, 2015). As knowledge diversity is a well-established driver of invention output (Carnabuci & Operti, 2013, Miller, 2006; Leiponen & Helfat, 2010; Kim et al., 2013; Nagle & Teodoridis, 2019; Anderson et al., 2014), we focus on OKD to explore organizational context effects with respect to openness and extraversion.

On the one hand, OKD can increase the complexity and cost of knowledge recombination and harm productivity (Carnabuci & Operti, 2013; Kim et al., 2013; Kaplan & Vakili, 2015; Caner, Cohen & Pil, 2017). The integration of diverse knowledge components in functioning recombinations typically requires a basic understanding of technology fields, some of which are likely to be unfamiliar to a focal inventor (Teodoridis et al., 2019; Ehls, Polier & Herstatt, 2020). Increasing the diversity of an organization's knowledge context will increase the number of unfamiliar technology fields and overwhelm inventors as a result (Ehls et al., 2020; Caner et al., 2017). To make use of knowledge components from unfamiliar fields, inventors need support from peers within or beyond their organization.

On the other hand, the diversity of available knowledge components increases the potential to identify new recombinations leading to invention output (Miller, 2006; Boh, Evaristo & Ouderkirk, 2014; Nagle & Teodoridis, 2019; Savino et al., 2017). As Cohen and Levinthal (1990, p. 130) emphasize, "knowledge diversity […] facilitates the innovative process by enabling the individual to make novel associations and linkages." Ceteris paribus, OKD increases invention output by surrounding inventors with a greater variety of knowledge components, many of which may be distant from the inventors' knowledge resource base (Miller, Fern, & Cardinal, 2007; Lettl et al., 2009; Zhou & Li, 2012; Schillebeeckx et al., 2021). By disrupting existing assumptions and conceptualizations, OKD promotes invention approaches and recombination opportunities (Carnabuci & Operti, 2013; Karim & Kaul, 2015; Nagle & Teodoridis, 2019).

Thus, OKD can both increase the potential of *what* can be recombined and the complexity of *how* knowledge components are recombined. Depending on organization-person fit, OKD may benefit or harm knowledge recombination performance. We argue that OKD's effect on invention output depends on the personality traits of the inventors and thus moderates the baseline effects specified in Hypothesis 1 and Hypothesis 2 above.

2.2.6 Moderating openness

We contend that the availability of highly diverse knowledge components can create difficulties for open inventors. As mentioned above, OKD entails increased component novelty and potential for novel combinations. As open inventors are curious and more likely to search for novel knowledge components (Batey & Furnham, 2006; Heinström, 2003; Heinström, 2010; Sawyer, 2011; Feist, 2019), they are more likely to excessively explore the more distant and novel knowledge entailed by OKD (Connelly et al., 2014; Silvia & Christensen, 2020; Ng et al., 2021).

However, excess exploration of OKD's increased combinatorial potential may overwhelm inventors. The combined effect of both high OKD and high openness may exponentially increase the complexity of recombination (Lettl et al., 2009; Carnabuci & Operti, 2013; Kaplan & Vakili, 2015). Whereas inventors' efficiency in knowledge recombination suffers if recombination complexity exceeds an inventor's cognitive capacity (Fleming & Sorenson, 2001; Laursen & Salter, 2006; Caner et al., 2017), OKD may reduce open inventors' output despite (or rather, because of) increases in available knowledge. Because OKD increases exploration potential, open inventors' knowledge recombination increases in complexity which, *ceteris paribus,* lowers invention output. While openness and OKD affect the novelty and diversity of available knowledge components for recombination, we hypothesize their interaction to be negative. Hence, we propose,

Hypothesis 3: Organizational knowledge diversity negatively moderates the relationship between inventor openness and invention output.

2.2.7 Moderating extraversion

Contrary to openness, extraversion increases an inventor's ability to resolve the greater complexity that arises with OKD rather than being overwhelmed by it, and thereby realize the potential offered by OKD. While

OKD increases the potential for knowledge recombination, it also entails complexity problems. Carnabuci & Operti (2013) show that in highly diverse environments, "cognitive barriers […] make it more difficult for inventors to understand each other and solve problems together, particularly when knowledge is complex and sticky" (Carnabuci & Operti 2013, p.1596). Problem-solving ability becomes particularly important in organizations characterized by high knowledge diversity.

Indeed, communication with peer inventors can help to overcome the challenges of recombining more complex, context-specific organizational knowledge (Morris, Zhong & Makhija, 2015; Paruchuri & Awate, 2017). Extraverted inventors' sociability fosters communication, feedback, distributed problem-solving, and support from a variety of others who possess expert and tacit knowledge. We argue such benefits help inventors filter out poor ideas and guide them towards effective ones. Thus, extraverted inventors are uniquely suited to resolve complexities associated with knowledge diversity. By mitigating the complexity associated with OKD, extraversion helps inventors realize the additional potential provided by OKD. We hypothesize that OKD positively moderates the relationship between extraversion and invention output.

Hypothesis 4: Organizational knowledge diversity positively moderates the relationship between inventor extraversion and invention output.

2.3 Methods

2.3.1 Empirical context and data sources

Given our interest in corporate R&D, we rely on observational data that contain information on corporate inventors' characteristics, invention output, and organizational environments. To obtain these data, we conducted a targeted online survey of German industrial inventions and extracted these inventors' patent records from the European Patent Office's (EPO) research database, PATSTAT. Separately searching archival data in patent databases yields a measurement of invention output that is not based on self-assessment but rather stems from the patent system, which uses strict guidelines for classifying and assessing inventions seeking patent protection. Since the dependent and independent variables were obtained from different data sources, this approach avoids a common method bias.

For our survey, we targeted inventors who have at least one patent in clean technology, nanotechnology, or mechanical engineering. These technology fields have a high propensity to patent, allowing us to derive valid proxies for invention output from patent data. To identify these inventors, we extracted patent applications in clean technology, nanotechnology, and 35% of mechanical engineering.[14] We then selected those patents listing at least one inventor with a home address in Germany and a filing (priority) date between 2004 and 2008.

Our survey collected information on these inventors' personality traits, demographics, and their use and search of knowledge sources in the inventive process. In our survey, we also collected information on inventors' employers at the time of patent filing. This information enabled us to create a measure of OKD (Trajtenberg et al., 1997), patenting output, and the types of applicants' organization(s). We received responses from 1,932 inventors with 1,327 complete questionnaires.

To measure invention output, we gathered these inventors' patent applications filed between 1978 and 2010, as well as a variety of control variables common to studies on invention output, including bibliographic and procedural information on filing dates, technology classes, forward and backward citations, and the number of co-inventors (Savino et al., 2017; Xiao et al., 2022). Our regression analyses are based on the responses of 1,327 inventors for whom every variable was measured, who were listed 16,485 EP patent applications between 1978 and 2010.

[14] For budgetary reasons, we randomly selected 35% of the pool of mechanical engineering patents.

2.3.2 Dependent variable

Invention output – Following existing literature, we operationalize invention output as the number of patents filed by the focal inventor during the observational period (Fleming, 2001; Conti, Gambardella & Mariani, 2014; Dahlander et al., 2016). To account for the fact that most patents list multiple inventors, we use fractional patent counts, i.e., the sum of patents filed by an inventor divided by the average number of inventors listed on these patents.[15] We acknowledge that not all inventions are patented. However, given that we chose technology fields characterized by a high propensity to patent, the number of patents filed is a valid proxy for the number of inventions (Griliches, 2007).

2.3.3 Independent variables

Personality traits – To measure inventor personality, we rely on a personality inventory based on a 15-item short version of the FFM personality inventory used in the German Socio-Economic Panel, SOEP (Gerlitz & Schupp, 2005). Each of the five personality traits is represented by three items (see Appendix A.6). The items reflect a 7-point Likert scale with values between 1 "does not apply" and 7 "completely applies".[16] To measure each personality trait, we follow Gerlitz & Schupp (2005) and use a composite index equaling the average of the three-item scores per trait. The openness items have an average interitem correlation of 0.83, while the extraversion items have an average interitem correlation of 0.91.

Organizational knowledge diversification – OKD measures how concentrated an organization's patenting activities are across different technology fields. For this purpose, we first classify all patent applications filed by an

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[15] Where $\boldsymbol{O_i}$ is invention output of inventor $\boldsymbol{i}$ who has $\boldsymbol{n}$ patents, and $\boldsymbol{X}$ is the number of inventors on patent $\boldsymbol{p}$ of those $\boldsymbol{n}$ patents, $$O_i = \sum_{p=1}^{n} \frac{1}{X_p}$$

[16] For example, one item for extraversion presented to inventors reads "I am someone who is communicative and talkative" while an item to measure openness reads "I am someone who is original and brings new ideas."

organization into 34 different technology fields based on the international patent classification concordance (IPC-class) proposed by Schmoch (2008). In a second step, we calculate *OKD* as one minus the Herfindahl-Hirschman Index (HHI) of concentration of an organization's patent applications across these 34 areas (Trajtenberg et al., 1997; Hall, Jaffe & Trajtenberg, 2001). The measure is calculated on an annual basis and considers all patent applications filed in the focal and the four preceding years (*t* to *t-4*) as

$$OKD = 1 - HHI_t = 1 - \sum_{j=1}^{34} \left(\frac{patent\ applications\ in\ area\ j\ in\ years\ t\ to\ (t-4)}{patent\ applications\ in\ years\ t\ to\ (t-4)} \right)^2.$$

(1-HHI_t) is bound between 0 and 1, and higher values indicate higher knowledge diversification.[17] As the resulting measure at the organization level is time-varying, we construct a variable to capture *OKD* throughout the inventive history of an inventor. For this purpose, we match each patent of each inventor to the corresponding organization-level HHI measure at the time of that patent's filing. Then, for each inventor, we calculate the weighted average HHI of all patents belonging to that inventor. This calculation captures organization and year differences in knowledge diversity to produce an inventor-level measure of *OKD*.[18]

We additionally report regression models which include *OKD* as an explanatory variable. Moreover, we also split the sample and report results for organizations characterized by a low *OKD* (below-median level) and organizations characterized by high *OKD* (above-median level).

[17] We chose a time window of five years to reflect the fact that inventors are more likely to access recent knowledge residing in an organization. Our main findings are robust towards changes in the time window considered.

[18] For example, let us assume that an inventor files a total of 5 patents. 3 patents originate from her inventive activities in years y_1, y_2, and y_3 at organization A and 2 patents from his inventive activities in the years y_4 and y_5 at organization B. The OKD of organization A in y_1 is OKD_{A1}, in y_2 OKD_{A2}, and in y_3 OKD_{A3}. The OKD of organization B in y_4 is OKD_{B4}, in y_5 OKD_{B5}. Therefore, the OKD of this inventor is calculated as (OKD_{A1} + OKD_{A2} + OKD_{A3}+ OKD_{B4} + OKD_{B5})/5.

2.3.4 Control variables

Education – As the level of formal education correlates with improvements in general cognitive ability and accumulated knowledge (Ritchie, Bates & Deary, 2015), inventors with higher educational attainment may produce more inventions. The respondents were asked for their highest attained educational qualification. We create three dummy variables to reflect if the inventor obtained: 1) vocational education; 2) a diploma, bachelor's, or master's degree[19]; and 3) a PhD or doctoral degree.

Age, tenure, and mobility – We used inventors' birth years from our survey to compute an inventor's age when filing each patent. We then use the inventors' age at filing each patent to calculate the average age of an inventor at the time of patent filing. We use this average age to control for age-related effects on invention output.[20] Further, inventor experience in terms of tenure might be an important determinant of invention output. Our analyses include indicator variables reflecting inventors' labor market entry cohort (1960-1969, 1970-1979, 1980-1989, and 1990-1999, with 2000 or later as a reference group) to capture their overall work experience at the time of the survey. Finally, we include a dummy variable indicating whether an inventor changed employers at least once during his or her career.

Size of the organization – To control for the size of an inventor's organization, we use the size of the organization's patent portfolio as a proxy. We aggregate the number of patent applications filed by an organization over the inventor's entire career (i.e., we calculate the number of patent applications produced by organization *j* while associated with inventor *i*).[21] We assign the number of patents per organization to five categories: 1 patent

[19] This category is used as the reference group in regression analyses.

[20] Where a given inventor's average age of filing is the average of that inventor's ages on the dates that they filed each patent in their portfolio. The mean filing age of the sample is the average filing age across all inventors. Differences in the time available to each inventor are controlled through our sample window of four years.

[21] In the rare case that an inventor changed their employer, we calculate the average applicant size weighted by the number of patents filed while employed at a given firm.

(= reference group), 2-24 patents, 25-249 patents, 250-999 patents, and 1,000 or more patents. We then calculate the mode overall patents.

A large organization additionally confers two distinct advantages: Firstly, it embodies a more comprehensive pool and range of knowledge, thereby enhancing the opportunities for knowledge recombination. Secondly, a larger cadre of inventors inherently heightens the dissemination and discourse surrounding an invention, which consequentially elevates its tendency to be widely discussed, generating greater awareness about an invention, and driving up its impact.

Technology fields and firm indicators – We include technology dummies to account for whether the inventors in the sample were originally classified as clean technology, nanotechnology, or mechanical engineering inventors. Moreover, we include indicator variables to control for unobserved firm-level effects.

2.3.5 Analytical approach

In our multivariate analyses, we model invention output as the count of the number of patent applications (fractional counts) filed by a given inventor. Thus, we rely on count-data regression models. A model of the *number of patents* Pat_i filed by inventor *i* assumes that the observed counts follow a Poisson distribution with parameter λ_i (Cameron & Trivedi, 2001)[22]:

$$Pat_i|\lambda_i \sim Poisson(\lambda_i)$$

[22] While the negative binomial model is more flexible and allows for overdispersion in the dependent variable, it is more sensitive toward violations of the underlying distribution assumptions. The Poisson model, on the other hand, does not allow for overdispersion but is robust towards violations of the distributional assumptions. For this reason, we have chosen a Poisson specification. Note that we find comparable results when using a negative binomial model instead (see Table A.3 in the Appendix).

where in the Poisson model λ_i is the expected value and the variance of the number of patents filed by a given inventor. For the expected count, we consider specifications of the form.

$$\lambda_i = E(Pat_i|X_i) = \exp{(X_i\beta)},$$

where X_i is a vector of regressors describing the characteristics of inventor *i* and their employer, while β is a vector of regression coefficients.

To account for the fact that patents are often based on team inventions, we adapt the Poisson model to model fractional patent counts. As highlighted above, an inventor's fractional patent count is obtained by dividing the inventor's total number of patents Pat_i filed by the average number of co-inventors on these patents ($coinventors_i$). A straightforward approach is to include the log of $coinventors_i$ as offset in the Poisson regression. Doing so allows us to directly measure the effect of our explanatory variables in the regression on the fractional patent count without further adjustments. If the expected *fractional patent count* is given by $\tilde{\lambda}_i * 1/co - inventors_i$, where $\tilde{\lambda}_i$ is the expected value of the total number of patents filed by an inventor. Given the specification in (2), this reasoning yields a specification that can readily estimate invention output:

$$\frac{\tilde{\lambda}_i}{coinventors_i} = \tilde{\lambda}_i * \exp(-\,log(coinventors_i)) = \exp{(X_i\beta - \log(coinventors_i))}.$$

Compared to alternative specifications, such as a simple linear regression framework, this modeling approach better captures the skewed distribution and the non-negativity of patent counts. As a result, it avoids an underestimation of the standard errors of the coefficient estimates and yields more robust inferences (Cameron & Trivedi, 2001).

In the absence of a (quasi-)experimental variation, we cannot rule out that some of our explanatory variables are endogenous to invention output. It is important to stress, however, that personality has been shown to be stable over time (Roberts & DelVecchio, 2000; Cobb-Clark & Schurer, 2012;

Specht, Egloff & Schmukle, 2011). As a result, our variables of interest (openness and extraversion) can be expected to be independent of invention output. While inventors of different productivity levels might self-select (sort) in organizations that systematically differ in their level of knowledge diversification, which would render invention output to be endogenous to OKD, it is unclear whether more productive inventors would prefer to work in high OKD or low OKD environments, reducing the potential for endogeneity.[23] To alleviate this concern, we have included firm fixed effects, to capture the effect of unobserved firm characteristics which might drive potential selection.[24]

2.4 Results

2.4.1 Descriptive statistics

The descriptive statistics of our dependent and independent variables are summarized in Table 1. On average, an inventor in our sample has filed 3.6 fractional patents during their career. In our sample, 54.2% have a university degree as the highest educational qualification (which is used as the reference group), and another 37.2% have completed a PhD.[25] Only 8.6% reported an apprenticeship (vocational training) as their highest educational qualification. Holding a PhD is weakly positively correlated with the number of patents created whereas vocational training is weakly negatively correlated. The average job tenure is 19.6 years, and the average inventor age at the time of patent filing is 42.5 years old.[26] The pairwise correlations between openness

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[23] We can reproduce key findings on the main effects also in regression specifications, excluding the OKD variable. This is a further indication that our results are not prone to endogeneity bias arising from the inclusion of the OKD variable.

[24] The literature that analyses hiring processes through the lenses of formal matching models has developed estimation approaches to tackle the endogeneity problem resulting from sorting.

[25] To note, education is a categorical variable that uses "a diploma, bachelor's, or master's degree" as a reference group, and so has no linear dimension upon which to calculate the standard deviation. Only the mean is calculable. Therefore, the standard deviation of education does not appear in our descriptive statistics.

[26] The correlation between job tenure and age is large (0.78). Our regression specifications include age as a continuous variable but split tenure in different cohorts using dummy variables to alleviate potential

and the fractional patent count are positive (corr=0.161, $p<0.01$), though small. Similarly, extraversion is positively correlated with the number of patents, albeit the correlation is even smaller in absolute terms (corr=0.016, $p=0.10$).

problems from multicollinearity. In unreported robustness tests, we have estimated alternative specifications, including only age or job tenure. The results regarding the key variables remain unchanged.

Paper 1, Table 1: Summary statistics and correlations of key variables

	Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Invention output	13.45	11.87	1												
(2)	Invention output	3.57	5.11	0.87	1											
(3)	Openness	4.96	1.04	0.13	0.16	1										
(4)	Extraversion	4.35	1.14	0.03	0.07	0.31	1									
(5)	Neuroticism	3.43	1.13	0.02	0.01	-0.04	-0.21	1								
(6)	Agreeableness	5.06	0.98	-0.07	-0.06	0.08	0.02	-0.20	1							
(7)	Conscientiousness	5.54	0.93	-0.02	-0.01	0.00	0.05	-0.11	0.15	1						
(8)	Organizational knowledge diversity (OKD)	0.72	0.17	0.03	-0.01	-0.03	0.01	0.00	-0.03	-0.05	1					
(9)	Number of co-inventors	3.77	1.87	0.01	-0.20	-0.07	0.02	0.03	0.06	0.01	0.11	1				
(10)	Vocational education (0/1)	0.09	-	-0.03	-0.02	0.02	0.08	-0.04	0.01	0.04	-0.04	-0.05	1			
(11)	PhD education (0/1)	0.37	-	0.08	0.01	0.05	-0.01	-0.06	0.04	0.04	0.15	0.10	-0.24	1		
(12)	Tenure	19.61	8.83	0.12	0.13	0.10	-0.03	0.04	-0.03	0.06	0.00	-0.05	0.19	-0.14	1	
(13)	Age	42.44	9.07	0.03	0.06	0.12	-0.05	0.03	0.02	0.02	0.02	-0.02	0.07	0.08	0.77	1

Notes: Based on 1,327 inventors, "Invention output" reflects patents filed, adjusted for shared credit among listed inventors. "Personality traits" come from the 15-item FFM SOEP inventory. "Organizational knowledge diversification (OKD)" gauges patent activity variety across tech fields, factoring in the current and previous four years. "Education" uses dummy variables for highest qualification and is a categorical variable that uses “a diploma, bachelor’s, or master’s degree” as a reference group. "Age, Tenure, and Mobility" report average age at patent time and entry cohort. The "Size of the Organization" considers patents across an inventor's career. "Technology fields and firm indicators" classify inventors by tech domain and firm influences. The table's diagonal shows correlation coefficients with themselves (=1), with off-diagonals showing variable pairwise correlations. In Table 2, we report the average number of patents filed by inventors in our sample (fractional counts).

Paper 1, Table 2: Average invention output (fractional patent count).

	Openness		Extraversion	
	Invention output	n	Invention output	n
All	3.57	1,327	3.57	1,327
Trait: Low	2.76	578	3.60	600
Trait: High	4.19	749	3.54	727
OKD: Low	3.88	664	3.88	664
Trait: Low	2.93	287	4.28	303
Trait: High	4.60	377	3.54	361
OKD: High	3.26	663	3.26	663
Trait: Low	2.59	291	2.91	297
Trait: High	3.79	372	3.55	366

Notes: Table 2 shows inventors' average invention outputs using fractional patent counts, categorized by openness, extraversion, and organizational knowledge diversity (OKD). Inventors are grouped based on the median of these variables. High openness inventors outpace low openness peers in patent outputs. Extraversion does not show significant output differences. Notably, all inventors have higher outputs in low OKD settings, but high openness inventors excel most in these environments. Low extraversion inventors vary more with OKD, while high extraversion inventors remain consistent.

In line with our first hypothesis, high openness inventors (with scores above the median) filed more patents than low openness inventors (with scores below the median) (4.19 vs. 2.76 fractional patents; p=0.00).[27] Contrary to our second hypothesis, the bi-variate cross-tabulation does not show a meaningful difference between the number of patents filed by high and low extraversion inventors (above and below the median extraversion score) (3.54 vs. 3.60 fractional patents, p=0.825).

In the lower part of Table 2, we report comparisons for a split-sample of inventors working in organizations with either high (diverse) or low (focused)

[27] Note, t-test statistics are not reported in Table 2 to keep Table 2 concise.

OKD (above and below the median OKD). The split sample reveals that inventors are, on average, more productive if OKD is low than if OKD is high (3.88 vs. 3.26 fractional patents, p=0.034). This finding is in line with those reported by Carnabuci & Operti (2013), who argue that high OKD hinders the ability of inventors to identify and reuse well-known combinations (Carnabuci & Operti, 2013).

However, the split sample suggests that heterogeneity may be hidden within these aggregate results. First, high openness inventors in high OKD environments are associated with reduced invention output; conversely, high openness inventors are more productive if OKD is low (4.60 vs. 3.79 fractional patents; p=0.060). For low openness inventors, the effect of OKD seems to disappear (2.93 vs. 2.59 fractional patents; p=0.264). This shift in the moderation effect suggests that OKD negatively moderates the effect of openness on invention output, but only for inventors high in openness.

Second, we also observe a negative effect of OKD on the relationship between extraversion and invention output. High extraversion inventors are unaffected by high OKD compared to low OKD (3.54 vs. 3.55 fractional patents, p=0.979). In contrast, low extraversion inventors are far less productive if OKD is high than if OKD is low (4.28 vs. 2.91 fractional patents, p=0.001). In the following section, we will scrutinize whether these patterns hold in a multivariate analysis that controls for other determinants of invention output.

2.4.2 Main results

The results of our regression analyses are reported in Table 3. All estimations include a comprehensive set of controls, including the number of co-inventors listed on a patent, indicators of inventors' highest educational qualification, age, as well as dummies for tenure, size of the organization, and technical field.[28] We do not report the coefficients of these control dummies but restrict ourselves to a discussion of the most important insights.

In Column (1) of Table 3, we report the results from a regression specification testing only the main effects of our key independent variables, openness, and extraversion. Our results provide strong support for Hypothesis 1, as openness is positively ($p<0.01$) related to invention output. One standard deviation increase in openness increases invention output by 21.7% ((e^0.1885-1) *1.044=0.217). Contrary to Hypothesis 2, however, extraversion is negatively related to invention output ($p<0.01$). Yet, the effect is comparably smaller: A one standard deviation increase in extraversion reduces invention output by only 2.43% ((e^-0.0216-1) *1.135=-0.0243). Our control variables mostly have the expected effects. As pointed out in existing literature, OKD is negatively related to invention output ($p<0.01$) (Carnabuci & Operti, 2013). Also, as expected, inventors holding a PhD have higher invention output ($p<0.01$) and produce an average of 43.0% (e^0.3577-1= 0.344) more patents than other inventors.

To test the moderating effect of OKD, we first split our sample into two subsets (Columns 2 and 3 of Table 3) and then subsequently interacted the openness and extraversion variables with OKD (Columns 4 to 6 of Table 3). In the split sample, one subset contains organizations with below-median OKD (low OKD, column 2); the other subset contains organizations with above-median OKD (high OKD, column 3).

Splitting the sample reveals that the positive relationship between openness and invention output is less pronounced in organizations characterized by high OKD than in those characterized by low OKD. This supports our third hypothesis and points to OKD's negative moderation on the relationship between openness and invention output. The split sample further reveals that the pooled sample masks a differential effect in the negative association between extraversion and invention output. In organizations characterized by low OKD, extraversion reduces invention output, with a one standard deviation increase in extraversion reducing

[28] As an offset in the Poisson regression.

output by -7.3% ((e^-0.0666-1) *1.135=-0.0731, $p<0.01$). However, in organizations with high OKD, extraversion increases invention output by 1.92% ((e^0.0168-1) *1.135=0.0192, $p<0.01$). Thus, extraversion is beneficial in organizations with high OKD but detrimental if OKD is low, which is in line with our expectations underlying Hypothesis 4.

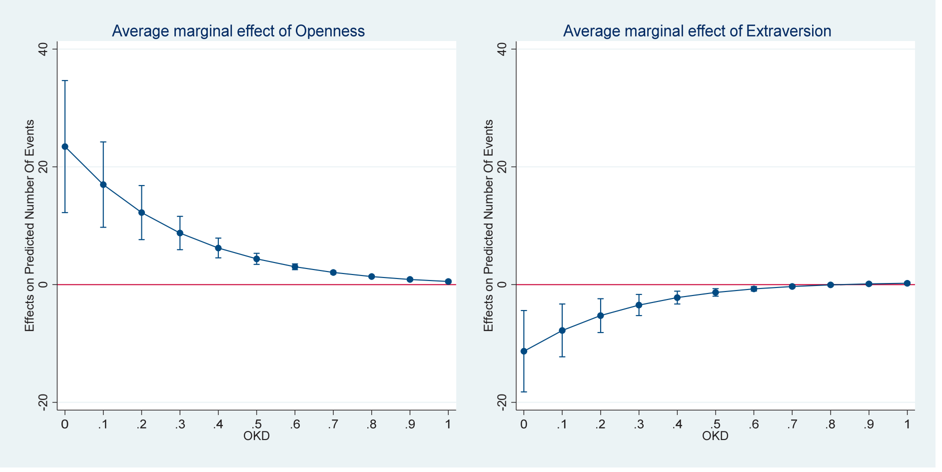
For contrast, we present pooled-sample interaction models in columns 4 to 6 of Table 3. Columns 4 and 5 present results from models interacting openness with OKD and extraversion with OKD independently. Column 6 reports findings from the fully interacted model. The results of the fully interacted model are consistent with the findings from the split sample models. Openness is positively related to invention output (0.3953, $p<0.01$), while extraversion is negatively related to invention output (-0.2044, $p<0.01$). The interaction effects reveal that OKD negatively moderates openness's effect on invention output (-0.2802, $p<0.01$) but positively moderates extraversion's effect (0.2521, $p<0.01$). Figure 1 provides the corresponding plot of the marginal effects of openness (left part of Figure 1) and extraversion (right part of Figure 1) on the expected number of fractional patents filed for different values of OKD.

Paper 1, Table 3: Coefficient estimates from a Poisson regression modelling.

Invention output	(1)	(2)	(3)	(4)	(5)	(6)
		OKD				
	pooled	low	high		interacted	
Openness	0.189***	0.199***	0.147***	0.336***	0.187***	0.395***
	[0.012]	[0.020]	[0.016]	[0.055]	[0.012]	[0.057]
Openness * OKD				-0.197**		-0.280***
				[0.072]		[0.075]
Extraversion	-0.022	-0.066***	0.017	-0.0207	-0.149**	-0.204***
	[0.011]	[0.017]	[0.016]	[0.011]	[0.049]	[0.051]
Extraversion*OKD					0.174**	0.252
					[0.065]	[0.068]
OKD	-2.324***			-1.371**	-3.053***	-2.025***
	[0.238]			[0.422]	[0.361]	[0.456]
Neuroticism	-0.025*	-0.057**	-0.020	-0.027*	-0.026*	-0.029**
	[0.011]	[0.018]	[0.014]	[0.011]	[0.011]	[0.011]
Agreeableness	-0.074***	-0.072***	-0.077***	-0.072***	-0.077***	-0.076***
	[0.012]	[0.020]	[0.018]	[0.012]	[0.012]	[0.012]
Conscientiousness	-0.072***	-0.086***	-0.036	-0.072***	-0.071***	-0.071***
	[0.014]	[0.023]	[0.018]	[0.014]	[0.014]	[0.014]
Voc. Education	-0.056	0.035	-0.291***	-0.057	-0.062	-0.066
	[0.0492]	[0.0746]	[0.0702]	[0.0493]	[0.0493]	[0.0495]
PhD	0.358***	0.383***	0.285***	0.360***	0.356***	0.359***
	[0.0295]	[0.0486]	[0.0393]	[0.0295]	[0.0295]	[0.0295]
Age	-0.013***	-0.003	-0.012***	-0.013***	-0.013***	-0.013***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
Mobility	-0.248***	-0.229***	-0.285***	-0.252***	-0.250***	-0.256***
	[0.024]	[0.040]	[0.033]	[0.025]	[0.024]	[0.025]
Applicant size	Yes	Yes	Yes	Yes	Yes	Yes
Labor market entry	Yes	Yes	Yes	Yes	Yes	Yes
Technology fields	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,327	664	663	1,327	1,327	1,327

Notes: Table 3 examines how openness and extraversion affect invention output, moderated by Organizational Knowledge Diversity (OKD). Outputs are percentage-based; traits use a z-standardized 1-5 Likert scale. Using a two-stage regression accounting for industry, year, and firm specifics, we found that increased openness enhances invention output by 21.7%, but similar growth in extraversion reduces it by 2.43%. High OKD diminishes openness's positive impact but boosts extraversion's effect by 1.92%. Conversely, in low OKD settings, extraversion reduces output by 7.3%. We suggest caution in interpretation due to potential trait-output overlaps. Vocational education and PhD reflect dummy variables using the reference group diploma, bachelor, or master's degree. Standard errors included in upper square brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Paper 1, Figure 1: Marginal effects.



Notes: Openness' (left panel) and extraversion's (right panel) marginal effects at the mean on the expected invention output (fractional patent counts) filed by an inventor for different values of OKD.

2.4.3 Robustness tests

We conducted various robustness tests to ensure that our results were not driven by our model choice. We provide results from these tests in the Appendix of the paper. In Tables A.2 and A.3 in the Appendix, we report the results from regression models with alternative specifications to the Poisson models used to produce our main results. First, we conduct linear (OLS) regressions (Table A.2) using the same set of independent variables and the log of invention output as the dependent variable. Second, we conduct negative binomial regressions (Table A.3) with the same independent and dependent variables used in our main results. As in our main Poisson specification, we include the log of the average number of co-inventors as an offset in these negative binomial regressions. The results from the linear and negative binomial regressions are consistent with our main findings reported in Table 3. The estimated coefficients for the independent variables are comparable in magnitude, though the interaction effects are estimated less precisely. Finally, while OKD has been computed using the five-year period (*t to t-4*), Table A.4 reports results from a Poisson regression, including a measure of OKD, which has been computed using only a three-year period (*t to t-3*). Again, our results are comparable to the main results reported in Table 3.

2.5 Discussion and conclusion

We study how inventors' personalities shape their invention output conditional on their organizational knowledge context. Specifically, we link established personality traits to invention output in different organizational settings to understand how openness and extraversion shape invention output while considering differences in OKD. Within the established knowledge recombination framework, we differentiate the two blades of bounded rationality – *what* and *how* (Puranam et al., 2015; Ehls et al., 2020). We argue that these two blades function differently for open inventors due to their attraction to novelty and for extraverted inventors due to sociability (Dunbar, 1995; Kauppila et al., 2018). Openness seems to relate more to internal cognition ("what") and extraversion to behavior ("how") (Zillig, Hemenover & Dienstbier, 2002).

We test the predictions derived from this theoretical framework using a unique dataset on 1,327 industrial inventors combining survey evidence and patent information. We show that personality traits openness and extraversion are important individual characteristics that affect decision processes and that are moderated by inventors' organizational knowledge contexts. While we hypothesized that openness and extraversion are positively associated with invention output, our regressions uncover a more nuanced pattern. Openness is positively associated with invention output, while extraversion is negatively related to invention output. These diverging effects may be explained through differences in how extraversion and openness affect knowledge recombination through individuals' behavior and cognition. As invention, i.e., knowledge recombination, is a cognitive task, it is not surprising that our regressions highlight a clear and positive relationship between openness and invention output.

Extraversion, however, requires an organization that is characterized by high OKD to realize its full potential.[29] The interaction between extraversion and OKD appears to be more nuanced than that of openness and OKD. Whereas openness may aid knowledge recombination by promoting more exploratory use of and search for knowledge components, thereafter, being negatively moderated by OKD, extraversion may itself have little benefit for knowledge recombination but only serve to attenuate the negative effects of high OKD. In other words, OKD may moderate openness and extraversion may moderate OKD, or some combination thereof. These mechanisms may be explored and parsed in future research.

Our study contributes to several literature areas. First, our findings contribute to knowledge recombination literature while re-emphasizing the cognitive, individual-level nature of invention (Felin & Hesterly, 2007; Fleming, 2007; Ployhart & Moliterno, 2011). Knowledge components do not recombine in a vacuum: It is necessary to consider the interaction of individual and organizational characteristics in which knowledge-based processes take place (Eggers & Kaplan, 2013; Zahra et al., 2020). Whereas innovation management literature has focused on individual-level determinants of recombination outputs, such as knowledge sourcing (Dahlander et al., 2016; Laursen & Salter, 2006), socio-demographic factors (Gruber et al., 2013), experience (Conti et al., 2014), or individual-level knowledge diversification (Nagle & Teodoridis, 2019), we introduce personality traits of inventors as an underexplored determinant of invention output. In doing so, we contribute to the small but growing collection of

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[29] Since extraversion is related to the "*how*" of knowledge recombination, we also tested to what extent the novelty of inventions made is related to an inventor's extraversion. In the results of Table A.5 in the Appendix, we model the share of radical inventions relative to all patents filed by an inventor (Conti et al., 2014) as a function of the set of variables used in the regressions reported in Table 3. For this purpose, we rely on the approach of Verhoeven, Bakker, and Veugelers (2016), as well as Arts and Veugelers (2014). For each patent application, we determine the extent to which the invention recombines knowledge components from different technological domains in a way that did not exist before (radical invention) and compute the share of radical inventions relative to all patents filed by an inventor. These regressions reveal a positive association of extraversion with the share of radical inventions patented by an inventor.

studies that examine individual differences in inventor output (Gruber et al., 2013; Zwick et al., 2016; Tandon & Toh, 2022). This contribution provides a more comprehensive picture of the determinants of knowledge recombination and observed heterogeneity in invention output.

Second, our study speaks to behavioral strategy literature (Powell et al., 2011). Behavioral strategy literature breaks down individual decision-making in terms of their framing and salience dimensions (Lovallo & Sibony, 2018). Some knowledge may be more relevant to individuals with certain cognitive characteristics in certain contexts. This relationship between cognitive characteristics and context changes the way knowledge is used (Helfat & Peteraf, 2015; Judge & Zapata, 2015). Whereas personality traits reflect stable patterns in behavior and cognition across an individual's lifetime, demonstrating the relationship between these traits and strategically-value firm resources, namely technological inventions, contributes to behavioral strategy.

Finally, our study generates implications for the emerging literature on the allocation of human, knowledge, and technological resources (Coen & Maritan, 2011; Maritan & Lee, 2017). Our results highlight that highly open inventors might be overwhelmed by the complexity of recombining knowledge components rooted in different fields of technology. Extraverts, on the other hand, benefit from additional information which directs their inventive efforts. The available knowledge resources of an organization are used differently depending on human resource characteristics, such as psychological characteristics that modulate how those knowledge resources will be used, recombined, or developed (Felin, Tomsik & Zenger, 2008; Brennecke & Rank, 2017). Moreover, human resources can function differently depending on their characteristics and within their specific organizational knowledge context (Kristof, 1996; Witt et al., 2002; Zhou & Li, 2012). By altering the knowledge available (context) for inventors, their performance can be altered (Witt et al., 2002; Morris et al., 2015). Thus, these results suggest that human, knowledge, and technological resources may be deeply interdependent: Inventors themselves are human resources but also decision-makers who choose how to use available knowledge components (Caner et al., 2017).

Our study has several limitations to be addressed in future research. Most importantly, inventions are the results of a collaborative effort between co-inventors. Many of the knowledge recombination mechanisms identified in research result from team composition and the aggregate behavioral dynamics within teams (Morgeson, Reider & Campion, 2005; Somech & Drach-Zahavy, 2013; Melero & Palomeras, 2015; Aggarwal & Woolley, 2019) including those dynamics that result from the team-level aggregation of personality traits (Morgeson et al., 2005). The survey design has not allowed us to characterize the personality traits and search behavior of the entire set of co-inventors.

Existing literature has also identified a relationship (albeit weak) between personality and an individual's network position, which might have an additional effect on invention output (Fleming et al., 2007; Paruchuri & Awate, 2017). We cannot observe the structure of an inventor's social network and the exact positioning of an inventor in their network. To deal with this limitation, we control for the number of co-inventors of the underlying inventors as this variable should be correlated with important characteristics of the inventor's social (professional) network. Future work that aims to link personality and invention performance will have to overcome this data collection challenge by engaging in a more complex research design that surveys not only the focal inventor on a patent, but also their entire network of co-inventors (Schmickl & Kieser, 2008; Schillebeeckx et al., 2021).

Despite its limitations, our study entails important managerial implications for corporate R&D. Our findings highlight that personality traits should be included in human resources acquisition strategies and allocation strategies (Tzabbar, 2009; Sim et al., 2007; Wang & Zatzick, 2019). The direct effect of personality on invention outputs indicates that human resources should emphasize the personality traits of an inventor not only at the time of hiring but also when assigning inventors to specific projects.

APPENDIX TO PAPER 1: ADDITIONAL TABLES

Paper 1, Table A.1: Coefficient estimates from a Poisson regression.

	(1)	(2)	(3)	(4)	(5)	(6)
		OKD				
Number of patents **Independent Variables**	pooled	low	high		interacted	
Openness	0.189***	0.199***	0.147***	0.336***	0.187***	0.395***
	[0.012]	[0.020]	[0.016]	[0.055]	[0.012]	[0.057]
Openness * OKD				-0.197**		-0.282***
				[0.072]		[0.075]
Extraversion	-0.022	-0.067***	0.017	-0.021	-0.149**	-0.204***
	[0.011]	[0.017]	[0.016]	[0.011]	[0.049]	[0.051]
Extraversion*OKD					0.174***	0.252***
					[0.065]	[0.068]
Control variables						
OKD	-2.324***			-1.371***	-3.053***	-2.025***
	[0.238]			[0.422]	[0.361]	[0.456]
Neuroticism	-0.025*	-0.057**	-0.020	-0.027*	-0.026*	-0.029**
	[0.011]	[0.018]	[0.014]	[0.011]	[0.011]	[0.011]
Agreeableness	-0.074***	-0.072***	-0.077***	-0.072***	-0.077***	-0.076***
	[0.012]	[0.020]	[0.018]	[0.012]	[0.012]	[0.012]
Conscientiousness	-0.072***	-0.086***	-0.037	-0.072***	-0.071	-0.071
	[0.014]	[0.027]	[0.018]	[0.014]	[0.014]	[0.014]
Voc. education	-0.056	0.035	-0.291***	-0.057	-0.062	-0.066
	[0.049]	[0.075]	[0.070]	[0.049]	[0.049]	[0.050]
PhD	0.358***	0.383***	0.285***	0.360***	0.356***	0.359***
	[0.030]	[0.049]	[0.039]	[0.030]	[0.030]	[0.030]
Age	-0.013***	-0.003	-0.012	-0.012***	-0.013***	-0.013***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
Mobility	-0.248***	-0.229***	-0.285***	-0.252***	-0.250***	-0.256***
	[0.024]	[0.040]	[0.033]	[0.025]	[0.024]	[0.025]
1 < Appl. size < 25	0.382	1.119	-0.018	0.424	0.333	0.372
	[0.506]	[0.809]	[0.714]	[0.506]	[0.507]	[0.507]
24 < Appl. Size < 250	-0.324	1.369	-0.992	-0.268	-0.364	-0.301
	[0.491]	[0.803]	[0.672]	[0.491]	[0.492]	[0.492]
249 < Appl. Size < 1000	0.309	1.587	-0.326	0.360	0.254	0.302
	[0.492]	[0.815]	[0.668]	[0.492]	[0.493]	[0.493]
Appl. Size > 999	0.189	1.163	-0.040	0.242	0.132	0.182
	[0.484]	[0.799]	[0.654]	[0.484]	[0.485]	[0.485]
1969 < Labour market entry < 1980	0.069	0.425***	-0.231	0.0733	0.0638	0.0672
	[0.075]	[0.118]	[0.102]	[0.075]	[0.075]	[0.075]
1979 < Labour market entry < 1990	-0.004	0.141	-0.111	0.012	-0.014	0.003

	[0.078]	[0.123]	[0.105]	[0.078]	[0.078]	[0.078]
1989 < Labour market entry < 2000	-0.307***	-0.1302	-0.368**	-0.289***	-0.322***	-0.303***
	[0.085]	[0.138]	[0.115]	[0.086]	[0.086]	[0.086]
Labour market entry > 1999	-0.937***	-0.656***	-1.052***	-0.921***	-0.947***	-0.929***
	[0.098]	[0.159]	[0.131]	[0.098]	[0.098]	[0.098]
Cleantech	0.021	0.016	0.036	0.021	0.026	0.028
	[0.040]	[0.068]	[0.054]	[0.040]	[0.040]	[0.040]
Mechanical engineering	-0.141**	0.151	-0.284***	-0.139**	-0.139**	-0.135**
	[0.048]	[0.089]	[0.061]	[0.048]	[0.048]	[0.048]
Constant	2.459*	0.759	0.911	1.712	3.048***	2.250
	[1.149]	[1.001]	[1.228]	[1.181]	[1.170]	[1.190]
Observations	1,327	664	663	1,327	1,327	1,327

Notes: This table reflects the same variable operationalizations as Paper 1, table 3. These estimates model the determinants of invention output (fractional patent count). Standard errors included in square brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Paper 1, Table A.2: Coefficient estimates from a log-linear regression.

Log (Number of patents)	(1) pooled	(2) OKD low	(3) OKD high	(4) interacted	(5) interacted	(6) interacted
Independent Variables						
Openness	0.100***	0.122**	0.082**	0.126	0.097***	0.211
	[0.024]	[0.043]	[0.032]	[0.113]	[0.024]	[0.118]
Openness * OKD				-0.035		-0.151
				[0.147]		[0.154]
Extraversion	-0.028	-0.106**	0.028	-0.0283	-0.244	-0.275
	[0.024]	[0.038]	[0.032]	[0.024]	[0.100]	[0.105]
Extraversion*OKD					0.292*	0.335*
					[0.132]	[0.139]
Control variables						
OKD	-1.228**			-1.064	-2.478***	-1.956*
	[0.474]			[0.833]	[0.736]	[0.909]
Neuroticism	-0.029	-0.067	-0.014	-0.029	-0.031	-0.032
	[0.022]	[0.038]	[0.029]	[0.022]	[0.022]	[0.022]
Agreeableness	-0.041	-0.048	-0.041	-0.041	-0.047	-0.047
	[0.0260]	[0.0434]	[0.0347]	[0.0260]	[0.0260]	[0.0260]
Conscientiousness	-0.012	-0.028	0.008	-0.012	-0.011	-0.010
	[0.027]	[0.047]	[0.035]	[0.027]	[0.027]	[0.027]
Voc. education (yes=1)	-0.033	-0.046	-0.144	-0.034	-0.034	-0.037
	[0.099]	[0.154]	[0.137]	[0.099]	[0.099]	[0.099]
PhD (yes=1)	0.232***	0.196	0.240**	0.232***	0.228***	0.229***
	[0.062]	[0.106]	[0.080]	[0.062]	[0.061]	[0.061]
Age	-0.014**	-0.006	-0.016**	-0.014**	-0.014**	-0.014**
	[0.005]	[0.009]	[0.006]	[0.005]	[0.005]	[0.005]
Mobility	-0.141**	-0.197*	-0.106	-0.141**	-0.145**	-0.147**
	[0.052]	[0.089]	[0.068]	[0.052]	[0.052]	[0.052]
1 < Appl. size < 25	-0.370	-0.579	0.006	-0.363	-0.462	-0.445
	[0.914]	[1.406]	[1.285]	[0.915]	[0.913]	[0.913]
24 < Appl. Size < 250	-0.516	-0.122	-0.384	-0.507	-0.601	-0.576
	[0.901]	[1.426]	[1.244]	[0.903]	[0.900]	[0.900]
249 < Appl. Size < 1000	-0.386	-0.363	-0.273	-0.378	-0.489	-0.468
	[0.905]	[1.441]	[1.237]	[0.906]	[0.904]	[0.904]
Appl. Size > 999	-0.473	-0.722	-0.118	-0.465	-0.573	-0.553
	[0.886]	[1.411]	[1.202]	[0.888]	[0.885]	[0.886]
1969 < Labour market entry < 1980	0.020	0.436	-0.221	0.021	0.029	0.031
	[0.159]	[0.279]	[0.202]	[0.159]	[0.159]	[0.159]
1979 < Labour market entry < 1990	-0.003	0.229	-0.147	-0.002	0.002	0.009
	[0.166]	[0.282]	[0.214]	[0.166]	[0.165]	[0.165]
1989 < Labour market entry < 2000	-0.306	-0.010	-0.465*	-0.304	-0.305	-0.297

	[0.181]	[0.316]	[0.233]	[0.182]	[0.181]	[0.181]
Labour market entry > 1999	-0.708***	-0.324	-0.883***	-0.706***	-0.700***	-0.693***
	[0.202]	[0.352]	[0.260]	[0.202]	[0.201]	[0.202]
Cleantech	0.061	0.158	0.021	0.061	0.066	0.067
	[0.086]	[0.164]	[0.108]	[0.086]	[0.086]	[0.086]
Mechanical engineering	0.140	0.286	0.076	0.141	0.143	0.147
	[0.098]	[0.197]	[0.121]	[0.099]	[0.098]	[0.098]
Constant	2.746*	2.983	1.260	2.618*	3.770***	3.367**
	[1.267]	[1.790]	[1.493]	[1.377]	[1.346]	[1.408]
Observations	1,327	664	663	1,327	1,327	1,327

Notes: This table employs the same variable operationalizations as previous results tables. previous tables. However, these estimates model the determinants of the invention output in a log-linear dependent variable of the fractional patent count. Standard errors included in square brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Table A.3: Coefficient estimates from a negative binomial regression.

	(1)	(2)	(3)	(4)	(5)	(6)
		OKD				
Number of patents	pooled	low	high	interacted		
Independent Variables						
Openness	0.168***	0.197***	0.139***	0.307*	0.164***	0.367**
	[0.028]	[0.044]	[0.039]	[0.135]	[0.028]	[0.139]
Openness * OKD				-0.184		-0.268
				[0.174]		[0.180]
Extraversion	-0.035	-0.136***	0.025	-0.033	-0.215	-0.256*
	[0.027]	[0.038]	[0.037]	[0.027]	[0.117]	[0.120]
Extraversion*OKD					0.244	0.302*
					[0.153]	[0.158]
Control variables						
OKD	-1.752**			-0.893	-2.765**	-1.7502
	[0.557]			[0.987]	[0.847]	[1.084]
Neuroticism	-0.037	-0.099*	-0.014	-0.038	-0.040	-0.042
	[0.026]	[0.040]	[0.035]	[0.026]	[0.026]	[0.026]
Agreeableness	-0.098***	-0.121**	-0.091*	-0.097***	-0.103***	-0.103***
	[0.031]	[0.046]	[0.043]	[0.031]	[0.031]	[0.031]
Conscientiousness	-0.030	-0.054	0.010	-0.028	-0.029	-0.026
	[0.032]	[0.048]	[0.043]	[0.032]	[0.032]	[0.032]
Voc. education	0.022	0.082	-0.184	0.017	0.021	0.015
	[0.114]	[0.154]	[0.170]	[0.114]	[0.114]	[0.114]
PhD	0.344***	0.269*	0.361***	0.343***	0.342***	0.340***
	[0.073]	[0.112]	[0.100]	[0.073]	[0.073]	[0.073]
Age	-0.018***	-0.007	-0.020***	-0.018***	-0.018***	-0.018***
	[0.006]	[0.009]	[0.007]	[0.006]	[0.006]	[0.006]
Mobility	-0.170***	-0.222*	-0.149	-0.171***	-0.171***	-0.174***
	[0.060]	[0.091]	[0.082]	[0.060]	[0.060]	[0.060]
1 < Appl. size < 25	0.091	0.502	0.275	0.115	0.027	0.047
	[1.162]	[1.581]	[1.661]	[1.162]	[1.162]	[1.162]
24 < Appl. Size < 250	-0.122	1.203	-0.420	-0.095	-0.184	-0.160
	[1.152]	[1.602]	[1.616]	[1.152]	[1.152]	[1.152]
249 < Appl. Size < 1000	0.300	1.034	0.017	0.323	0.220	0.233
	[1.157]	[1.623]	[1.612]	[1.158]	[1.158]	[1.158]
Appl. Size > 999	-0.037	-0.099*	-0.014	-0.038	-0.040	-0.042
	[0.026]	[0.040]	[0.035]	[0.026]	[0.026]	[0.026]
1969 < Labour market entry < 1980	-0.098***	-0.121**	-0.091*	-0.097***	-0.103***	-0.103***
	[0.031]	[0.046]	[0.043]	[0.031]	[0.031]	[0.031]
1979 < Labour market entry < 1990	-0.030	-0.054	0.010	-0.028	-0.029	-0.026
	[0.032]	[0.048]	[0.043]	[0.032]	[0.032]	[0.032]

1989 < Labour market entry < 2000	0.022	0.082	-0.184	0.017	0.021	0.015
	[0.114]	[0.154]	[0.170]	[0.114]	[0.114]	[0.114]
Labour market entry > 1999	0.344***	0.269*	0.361***	0.343***	0.342***	0.340***
	[0.073]	[0.112]	[0.100]	[0.073]	[0.073]	[0.073]
Cleantech	-0.018***	-0.007	-0.020***	-0.018***	-0.018***	-0.018***
	[0.006]	[0.009]	[0.007]	[0.006]	[0.006]	[0.006]
Mechanical engineering	-0.170***	-0.222*	-0.149	-0.171***	-0.171***	-0.174***
	[0.060]	[0.091]	[0.082]	[0.060]	[0.060]	[0.060]
Dispersion	0.091	0.502	0.275	0.115	0.027	0.047
	[1.162]	[1.581]	[1.661]	[1.162]	[1.162]	[1.162]
Constant	-0.122	1.203	-0.420	-0.095	-0.184	-0.160
	[1.152]	[1.602]	[1.616]	[1.152]	[1.152]	[1.152]
Observations	1,327	664	663	1,327	1,327	1,327

Notes: These estimates model the determinants of the invention output (fractional patent count) using a negative binomial regression. Standard errors included in square brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Paper 1, Table A.4: Coefficient estimates from a Poisson regression.

	(1)	(2)	(3)	(4)	(5)	(6)
		OKD				
Number of patents	pooled	low	high		interacted	
Independent Variables						
Openness	0.188***	0.178***	0.149***	0.286***	0.186***	0.347***
	[0.012]	[0.019]	[0.016]	[0.053]	[0.012]	[0.056]
Openness * OKD				-0.133		-0.218**
				[0.070]		[0.073]
Extraversion	-0.023*	-0.061***	0.0148	-0.0220	-0.154**	-0.199***
	[0.011]	[0.017]	[0.016]	[0.011]	[0.048]	[0.050]
Extraversion*OKD					0.181**	0.245***
					[0.064]	[0.067]
Control variables						
OKD (3 years)	-1.731***			-1.078**	-2.492***	-1.692***
	[0.213]			[0.403]	[0.342]	[0.436]
Neuroticism	-0.026***	-0.011	-0.068***	-0.027**	-0.028***	-0.030***
	[0.011]	[0.017]	[0.014]	[0.011]	[0.011]	[0.011]
Agreeableness	-0.076***	-0.084***	-0.055***	-0.075***	-0.080***	-0.079***
	[0.012]	[0.020]	[0.017]	[0.012]	[0.012]	[0.012]
Conscientiousness	-0.071***	-0.046**	-0.067***	-0.071***	-0.069***	-0.069***
	[0.014]	[0.023]	[0.018]	[0.014]	[0.014]	[0.014]
Voc. education (yes=1)	-0.058	0.013	-0.287***	-0.059	-0.064	-0.068
	[0.049]	[0.076]	[0.072]	[0.049]	[0.049]	[0.049]
PhD (yes=1)	0.354***	0.464***	0.227***	0.356***	0.351***	0.353***
	[0.030]	[0.050]	[0.039]	[0.030]	[0.030]	[0.030]
Age	-0.012***	-0.002	-0.012***	-0.012***	-0.012***	-0.013***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]
Mobility (at least one in career=1)	-0.245***	-0.240***	-0.244***	-0.247***	-0.247***	-0.251***
	[0.024]	[0.040]	[0.033]	[0.024]	[0.024]	[0.025]
1 < Appl. size < 25	0.225	2.194**	0.391	0.276	0.152	0.210
	[0.501]	[0.801]	[0.699]	[0.502]	[0.502]	[0.504]
24 < Appl. Size < 250	-0.026***	-0.011	-0.068***	-0.027**	-0.028***	-0.030***
	[0.011]	[0.017]	[0.014]	[0.011]	[0.011]	[0.011]
249 < Appl. Size < 1000	-0.076***	-0.084***	-0.055***	-0.075***	-0.080***	-0.079***
	[0.012]	[0.020]	[0.017]	[0.012]	[0.012]	[0.012]
Appl. Size > 999	-0.071***	-0.046**	-0.067***	-0.071***	-0.069***	-0.069***
	[0.014]	[0.023]	[0.018]	[0.014]	[0.014]	[0.014]
1969 < Labour market entry < 1980	-0.058	0.013	-0.287***	-0.059	-0.064	-0.068
	[0.049]	[0.076]	[0.072]	[0.049]	[0.049]	[0.049]
1979 < Labour market entry < 1990	0.354***	0.464***	0.227***	0.356***	0.351***	0.353***
	[0.030]	[0.050]	[0.039]	[0.030]	[0.030]	[0.030]
1989 < Labour market entry < 2000	-0.012***	-0.002	-0.012***	-0.012***	-0.012***	-0.013***
	[0.002]	[0.004]	[0.003]	[0.002]	[0.002]	[0.002]

Labour market entry > 1999	-0.245***	-0.240***	-0.244***	-0.247***	-0.247***	-0.251***
	[0.024]	[0.040]	[0.033]	[0.024]	[0.024]	[0.025]
Cleantech	0.225	2.194**	0.391	0.276	0.152	0.210
	[0.501]	[0.801]	[0.699]	[0.502]	[0.502]	[0.504]
Mechanical engineering	-0.026***	-0.011	-0.068***	-0.027**	-0.028***	-0.030***
	[0.011]	[0.017]	[0.014]	[0.011]	[0.011]	[0.011]
Constant	-0.076***	-0.084***	-0.055***	-0.075***	-0.080***	-0.079***
	[0.012]	[0.020]	[0.017]	[0.012]	[0.012]	[0.012]
Observations	1,327	664	663	1,327	1,327	1,327

Notes: These estimates model the determinants of invention output (fractional patent count) as the dependent variable using a Poisson regression. Standard errors included in square brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Paper 1, Table A.5: Coefficient estimates from a Poisson regression

	(1)	(2)	(3)	(4)	(5)	(6)
		OKD				
Share of radical patents		low	high		interacted	
Independent Variables						
Openness	0.018	0.001	0.005	-0.173	0.017	-0.156
	[0.035]	[0.064]	[0.046]	[0.171]	[0.035]	[0.178]
Openness * OKD				0.250		0.228
				[0.220]		[0.230]
Extraversion	0.099*	0.079	0.156***	0.098**	0.008	0.050
	[0.031]	[0.051]	[0.043]	[0.031]	[0.145]	[0.151]
Extraversion*OKD					0.122	0.065
					[0.190]	[0.198]
Control variables						
OKD	0.083			-1.160	-0.429	-1.324
	[0.676]			[1.284]	[1.044]	[1.376]
Neuroticism	0.032	0.041	0.027	0.034	0.030	0.033
	[0.031]	[0.053]	[0.042]	[0.032]	[0.032]	[0.032]
Agreeableness	-0.034	0.037	-0.045	-0.036	-0.037	-0.038
	[0.037]	[0.064]	[0.050]	[0.037]	[0.037]	[0.037]
Conscientiousness	0.014	-0.176	0.051	0.014	0.015	0.014
	[0.038]	[0.068]	[0.050]	[0.038]	[0.038]	[0.038]
Voc. Education (yes=1)	-0.090	-0.221	-0.108	-0.079	-0.087	-0.078
	[0.134]	[0.223]	[0.191]	[0.134]	[0.134]	[0.134]
PhD (yes=1)	0.047	0.340*	-0.085	0.051	0.049	0.052
	[0.086]	[0.154]	[0.111]	[0.086]	[0.086]	[0.086]
Age	-0.005	-0.016	-0.004	-0.005	-0.006	-0.005
	[0.007]	[0.012]	[0.008]	[0.007]	[0.007]	[0.007]
Mobility	-0.064	-0.233	-0.020	-0.062	-0.065	-0.063
	[0.071]	[0.126]	[0.095]	[0.071]	[0.071]	[0.071]
Average team size	0.053	0.112	-0.052	0.050	0.053	0.050
	[0.107]	[0.198]	[0.138]	[0.107]	[0.107]	[0.107]
1 < Appl. Size < 25	-3.094*	-12.367***	-0.915	-3.090	-3.112*	-3.100*
	[1.530]	[3.230]	[1.962]	[1.533]	[1.532]	[1.534]
24 < Appl. Size < 250	-2.295	-8.993**	-0.937	-2.278	-2.304	-2.284
	[1.416]	[2.907]	[1.862]	[1.420]	[1.418]	[1.421]
249 < Appl. Size < 1000	-1.790	-9.286*	-0.307	-1.780	-1.808	-1.791
	[1.429]	[3.012]	[1.844]	[1.433]	[1.431]	[1.434]
Appl. Size > 999	-2.374	-9.620	-0.645	-2.379	-2.397	-2.391
	[1.403]	[2.935]	[1.812]	[1.406]	[1.405]	[1.407]
1969 < Labour market entry < 1980	0.242	-0.114	0.456	0.238	0.244	0.240
	[0.217]	[0.395]	[0.274]	[0.216]	[0.217]	[0.216]
1979 < Labour market entry < 1990	0.104	0.014	0.187	0.090	0.100	0.089
	[0.225]	[0.402]	[0.285]	[0.225]	[0.225]	[0.225]

1989 < Labour market entry < 2000	0.035	0.039	-0.001	0.023	0.029	0.021
	[0.246]	[0.447]	[0.312]	[0.246]	[0.246]	[0.246]
Labour market entry > 1999	-0.145	-0.309	-0.144	-0.147	-0.147	-0.148
	[0.286]	[0.517]	[0.367]	[0.286]	[0.286]	[0.286]
Cleantech	-0.110	0.186	-0.203	-0.110	-0.108	-0.109
	[0.099]	[0.192]	[0.125]	[0.099]	[0.099]	[0.099]
Mechanical engineering	-0.043	0.204	-0.098	-0.047	-0.042	-0.046
	[0.128]	[0.290]	[0.159]	[0.129]	[0.128]	[0.129]
Constant	1.287	11.054*	-0.313	2.177	1.689	2.313
	[1.940]	[3.415]	[2.242]	[2.095]	[2.040]	[2.136]
Observations	1,327	664	663	1,327	1,327	1,327

Notes: In these estimates, we change the dependent variable of inventive output to the share of radical inventions and use a Poisson regression. Standard errors included in square brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Paper 1, Figure A.2 - 15-item short version of the FFM personality inventory

G 1 Our **everyday actions** are influenced by our **core beliefs**. In science, however, there is still very little knowledge about this. Therefore, the following section contains **questions on various characteristics** a person can have. Some questions will pertain more or less to you, and for some question you may be undecided.

		Strongly disagree						Strongly agree
	I am someone who...	**1**	**2**	**3**	**4**	**5**	**6**	**7**
a)	works thoroughly	□1	□2	□3	□4	□5	□6	□7
b)	is communicative and talkative	□1	□2	□3	□4	□5	□6	□7
c)	sometimes is a little rough, harsh to others	□1	□2	□3	□4	□5	□6	□7
d)	is original and brings new ideas	□1	□2	□3	□4	□5	□6	□7
e)	worries often	□1	□2	□3	□4	□5	□6	□7
f)	can forgive	□1	□2	□3	□4	□5	□6	□7
g)	is rather lazy	□1	□2	□3	□4	□5	□6	□7
h)	is outgoing and social	□1	□2	□3	□4	□5	□6	□7
i)	appreciates artistic experience	□1	□2	□3	□4	□5	□6	□7
j)	easily gets nervous	□1	□2	□3	□4	□5	□6	□7
k)	performs tasks effectively and efficiently	□1	□2	□3	□4	□5	□6	□7
l)	is reserved	□1	□2	□3	□4	□5	□6	□7
m)	interacts friendly and considerate with others	□1	□2	□3	□4	□5	□6	□7
n)	has a vivid imagination	□1	□2	□3	□4	□5	□6	□7
o)	is relaxed and is good at dealing with stress	□1	□2	□3	□4	□5	□6	□7

Chapter 3

As Good as New:

Trajectory integration affects technological impact

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ABSTRACT

In this study, we link theory on knowledge recombination and technological trajectories to develop a dimension of knowledge recombination we term trajectory integration. We explain how sequential knowledge components in a trajectory can be integrated to generate technological impact. Using data from the European Patent Office's PATSTAT database, we show that trajectory integration has a strong positive relationship with technological impact. Additionally, we find that trajectory integration positively moderates a well-known knowledge characteristic, technological distance, by helping distant knowledge to flow forward through the trajectory and into the focal knowledge domain. Taken together, the findings contribute to and link knowledge recombination and technological trajectories literature.

3.1 Introduction

Impactful inventions, i.e., inventions that form the basis of significant future technological development, are a major source of economic value and competitive advantage for firms (Porter, 1985; Ahuja & Lampert, 2001). Invention occurs through knowledge recombination, meaning an inventor's search for and combination of knowledge components[30] (Fleming, 2001; Xiao et al., 2022). Indeed, the impact of an invention is associated with what and how components are combined (Capaldo et al., 2017). Components are both static, i.e., time-stable (Nemet & Johnson, 2012; Phene, Fladmoe-Lindquist & Marsh, 2006), and dynamic, i.e., time-varying, or time-dependent (Nerkar, 2003; Kok et al., 2019), in nature. How these characteristics evolve shape a component's technological trajectory, i.e., the direction of progress and advance (Dosi, 1982; Huenteler et al., 2016) to which an invention belongs. In this paper, we introduce the concept of *trajectory integration* – the degree to which an invention recombines components from along the same technological trajectory – and examine its effect on invention impact.

Knowledge components' dynamic characteristics can be time-dependent (change directly due to time) or time-varying (change with time). For example, component age is time-dependent and regards how the mere passage of time changes the value of components (Katila, 2002; Nerkar, 2003; Capaldo et al., 2017). In contrast, time-varying dynamic characteristics vary with respect to components' unique histories, such as their individual use frequency (Fleming, 2001; Arts & Veugelers, 2015; Schillebeeckx et al., 2021), whether or how frequently components have been previously paired in use (Yayavaram & Ahuja, 2008; Verhoeven et al., 2016), use timing (Kok et al., 2019), and organizational use contexts (Yang, Phelps & Steensma, 2010).

However, these approaches overlook technological trajectories as a dynamic characteristic. Trajectories are time-varying because they are

[30] Components are defined as "any fundamental bits of knowledge or matter that inventors might use to build inventions" (Fleming & Sorenson, 2004: 910).

cumulative: recombining existing components generates new inventions which become components for subsequent recombination (Kogut & Zander, 1992; Arthur, 2007; Weitzman, 1998). Recombined components may be prior inventions that belong to the same technological trajectory upon which the focal invention builds (Arts, Appio & Van Looy, 2013). These components both constitute an invention's historical context and form a part of its knowledge content (Huenteler et al., 2016). Therefore, we expect that the recombination of components that pertain to the same trajectory, i.e., trajectory integration, is likely to affect technological impact.

Using a knowledge recombination lens, we develop two hypotheses connecting trajectory integration to invention impact. First, we hypothesize a positive relationship between trajectory integration and technological impact. Knowledge components are better understood and utilized when their antecedents are also better understood. When antecedent components are better utilized, the resulting invention is more valuable (Fleming, 2001). We theorize that this enhanced understanding results from contrasting differences in components' use contexts, despite their similar function, such as between components from distant technological domains.

Second, we hypothesize that trajectory integration positively interacts with technological distance, i.e., the extent to which recombined knowledge components originate outside the focal technological domain (Nemet & Johnson, 2012; Keijl et al., 2016), to increase technological impact. Technological distance implies the recombination of inventions from different areas of thought (Aharonson & Schilling, 2016; Capaldo et al., 2017). As such, distance promotes incongruent and unusual framing, interpretation, and use of recombined components (Carnabuci & Operti, 2013), thereby enabling greater variety and recombination possibilities (Fleming, 2001). However, recombining distant components is difficult as component differences entail that inventors must have a more systematic and thorough understanding of components' technical functions (Rosenkopf & Nerkar, 2001; Miller et al., 2007; Jung & Lee, 2016). We anticipate that trajectory integration will alleviate the difficulties associated with recombining distant components by utilizing the trajectory's shared pattern of inventive problem-solving to assist knowledge in "flowing forward" through the trajectory and into the focal domain. Thus, we hypothesize that trajectory integration moderates technological distance to increase technological impact.

We test our hypotheses on trajectory integration using rich data on global patenting activities in the nuclear energy field. Specifically, analyzing 38, 245 patent families created between 1933 and 2012, we find that trajectory integration increases technological impact, and that technological distance positively moderates this relationship. The findings are robust to alternative operationalizations of impact and trajectory integration, further lending support to our theoretical arguments.

Our paper offers three main contributions. First, we bridge knowledge recombination and technological trajectories literature in a way that highlights how recombination and trajectory knowledge are mutually dependent. By introducing trajectory integration as a concept, we consider knowledge recombination's broader context as occurring within technological trajectories. Conversely, trajectories vary in how successive inventions integrate and develop knowledge during recombination. Second, we provide a more nuanced understanding of how the knowledge accumulation that co-occurs with the development of technological trajectories can be beneficially utilized in knowledge recombination. Third, we distinguish between static and dynamic dimensions of component characteristics to highlight the importance of context-specific, time-varying features in predicting technological impact. We introduce a new association that components form, namely, to the invention in which they are used. In this way, we complement the existing research that mainly considers the other components with which a given component is recombined.

3.2 Theoretical background

3.2.1 Bounded rationality

It is axiomatic that inventions are not developed in a vacuum, which stresses the need to understand the inventors involved in knowledge recombination activities. Scholars have used Herbert Simon's theory of bounded rationality (Simon, 1955; Puranam et al., 2015) to explain that inventors are boundedly rational in their search for, and recombination of, components. Bounded rationality explains that cognitive activities, such as invention and knowledge recombination, function like a pair of scissors to solve problems, with one blade representing the "structure of task environments" and the other the "computational capabilities of the actor" (Simon, 1990: p. 7). In the decades following the bounded rationality's introduction, scholars have further developed the theory to recognize the importance of environmental contextual factors in guiding search, such that humans are understood as *ecologically rational* (Todd & Gigerenzer, 2012; Gigerenzer, 2021). Adopting this view, inventors can be understood as relying on familiar environmental cues to apply their problem-solving heuristics (i.e., to bring the blades of their cognitive scissors together), whereas recombinatory search for invention improves through greater familiarity or understanding of knowledge environments.

Inventors are exposed to different task environments over time, creating differences in the set of components with which they develop contextual familiarity (Gruber et al., 2013). The number of components in existence is too large for inventors to be aware of and subsequently recombine. Thus, inventors focus on a cognitively proximate set of components (Fleming, 2001; Clancy, 2018) such that inventors vary in their familiarity with components; some are unfamiliar while others are very familiar.

Familiarity benefits inventors through an enhanced understanding of components' functional characteristics, thereby resulting in higher-impact inventions (Katila & Ahuja, 2002; Arts & Fleming, 2018; Xiao et al., 2022). Conversely, low familiarity implies a limited understanding of component functions, increasing the likelihood that this component will be misapplied and poorly recombined into new inventions (Hargadon & Sutton, 1997; Nemet & Johnson, 2012). Like familiarity, any effects that improve inventors' understanding of components' functional characteristics can increase their inventions' technological value.

Thus, the underlying reason why familiarity increases technological impact regards how boundedly rational inventors improve their understanding of—and therefore their ability to use—knowledge components. If the inventor's computational (i.e., recombinatory search) capabilities or task structure (i.e., available knowledge components or understanding of knowledge component characteristics) improve, then invention quality will improve. For example, knowledge and collaboration networks can structure an inventor's search environment in such a way that recombinatory search becomes more efficient (Schillebeeckx et al., 2021). The task environment supports better knowledge search or flow.

3.2.2 Static characteristics

Our survey of the knowledge recombination literature reveals two groups of component characteristics. Broadly, one group comprises characteristics that are static in nature and do not change over time because they are established upon the creation of an invention. For example, the year that an invention was invented. The other group of characteristics are dynamic characteristics, which change over time. For example, the number of years an invention has existed.

Generally, researchers study static characteristics (e.g., Rosenkopf & Nerkar, 2001; Nemet & Johnson, 2012). When analyzing the static attributes of individual components, the focus tends to be on the domain from which a component originated (Savino et al., 2017). Components originate with respect to three types of domains: organizational (Kim et al., 2013; Miller et al., 2007), geographical (Phene et al., 2006), and technological (Nemet & Johnson, 2012). Components from different domains will share fewer characteristics and so require more understanding to recombine together. For example, countries vary in how they approach certain technical problems, infusing components they generate with unique characteristics (Phene et al., 2006). As components from distant domains are likely to be less familiar, inventors will likely experience more difficulties accessing them. For example, scholars document how information transfer across organizations is imperfect and requires significant resource investments to facilitate (e.g., Rosenkopf & Almeida, 2003; Sorenson et al., 2006).

Using components from distant domains can complicate recombination. Distant components are, in general, harder to understand and so may lower invention impact (Keijl et al., 2016). If components' basic functionalities are not well-understood, it might not be clear which characteristics to incorporate into the focal invention—or in what manner to do so (Hargadon & Sutton, 1997; Nemet & Johnson, 2012). Similar issues emerge with respect to technological diversity (Trajtenberg et al., 1997), that is, recombining components that originate from a variety of different technological domains. Recombining diverse components is cognitively complex for inventors (Schoenmakers & Duysters, 2010; Ghosh et al., 2014). Resulting inventions can be rather incremental, as inventors might not have fully understood each component's unique contribution to the invention or have only poorly integrated features of one component into another (Hargadon & Sutton, 1997).

3.2.3 Dynamic characteristics

As static characteristics are determined during component creation and do not change afterward, to limit a study of recombination to static characteristics would be to implicitly assume that the functions and use of components are also static. However, a component's use and value are not always predetermined at creation. New information about a component's potential can improve its recombination (Yang et al., 2010). Based on this insight, scholars have developed an understanding of components' dynamic characteristics by tracing the history of components to better understand their present value in inventions (Kok et al., 2019). In other words, a component's current value may be affected by its unique history.

Scholars have considered two aspects of component history: their age and reuse. Research on component age reflects a mixture of seemingly contradictory findings. For example, older components are less familiar because of memory decay effects (Nerkar, 2003), have more available substitutes (Zhang et al., 2021), and can be rendered functionally outdated due to rapid technological developments. However, as knowledge about old components is more likely to have diffused broadly, they maintain greater legitimacy and familiarity than newer components (Katila, 2002; Capaldo et al., 2017).

To decompose these effects, scholars studying component reuse argue that components' current value more specifically depends on how frequently they were used before (Arts & Veugelers, 2015; Schillebeeckx et al., 2021). As a component is reused, inventors gain more familiarity and knowledge about its function (Katila & Chen, 2008; Kok et al., 2019). At the same time, reliance on heavily reused components can exhaust recombination possibilities, routinized invention processes, and so lower technological impact (Katila & Ahuja, 2002).

Scholars have also considered reuse context generated through components' frequent joint usage, which often creates associational links or couplings (Dibiaggio et al., 2014; Yang & Steensma, 2014; Yayavaram & Ahuja, 2008). For example, Hewlett-Packard's thermal inkjet printer, a highly impactful invention, combined two not-yet-paired components: electrostatic resistors and printing technology (Fleming, 2002). After this invention, these two components became associated in the minds of inventors. The effects of such familiar associations are twofold. First, search becomes more efficient: instead of considering knowledge components independently in search, inventors consider bundles of components together (Dibiaggio et al., 2014; Clancy, 2018), as if they represented one solution instead of several independent ones. Second, observing how familiar, coupled components are recombined enables inventors to learn about other, unfamiliar components more easily. The inventor can additionally observe how familiar components are modified to fit unfamiliar components (Yang et al., 2010; Yang & Steensma, 2014). Thus, through observing reuse, the inventor can infer the most up-to-date purposes of applying a component (Kok et al., 2019) and potential new advantages in future use (Brennecke & Rank, 2017).[31]

[31] In this paper, we focus on the knowledge component characteristics of inventors' task environments rather than collaboration or firm networks.

3.2.4 Technological trajectories

While important progress has been made in understanding component reuse, a core dynamic characteristic has been omitted from the analysis: the technological trajectory itself. Extant studies do not examine trajectory relationships that may exist between recombined components.

Trajectories were conceptualized by Dosi (1982) to describe the technological change of specific inventions within a broader context of technological progress.[32] Technological trajectories are an intuitive way to refer to the evolutionary lineage, prior versions of, and history of a technology, such as the evolutionary history of cars, airplanes, or data storage (e.g., from floppy disk to CD to flash drive to the cloud). A trajectory includes an invention's technological antecedents, lineage, or prior versions of that technology.

Building on this perspective, we view a technological trajectory as a progressively developed, sequentially dependent set of inventions. Inventions in a trajectory are sequentially dependent on past inventions, which they use as knowledge components, and so both integrate and alter extant knowledge from the trajectory (Garud & Nayyar, 1994; Mina et al., 2007). Each invention indirectly bridges the development of follow-on technologies (Cohen & Tripsas, 2018). This conceptualization aligns with Weitzman's (1998) contention that technological progress is cumulative and builds upon itself: When an invention is generated, it becomes a component to be used in subsequent inventions. Therefore, by considering the lineage of a component in terms of other upon which it builds, we can more clearly

[32] As a trajectory is inherently a changing phenomenon, Dosi (1982) defined trajectories as being associated with particular knowledge structures, patterns of problem-solving activities, and dominant designs that enabled successive inventions to occur. For example, invention in wind energy occurs through altering key features of the dominant design of wind turbines, which has remained unchanged for more than a century (Huenteler et al., 2016), while rotating turrets for army tank technology (Castaldi, Fontana & Nuvolari, 2009; Kim et al., 2020), have become a default feature of tank design since their origination. Thus, trajectories reflect an asymmetrical rate and direction of development around particular highly impactful inventions which integrate and resolve some outstanding problems in the trajectory. Once a new direction for the trajectory is established, the trajectory reverts to the typical pattern of a developing trajectory with cumulative progress (Tushman & Anderson, 1986; Funk & Owen-Smith, 2017).

delineate technological trajectories (Verspagen, 2007). A trajectory, thus, is identified by the components upon which an invention builds, such that trajectories are constituted by sequential interdependence structures in the successive emergence of technologies, much like phylogenetic lineage in the evolutionary history of species.

Thus, what has yet to be examined as an important part of a component's dynamic characteristics is how antecedent knowledge components in technological trajectories are used in the focal invention. While technological trajectory literature explains how inventions build directly on their antecedents, it does not address inventions which simultaneously build directly off several steps (components) along the trajectory. On the contrary, inventions that use components from several points along a trajectory constitute a case that is poorly explained by extant literature. Trajectories have likely been overlooked because scholars mainly consider reuse in terms of which other components a particular component was recombined with (Yayavaram & Ahuja, 2008; Dibiaggio et al., 2014; Wang et al., 2014) rather than the invention generated from recombination.

We aim to address this gap with the introduction of trajectory integration, when a focal invention recombines two or more components from the same trajectory.

Inventors' familiarity with a knowledge component undoubtedly influences their utilization of it (Fleming, 2001; Xiao et al., 2022). However, it's crucial to distinguish between trajectory integration and familiarity. While familiarity pertains to the extent an inventor has engaged with a knowledge component (Katila & Ahuja, 2002; Arts & Fleming, 2018; Clancy, 2018) or the frequency with which two knowledge components have been jointly employed (Yayavaram & Ahuja, 2008; Schoenmakers & Duysters, 2010), trajectory integration specifically emphasizes the concurrent re-use of knowledge components that share a technological trajectory (Dosi, 1982; Kok et al., 2019). These components, arising from a common trajectory, inherently share certain inventive challenges and technical characteristics. While such technological commonalities can enhance familiarity, they are distinct from and should not be conflated with an inventor's direct experience or familiarity.

3.3 Hypotheses

3.3.1 The effect of trajectory integration

Inventions retain many but not all characteristics of antecedent technologies (Ahuja & Lampert, 2001; Cohen & Tripsas, 2018; Furr & Snow, 2015). Successive inventions along a trajectory remove features without replacement, replace old features with new and improved ones, or add new features without removing any existing ones. However, as inventors are cognitively bounded, successive inventions along a trajectory are inherently imperfect (Fleming, 2001; Ghosh et al., 2014). Inventors' selections are relatively positive – e.g., poor features are removed, and beneficial features are added – or negative, such that poor features are added, and beneficial features are removed. We argue that trajectory integration increases the likelihood of positive changes in the focal invention, and its absence increases the likelihood of negative changes.

Inventors' problem-solving approach and design decisions will result from the problem context they face, including relevant environmental and information cues (Todd & Gigerenzer, 2012; Luan, Reb & Gigerenzer, 2019). Using more components from within the same trajectory provides broader and more relevant context for inventive problems facing an inventor, as well as more informational cues about why inventions succeeded in the past or may fail in the future.

When trajectory integration is absent, inventors use less knowledge from the trajectory. As a result, they are less likely to consider the value-adding or value-destroying steps of prior generations and so more likely to repeat the mistakes of prior generations (Furr & Snow, 2015). That is, the focal instance of knowledge recombination might miss helpful knowledge in the prior component that was not integrated into the recent component (Cohen & Tripsas, 2018).

In contrast, trajectory integration provides inventors with a deeper understanding of the knowledge underlying the current state-of-the-art in a particular technological trajectory. Inventors can compare different points along the technological trajectory, identifying differences, trends, and interdependencies in inventive problem-solving patterns. This helps them decide which (new or old) features to reuse, add, or remove from the focal invention to align it with future developments. The inventor is more likely to understand, for instance, which useful features of an earlier component are still present in the later component in the trajectory and will not remove those in the focal invention. Thus, trajectory integration involves the recombination of components from the same trajectory, such that inventors consider alternate uses, applications, and component characteristics in new contexts and from different perspectives.

To give an example of these mechanisms, consider the example of early nuclear reactor technology. In the 1950s and 60s, three reactors were developed at the Oak Ridge National Laboratory in the U.S.: the boiling water reactor, pressurized water reactor, and molten salt reactor. These reactors were invented in succession, with knowledge being sequentially developed to enable the next reactor to be invented. While the pressurized water reactor improved on the overall design and use of solid fuel rods in the boiler water reactor, Alvin Weinberg and his team identified that the improvements in the safety and performance of pressurized water reactors were inherently limited by the continued use of solid fuel rods. Hence, Weinberg redirected the Oak Ridge National Laboratory research towards exploring the use of liquid fuel reactors, where molten salt would act as both a medium and a moderator for nuclear fuel. By integrating knowledge about the sequentially dependent features observed in the pressurized water reactor (2nd reactor), including the source of those features in the boiling water reactor (1st reactor), Albert Weinberg and the Oak Ridge National Laboratory team were able to shift the overall design of from fuel rod-oriented designs to the liquid fuel-oriented design of the molten salt reactor (3rd reactor).

In sum, trajectory integration implies an improved understanding and use of knowledge components, both earlier and later ones in trajectories, leading to the generation of inventions that are functionally superior within the broader context of those trajectories. For these reasons, we hypothesize:

Hypothesis 1: Inventions where trajectory integration is present have a higher technological impact than inventions where trajectory integration is absent.

3.3.2 The moderating effect of technological distance

Technological domains refer to the technological area, such as computer technology or medical technology generally, to which components belong (Hall et al., 2001; Nemet & Johnson, 2012). In contrast to trajectories, a domain captures technologies with a similar purpose, function, or use.[33] Technological distance means the distance between domains, meaning the degree of dissimilarity between the functional uses that define these domains. In knowledge recombination, technological distance is the degree of overall distance between the components used in the focal technology. Though it has the potential to yield impactful inventions, recombining distant components is difficult.

As a result of inventors' bounded rationality, they are more likely to familiarize themselves with components in a narrower domain, often delimiting the breadth of search to those components that are technologically proximate to them (Stuart & Podolny, 1996; George et al., 2008). Technological distance increases the number of contrasting components and the degree of contrast between component contexts. Using distant

[33] Domains do not reduce to trajectories. A carpenter's hammer may belong to the same domain as a jack-hammer despite having very different mechanisms and knowledge components. Domains capture a group of functionally similar technologies at a point in time, whereas trajectories capture their sequential lineage. As Carnabuci and Bruggeman (2009) write "Technology domains may be thought of as cross-sectional "slices" of technological trajectories (Nelson and Winter 1982)." Moreover, as technological trajectories evolve, multiple similar trajectories often compete and develop in parallel, much like branches in a phylo-genetic tree. These trajectories have similar but different assumptions, ways of approaching technological problems, and patterns of inventive problem-solving (Dosi, 1982; Arthur, 2007). As trajectories continue to separately evolve, these differences may increase, even to the point where the state of technology in each trajectory belongs to different technological domains. Hence, a trajectory may cross multiple domains over time.

components requires considering unfamiliar component functions and patterns of inventive problem-solving. Moreover, inventors often mistakenly assume that technologically distant components function in a similar manner to those within the inventor's focal domain, thereby misunderstanding distant components (Nemet & Johnson, 2012; Ghosh et al., 2014). For distant components to be successfully recombined, inventors must have a more systematic and thorough understanding of those components' technical functions (Rosenkopf & Nerkar, 2001; Miller et al., 2007; Jung & Lee, 2016).

Recent advances in research on bounded rationality suggest that search performance increases through an improved understanding of environmental contextual cues (Gigerenzer, 2021). We expect trajectory integration to attenuate the negative effect of distance through the cues provided by a trajectory's shared pattern of inventive problem-solving, which helps distant component knowledge to "flow forward" through the trajectory into the focal domain. For instance, to use wind energy knowledge components in a nuclear energy invention would be difficult. However, if those components belong to the same trajectory, the inventor would benefit from understanding of their use context. In this sense, trajectory integration means inventors are better able to contextualize the knowledge upon which focal inventions build, which is especially important when recombining knowledge components from distance knowledge domains.

High-distance recombination is often cast as a form of speciation: using a component in a new domain lead to follow-on expansion in its range of functionalities (e.g., Levinthal, 1997) and helps to form bridges between domains that are otherwise disconnected such that inventions can become steppingstones for additional inventions in multiple domains (Battke et al., 2016; Kneeland et al., 2020). If trajectories already provide a bridge (via shared patterns of inventive problem solving) to enable recombination of distant components, trajectory integration can promote the benefits and help to resolve the difficulties of distant recombination. We therefore hypothesize:

Hypothesis 2: The technological distance of recombined components in the invention positively moderates the relationship between the presence of trajectory integration and invention impact. Specifically, the positive marginal effects of the presence of trajectory integration on invention impact are smaller (larger) effects when the technological distance of recombined components is lower (higher).

3.4 Methods

3.4.1 Empirical context

To test our hypotheses, we rely on patented inventions in the field of nuclear power technology. This technological domain should provide ample opportunity for testing hypotheses about knowledge recombination and technological trajectories. First, nuclear power technology has developed in distinct waves or generations, the last being "fourth-generation nuclear" (Lake, 2002). Second, successive generations of nuclear power technology have drawn on knowledge about the limitations and challenges of previous generations of technology (Ming et al., 2016), such as those highlighted by nuclear power plant disasters. Third, nuclear power technology has undergone a renaissance to reflect a variety of emerging and competing trajectories, with no single dominant design (Ho et al., 2019). Fourth, nuclear power technology reflects high heterogeneity in recombination performance because nuclear engineering is inherently complex, requiring extensive planning and a large knowledge base. As a result, we expect nation performance exists and where trajectory integration is likely to be obnuclear power technology to provide an empirical context with sufficient heterogeneity in recombination performance and where trajectory integration is likely to be observable. Finally, patents from different technologies may be hard to compare with one another (Squicciarini, Dernis & Criscuolo, 2013; Higham, De Rassenfosse & Jaffe, 2021), as factors which affect knowledge differ from a variety of market and domain-specific factor. Thus, examining patents from within one domain provides more interpretable results.

3.4.2 Data

To examine the effects of trajectory integration and knowledge recombination in nuclear energy technology, we rely on patent data. A community of practice has emerged using patent data to investigate knowledge recombination (Jaffe & De Rassenfosse, 2017; Savage et al., 2020), inventions' technological impact (Trajtenberg, 1990), and technological trajectories (Verspagen, 2007; Arts et al., 2013). The legal principle of patent citations is to capture prior inventions that delimit the boundaries of a new patent's claims. Consequently, citations are well-suited to analyze which (similar) prior inventions a focal patent builds upon. By operationalizing cited prior patents as an invention's constituent components, scholars examine the roles of those features of those prior inventions in knowledge recombination, impact, and trajectories.

In line with prior studies (Verhoeven et al., 2016; Moaniba, Su & Lee, 2018), we use the World Intellectual Property Office's (WIPO) International Patent Classification code (IPC code) system to define nuclear energy technology patents (IPC code G21).[34] To capture characteristics of inventions and minimize country-market and patent office-specific patent application patterns, we aggregate all data characteristics to the patent family level (Martínez, 2010). For example, we measure the first date of application filing, number of forward citations, and number of inventors by looking at all applications at the family level. Our sample of 38,245 inventions includes all nuclear power patent families filed globally from 1933 to 2012. This sample covers the entire history of the development of nuclear power reactors and technology developed and associated with the discovery of nuclear fission in 1938.

[34] We omit nuclear weapons technology (IPC code G21J) to remove influence of innovation efforts driven by geopolitical and defense interests.

3.4.3 Dependent variable

As patent citation frequency is related to the value of patented inventions forward citations to a patent are commonly used as a dependent variable and a proxy for technological impact or importance (Fleming, 2001; Nemet & Johnson, 2012). Technological impact, the dependent variable of this study, is proxied by the number of forward citations made to the focal patent (*Impact)*. The citations are aggregated to the patent family level and deduplicated, in line with prior studies (Kok et al., 2019; Barbieri et al., 2020). To reduce bias towards older patents, i.e., patents having been at risk of being cited for more extended periods, studies often implement a fixed 5 or 10-year window for forward citations (e.g., Nemet & Johnson, 2012). In this study, we implement a 5-year time window but also perform robustness tests using alternative windows. In other words, a forward citation is included in the measurement of the dependent variable when the citing patent's priority date falls within a time window of five years from the focal patent's priority date.

3.4.5 Independent variables

The first independent variable, *trajectory integration*, is measured using a patent's backward citations and those citations' backward citations (Von Wartburg, Teichert & Rost, 2005; Schillebeeckx et al., 2021). Citations reflect knowledge flows and therefore are proximate to the structured lineage of knowledge flows (Jaffe & De Rassenfosse, 2017). As such, the paths created by sequences of patent citations are taken as representative of both the sequentially dependent features of a technological trajectory and of knowledge components used in knowledge recombination.

To create the independent variable, we consider two sets of backward citations: Set 1 contains all the backward citations of the focal patent families in our sample and Set 2 contains the backward citations of those backward citations[35], that is, "second-generation" citations (Corredoira & Banerjee, 2015; Hur et al., 2021). We create a dummy variable when at least one citation in set 2 is also present in set 1. E.g., if a focal patent cites patents B, C, and D, and one of those three patents cites at least one of the other two ones, trajectory integration is present, and the variable takes a value of 1 and 0 otherwise. While the use of a dummy variable reduces to a black-and-white situation something where there could be much variance, we notice that this is not the case, and that trajectory integration is completely absent in 51% of the patents in our sample. This is not surprising, as citation data are known to be relatively sparse (Dahlin & Behrens, 2005), with many patents never being cited once (Arts & Veugelers, 2015). Nevertheless, we also conduct robustness tests with continuous measures, which we discuss in a later section.

The second independent variable, *technological distance*, is calculated as the percentage of backward citations made by the focal patent to prior art outside of nuclear energy technology (i.e., patent families that do not contain IPC codes relating to nuclear energy technology). This is in line with the approach taken by prior studies in other fields, like batteries (Battke et al., 2016), biotech (Phene et al., 2006; Keijl et al., 2016), and renewable energy technologies (Li et al., 2022).

3.4.6 Control variables

We include several control variables. We control for the number of backward citations (*backcites*) reflecting the number of components upon which the invention relies in knowledge recombination (Podolny & Stuart, 1995). The variable *citelag* controls for the age of backward citations using the mean citation age, measured in days (Nerkar, 2003; Capaldo et al., 2017). Patents relying on older components will tend to rely on more established and familiar knowledge, they will be easier to use and so have more

[35] Given that this variable is operationalized using backward citations, we omit all patents with zero backwards citations.

opportunity to generate impact. As granted patents are more likely to be cited, we control for whether the patent was granted (*granted*) with a dummy variable. The 'invention team size (inventors)' variable denotes the number of inventors associated with a specific invention. A larger team presents several benefits: it aggregates a wider variety of knowledge sources, fostering diverse knowledge recombination. Additionally, more inventors amplify the invention's visibility—given the increased personnel to advocate or discuss it—potentially boosting peer citations. Moreover, with inventors often building upon their work, inventions by larger teams inherently (and perhaps endogenously) have a higher citation propensity. Thus, by controlling for team size, we account for the availability of knowledge, projected awareness, and the potential for further innovation, each impacting technological significance.

We control for patent family size (*famsize*) using the number of offices at which applications were filed. Larger famsize entails that there are more opportunities to cite a given patent. We control for the number of technological domains spanned by an invention—i.e., its technological breadth (*breadth*). High-breadth patents span many domains and will have more use contexts, greater exposure for citation, and so more opportunity to generate impact. We measure domains using the World Intellectual Property Office's (WIPO) International Patent Classification code (IPC code) system to identify technological domains. We measure breadth as the number of unique 4-digit IPC codes that appear on the focal patent (Petruzzelli, Rotolo & Albino, 2015).

We control for technological diversity (*diversity*) of components in the backward citation set. The more backward citations are spread across technology classes, the more diverse the knowledge components used in knowledge recombination. We measure diversity as the spread of IPC codes according to the Herfindahl-Hirschman Index (Trajtenberg, Henderson & Jaffe, 1997) which has been widely employed in invention literature (Hall et al., 2001). Like patent breadth, greater diversity enables greater opportunity for use but also suggests greater novelty—hence diversity is an important control variable.

We control for overall invention-level interdependence (*interdependence*) using Fleming and Sorenson's (2001: p. 1027) NK model-based measure.[36]

We additionally provide dummy variables to control for whether applications were filed at the *USTPO, EPO*, and *JPO* given the strategic importance, patenting propensity, and efficiency of these offices, as well as the tendency for patent applicants and examiners to cite patents from these offices. Similarly, we control for the applicant type of organization that filed the patent using three dummy variables: *Company, University*, or *Government.* We additionally include year dummies in all models.

3.4.7 Models

We investigate the relationship between the independent variables (integration and distance) and the dependent variable (impact) in the context of nuclear energy technology. Given the count nature and overdispersion of the dependent variable, forward citations, we employ negative binomial regression models, which are widely used in studies analyzing patent data (Fleming, 2001; Capaldo et al., 2017). The choice of negative binomial regression models with robust standard errors (Cameron & Trivedi, 2001; Hall et al., 2001) is motivated by their ability to account for the specific characteristics of the dependent variable, such as its non-negative integer values and potential heteroscedasticity. By employing negative binomial regression models, we can estimate the coefficients for trajectory integration and distance and examine their impact on technological outcomes in the field of nuclear energy technology.

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[36] The interdependence K of patent l is calculated by first calculating, for each technology subclass i in year t, the subclass's ease of recombination E_i. Where I is the number of subclasses on the focal patent, N_i is the number of subclasses previously combined with subclass i, and P_i is the number of patents filed in subclass i in the preceding 10 years, $K_l = \frac{I}{\sum_{l\in i}\frac{P_i}{N_i}}$ or simply $K_l = \frac{I}{\sum_{l\in i} E_i}$

3.5 Results

3.5.1 Descriptive statistics

The descriptive statistics and correlation table are shown in Tables 1 and 2. Like prior studies, impact is skewed, with a high skewness of 8.71 and kurtosis of 173.01. Many patents do not receive any citations within the first five years after filing, and others receive a very large number (the maximum value is 377 in our sample). Conversely, integration seems to lean towards its higher values, as evidenced by its negative skewness of -0.28, with nearly half its values reaching the maximum; the mean stands close to 0.57 with a maximum of 1. In other words, integration is present in 57% of patent families in our sample. Distance ranges from 0 (the patent only cites other nuclear energy patents) to 1 (the patent only cites patents outside nuclear energy), with a mean value of 0.39.

The data reveals moderate correlations between several variables. Specifically, breadth is correlated with both diversity (0.41) and interdependence (0.44), while diversity moderately correlates with interdependence (0.45). To note, year and interdependence have a slightly stronger correlation of 0.66, indicating a growing trend in interdependence over time.

Paper 2, Table 1 – Descriptive Statistics

Variable	Min	Mean	Median	Max	StdDev	Skewness	Kurtosis
Impact	0.00	5.61	3.00	377.00	9.17	8.71	173.01
Integration	0.00	0.57	1.00	1.00	0.50	-0.28	-1.92
Distance	0.00	0.39	0.33	1.00	0.36	0.30	-1.37
Backcites	1.00	9.75	7.00	410.00	10.64	5.66	85.87
Citelag	1.00	3665.65	3196.17	21707.67	2216.27	1.32	2.81
Granted	0.00	0.88	1.00	1.00	0.33	-2.30	3.30
Inventors	1.00	2.62	2.00	28.00	1.94	2.24	8.64
Famsize	1.00	3.46	2.00	67.00	3.09	2.38	16.98
Breadth	1.00	2.44	2.00	18.00	1.61	1.61	4.13
Diversity	0.00	0.59	0.69	0.98	0.28	-1.16	0.14
Interdependence	0.14	1.14	1.07	3.28	0.46	0.69	-0.01
JPO	0.00	0.52	1.00	1.00	0.50	-0.10	-1.99
EPO	0.00	0.28	0.00	1.00	0.45	0.99	-1.02
USTPO	0.00	0.68	1.00	1.00	0.47	-0.77	-1.40
Company	0.00	0.80	1.00	1.00	0.40	-1.46	0.14
University	0.00	0.04	0.00	1.00	0.19	4.80	21.06
Government	0.00	0.15	0.00	1.00	0.35	2.01	2.05
Year	1933	1991.56	1993.00	2012	15.96	-0.61	-0.49

Notes: Table 1 presents the descriptive statistics for the primary variables used in the study. The dependent variable, 'Impact,' represents the technological significance of a patent, measured through its forward citations. 'Integration' (trajectory integration) and 'Distance' (technological distance) are the primary independent variables, capturing the extent of backward citation linkages and the breadth of technological knowledge sources, respectively. Control variables include 'Backcites' (number of backward citations), 'Citelag' (mean age of backward citations), 'Granted' (whether a patent was granted), 'Inventors' (number of inventors), 'Famsize' (patent family size), 'Breadth' (technological breadth), 'Diversity' (technological diversity of knowledge sources), and 'Interdependence' (interdependence among knowledge components). Dummy variables indicate applications filed at major patent offices: 'JPO' (Japan Patent Office), 'EPO' (European Patent Office), and 'USTPO' (United States Patent and Trademark Office). The sample size reflects 38,245 nuclear inventions between 1933 and 2012.

Paper 2, Table 2 – Correlation table

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
1. Impact	1.00																	
2. Integration	0.21	1.00																
3. Distance	0.21	0.16	1.00															
4. Backcites	0.31	0.42	0.27	1.00														
5. Citelag	-0.06	0.09	0.06	0.16	1.00													
6. Granted	0.11	0.15	0.05	0.12	0.01	1.00												
7. Inventors	0.07	0.02	-0.00	0.08	0.03	0.02	1.00											
8. Famsize	0.25	0.25	0.11	0.29	0.02	0.21	0.00	1.00										
9. Breadth	0.27	0.21	0.51	0.29	-0.03	0.06	0.06	0.27	1.00									
10. Diversity	0.18	0.30	0.31	0.34	0.04	0.03	0.08	0.14	0.41	1.00								
11. Interdependence	0.15	0.15	0.31	0.19	0.05	-0.10	0.15	-0.02	0.44	0.45	1.00							
12. JPO	0.07	0.03	0.00	0.07	-0.08	-0.01	0.06	0.33	0.21	0.11	0.08	1.00						
13. EPO	0.16	0.29	0.10	0.25	0.10	0.09	0.02	0.51	0.23	0.19	0.11	0.28	1.00					
14. USTPO	0.26	0.40	0.26	0.34	0.05	0.35	-0.11	0.34	0.20	0.19	0.00	-0.08	0.20	1.00				
15. Company	0.05	0.07	0.02	0.08	-0.06	0.00	0.05	0.07	0.10	0.06	0.03	0.29	0.10	-0.04	1.00			
16. University	0.05	0.01	0.06	0.01	0.02	-0.02	0.10	-0.03	0.06	0.07	0.19	-0.08	-0.00	-0.02	-0.28	1.00		
17. Government	-0.07	-0.06	-0.07	-0.08	0.01	0.09	0.09	0.06	-0.07	-0.06	-0.08	-0.12	-0.04	0.02	-0.53	-0.02	1.00	
18. Year	0.13	0.22	0.19	0.27	0.23	-0.12	0.27	-0.02	0.32	0.38	0.66	0.19	0.21	-0.13	0.14	0.16	-0.13	1.00

3.5.2 Main results

The regression results are reported in Table 3. Model 1 serves as the baseline model, only including the control variables. Model 2 adds our focal independent variable, *trajectory integration*, and demonstrates its positive and statistically significant relationship with impact ($\beta = 0.116$, $p < 0.000$). Model 3 includes the second explanatory variable, *distance*, which has a positive relationship with impact ($\beta = 0.148$, $p < 0.000$). Model 4 includes integration, distance, and the interaction between integration and distance, which has a positive and statistically significant relationship with impact ($\beta = 0.140$, $p < 0.000$). Notably, the coefficient for distance loses statistical significance in the presence of the interaction between integration and distance. These results support hypothesis 1 and 2.

Paper 2, Table 3 – Negative binomial regressions

	Model 1	Model 2	Model 3	Model 4
Integration		0.116*** [0.014]	0.122*** [0.014]	0.066*** [0.020]
Distance			0.148*** [0.019]	0.066 [0.028]
Integration* Distance				0.140*** [0.034]
Backcites	0.012*** [0.001]	0.011*** [0.001]	0.010*** [0.001]	0.010*** [0.001]
Citelag	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
Granted	0.256*** [0.021]	0.252*** [0.021]	0.253*** [0.021]	0.254*** [0.021]
Inventors	0.038*** [0.003]	0.039*** [0.003]	0.040*** [0.003]	0.040*** [0.003]
Famsize	0.040*** [0.002]	0.040*** [0.002]	0.040*** [0.002]	0.040*** [0.002]
Breadth	0.047*** [0.004]	0.048*** [0.004]	0.035*** [0.004]	0.033*** [0.004]
Diversity	0.105*** [0.025]	0.084** [0.026]	0.070* [0.025]	0.075** [0.025]
Interdependence	0.176*** [0.020]	0.180*** [0.020]	0.169*** [0.020]	0.166*** [0.020]
JPO	-0.052*** [0.014]	-0.047*** [0.014]	-0.039** [0.014]	-0.037* [0.014]
EPO	0.002 [0.016]	-0.008 [0.016]	-0.003 [0.016]	-0.002 [0.016]
USTPO	0.839*** [0.016]	0.802*** [0.017]	0.785*** [0.017]	0.790*** [0.017]
Company	0.009 [0.019]	0.006 [0.019]	0.008 [0.019]	0.009 [0.019]
University	0.229*** [0.031]	0.232*** [0.031]	0.233*** [0.031]	0.233*** [0.031]
Government	-0.151*** [0.021]	-0.151*** [0.021]	-0.145*** [0.021]	-0.143*** [0.021]
Domain Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
AIC	197707.96	197600.344	197507.796	197481.808
BIC	198494.723	198395.658	198311.662	198294.226
Log Likelihood	-98761.98	-98707.172	-98659.898	-98645.904
McFadden R2	0.365	0.367	0.368	0.368
Observations	38245	38245	38245	38245

Notes: Table 3 presents negative binomial regression results predicting 5-year invention impact. All models factor in year dummies (unreported) and feature robust standard errors in brackets. Significance is marked as: *p<0.05, **p<0.01, ***p<0.001.

Examining the goodness-of-fit indicators, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) progressively decrease from Model 1 to Model 4, suggesting progressively improved model fit. Model 4, with the lowest AIC and BIC values, highlights the added explanatory power of the interaction between integration and distance. This progression emphasizes the nuanced relationship between integration and distance in estimating invention impact. Other goodness-of-fit measures reflect negligible improvements.

3.5.3 Robustness tests

To gauge the robustness of our results, we conducted several additional analyses pertaining to the operationalization of our main variables. For the dependent variable, we use an alternative time window of 10 years and remove time windows altogether (i.e., all forward citations are included in the dependent variable, regardless of when the citing patent was filed relative to the focal patent). By extending the time window, we remove any biases towards inventions which may reflect a bias towards short-term technological change and emphasize, instead, overall technological impact. The results are stable using this alternative operationalization of invention impact.

For the independent variable, we re-ran our analyses using alternative operationalizations of trajectory integration. First, we measure the longest chain of components linked in trajectory integration in a patent's backward citation set (*Longest)*. Second, in cases of several instances of trajectory integration in the same invention, we measure the average length of the chains of components among the focal patent's set of backward citations *(MeanPath*). The results from these tests are consistent with our main results. Additionally, as these alternative operationalizations are continuous measures and their estimate coefficients are positive, these tests suggest that the more trajectory integration that occurs, the more positive impact is generated.

Endogeneity may be a concern in our analysis. While the dependent and independent variables are typically not simultaneous in our data structure where technological impact occurs after the explanatory variables, our analyses could still suffer from omitted variable bias. It may be the case that other related dynamic characteristics could be responsible for generating trajectory integration's positive effect on technological impact. For example, prior research has found that recombining components not reused for long periods can trigger temporal benefits. While we include average citation lag (citelag) in our control variables, we more precisely investigate the role of these temporal effects in trajectory integration by interacting trajectory integration with the average citation age of the trajectory components only. Interestingly, we find a negative coefficient from this interaction, suggesting that more distant temporal effects are not responsible for the benefit of trajectory integration.

3.5.4 CD index

The measure we employ for trajectory integration bears a resemblance to a component found within the emerging and recognized measure of technological disruption and stability: the consolidation-disruption index (CD-index), as articulated by Funk & Owen-Smith (2017) and further developed by Park, Leahey & Funk (2023). The CD index is adept at gauging the degree to which an invention veers away from or aligns with established technological paradigms. Structurally, it captures the balance between disruption and consolidation, where a score of 1 represents the pinnacle of disruptive invention, while a score of -1 epitomizes a wholly consolidatory invention.

However, the CD index aggregates both the effects of consolidation and disruption together. Instead, the CD index can be disaggregated to independently assess both consolidation and disruption, furnishing us with the capability to evaluate the influence of knowledge consolidation compared to disruption in shaping technological advancements.

In this post hoc analysis, we evaluate each invention using metrics based on the CD-index, as established by Funk and colleagues. Model 1 uses the "CD" metric to represent the CD index. In Model 2, "D" gauges the average disruptive degree among backward citations, while "C" determines the average consolidative degree. Model 3 combines CD, C, and D. Model 4 explores the interaction between C and D. Results are presented in Table 4.

Paper 2, Table 4 –C-D effects on invention impact

	Model 1	Model 2	Model 3	Model 4
CD	0.546*** [0.040]		-6.872*** [0.089]	
C		6.871*** [0.089]	0.000*** [NaN]	8.009*** [0.110]
D		1.413*** [0.035]	8.286*** [0.098]	1.573*** [0.036]
C & D				-7.565*** [0.504]
Distance	0.144*** [0.019]	0.292*** [0.017]	0.292*** [0.017]	0.298*** [0.017]
Backcites	0.012*** [0.001]	0.018*** [0.000]	0.018*** [0.000]	0.018*** [0.000]
Citelag	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
Granted	0.262*** [0.020]	0.206*** [0.018]	0.206*** [0.018]	0.205*** [0.018]
Inventors	0.038*** [0.003]	0.032*** [0.003]	0.032*** [0.003]	0.032*** [0.003]
Famsize	0.042*** [0.002]	0.036*** [0.002]	0.036*** [0.002]	0.036*** [0.002]
Breadth	0.030*** [0.004]	0.023*** [0.004]	0.023*** [0.004]	0.024*** [0.004]
Diversity	0.137*** [0.025]	0.290*** [0.022]	0.290*** [0.022]	0.295*** [0.022]
Interdependence	0.154*** [0.019]	0.117*** [0.017]	0.117*** [0.017]	0.119*** [0.017]
JPO	-0.059*** [0.014]	-0.083*** [0.012]	-0.083*** [0.012]	-0.086*** [0.012]
EPO	0.021 [0.016]	0.042** [0.013]	0.042** [0.013]	0.043** [0.013]
USTPO	0.860*** [0.016]	0.836*** [0.014]	0.836*** [0.014]	0.838*** [0.014]
Company	0.012 [0.019]	0.026 [0.016]	0.026 [0.016]	0.026 [0.016]
University	0.225*** [0.031]	0.195*** [0.027]	0.195*** [0.027]	0.193*** [0.027]
Government	-0.142*** [0.020]	-0.118*** [0.018]	-0.118*** [0.018]	-0.116*** [0.018]
Domain F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
AIC	197336.181	192154.809	192153.554	192051.324
BIC	198140.047	192967.227	192965.972	192872.294
Log Likelihood	-98574.091	-95982.405	-95981.777	-95929.662
McFadden R2	0.370	0.441	0.441	0.443
Observations	38245	38245	38245	38245

Notes: The table showcases regression results predicting 5-year invention impact. All models include domain and year Fixed Effects (F.E) with robust standard errors in brackets. Significance levels: *p<0.05, **p<0.01, ***p<0.001. Models 1 to 3 are anchored on "CD", "C", and "D", representing disruption and consolidation measures. Model 4 examines the "C" and "D" interaction. Each model is based on 38,452 observations with AIC, BIC, log likelihood, and McFadden R2 indicating model fit.

Both consolidation and disruption wield significant influence over technological impact. When decomposing the CD index into separate C and D measures, as presented in Model 2, we observe that both C (β = 6.871, p < 0.000) and D (β = 1.431, p < 0.000) positively predict heightened invention impact. Moreover, all goodness-of-fit measures improve substantially when comparing Model 1, which only included the CD index, to Models 2, 3, and 4, which include C and D separately. This improvement suggests that characterizing consolidation and disruption separately provides a useful predictor of technological impact.

Notably, within Model 2, C's influence is considerably more potent than that of D. Yet, when CD is incorporated again in Model 3, the β coefficient of C diminishes to zero. This alteration in the β coefficient for C intimates the presence of a significant interplay between C and D. Further empirical support for this interaction is discerned in Model 4. While the CD metric quantifies the relative magnitudes of C and D, the term C*D encapsulates their interaction, reflecting the product of the cumulative degrees of C and D. Within Model 4, this interaction manifests a robust negative coefficient, underscoring the notion that C and D might contribute differentially to technological impact. It is plausible that C and D exert their effects at divergent junctures of a technological trajectory's progression. However, when considered in isolation, consolidation's influence appears more salient. But in scenarios where it is either combined or compared with disruption, its impact attenuates, an observation that remains consistent across all interactions of C and D. This lends weight to the hypothesis that consolidation and disruption could propel technological progress via discrete mechanisms or cater to varied roles in the technological evolution spectrum.

3.6 Discussion and conclusion

3.6.1 Overview

By linking technological trajectories with knowledge recombination, we conceptualize trajectory integration, which involves recombining sequentially dependent components from within a trajectory. We develop two hypotheses governing the association between trajectory integration and invention impact.

First, we explore the main effect of trajectory integration. When trajectory integration is present, inventors are more likely to better understand components, find application contexts of components, and integrate valuable features of components. Hence, we postulate a positive association with invention impact.

Second, we argue that distance moderates the above primary relationship. Whereas technological distance implies greater contrast between components' previous inventive contexts, higher distance in trajectory integration serves to amplify the degree of contrast in the use of trajectory components' use contexts, amplifying the effect of trajectory integration. Thus, we argue that the relationship between trajectory integration and invention impact is positively moderated by the technological distance of recombined components.

We test our predictions using a dataset on nuclear energy technology patents. Our results support our hypotheses. Additionally, we run a series of post hoc tests to further understand our primary findings, demonstrate robustness, and increase the generalizability of our findings. These additional tests provide support to our main findings. Notably, we find trajectory integration's effect size on technological impact is large relative to relative to other well-known drivers of impact, such as technological diversity.

3.6.2 Research contributions

Our study significantly enhances the knowledge recombination literature (Xiao et al., 2022) in three respects. Our study bridges knowledge recombination and trajectories literature, re-characterizes the relationship between consolidation and disruption, and deepens our understanding of dynamic component characteristics.

i) Bridging recombination and trajectories literature

Extant knowledge recombination literature provides extensive research examining characteristics of individual components used in knowledge recombination, such as their year of creation, and collective characteristics, such as their diversity, but poorly understands the role of knowledge structures in driving knowledge recombination performance. (Xiao et al., 2022). By linking knowledge recombination performance to its dependence on particular knowledge structures, we can better understand drivers of knowledge recombination performance, i.e., invention performance. As technological trajectories are also knowledge structures, this study addresses the research gap above.

In particular, our study is positioned within a niche segment of research that links technological trajectories and knowledge recombination literature (Funk & Owen-Smith, 2017; Malhotra et al., 2021). On one hand, existing literature elucidates that various kinds of knowledge are instrumental during different stages of technological trajectory development (e.g., Kalthaus, 2020). However, this research is limited with respect to how trajectory structures are specifically involved in knowledge recombination. On the other hand, the emphasis within the recombination literature is on the importance of analyzing the temporal dynamics inherent to recombination processes (Nerkar, 2003; Kok et al., 2019), but do not extend these temporal dynamics to cover the broader dynamic of a technological trajectory. Following a handful of studies that emphasize the interrelationship between knowledge recombination and knowledge structures implicit in technological trajectories (e.g., Murmann & Frenken, 2006; Furr & Snow, 2015; Malhotra et al., 2021), this study evidences the importance of knowledge structures used by inventors in knowledge recombination. By showing that using knowledge structures—in the form of technological trajectories—benefits knowledge recombination, our study demonstrates that knowledge recombination performance depends not only on what knowledge components are used but how those components are structurally interrelated.

Additionally, exploring linkages trajectories and knowledge recombination opens avenues for research employing a similar approach. While technological trajectories not only encompass individual inventions but also trace back to their historical predecessors, structured by their sequential lineage, there exists potential to associate knowledge recombination with more complex knowledge hierarchies. To illustrate, future inquiries might explore how knowledge recombination interacts with competition across multiple trajectories or pertains to overarching technological domains. This paper paves the way for other, similar approaches.

ii) Valuing consolidation, not only disruption

Much of innovation management research emphasizes the value of disruption in driving technological change (Dahlin & Behrens, 2005; Christensen, Raynor & McDonald, 2013)—an emphasis which has cumulated in several measures of an invention's disruption, most notably the consolidation-disruption index (CD index) (Funk & Owen-Smith, 2017; Park, Leahey & Funk, 2023). For example, the CD index has been used to demonstrate that the overall degree of inventions' disruptiveness has been decreasing over time, a reduction in innovation performance which is poorly understood (Park et al., 2023).

However, trajectory integration highlights the potential role of consolidation processes in driving technological change. Trajectory integration means that, as a product of knowledge recombination, an inventor has consolidated knowledge from a given trajectory in an invention. As a particular form of knowledge consolidation, trajectory integration demonstrates that consolidation—not only disruption—plays a central role in promoting technological change. This paper provides reasons to value consolidation, not only disruption.

The concept of trajectory integration underscores the importance of consolidation processes in technological evolution. By definition, trajectory integration implies that, through knowledge recombination, an inventor consolidates insights from an established trajectory into an invention. As a specific manifestation of knowledge consolidation, trajectory integration suggests that consolidation — just as much as disruption — is pivotal in advancing technological change.

The broader research implications of pinpointing trajectory integration as a form of advantageous knowledge consolidation hinge upon our understanding of how knowledge is structured. If knowledge consolidates, how exactly does this process manifest? Adjacently, some research delves into the architectural organization of knowledge components, examining their structure within firm knowledge bases (Raveendran et al., 2020; Zahra et al., 2020), social and knowledge networks (Phelps et al., 2012; Schillebeeckx et al., 2021), and in the context of interdependency relationships among components (Fleming & Sorensen, 2001; Murmann & Frenken, 2006). While trajectory integration integrates knowledge from a trajectory into an invention, further explorations are warranted to understand other ways in which knowledge might be structured to optimize the benefits of consolidation processes like trajectory integration.

iii) Deeper understanding of dynamic characteristics

In our investigation of trajectory integration, we highlight the importance of dynamic characteristics within the context of knowledge recombination. Whereas much of existing literature provides static representations of knowledge structures, our approach emphasizes the need to recognize the evolutionary and iterative nature of knowledge.

The incorporation of intergenerational knowledge serves as more than just a record of prior insights; it facilitates a more comprehensive grasp of the constituent elements within a trajectory (Furr & Snow, 2015). As trajectories develop, they not only document the progression of knowledge but also elucidate potential avenues and methodologies for the recombination of components (Malhotra et al., 2021).

Furthermore, recognizing the dynamic nature of knowledge has implications for both theoretical frameworks and applied strategies. A focus on dynamism necessitates a continual examination of the evolution of knowledge structures, calling for methodological approaches that can capture these shifts. It also encourages a proactive stance in academic research, prompting scholars to evaluate the potential implications of these shifts on related knowledge trajectories. In sum, addressing dynamic characteristics enhances the depth and scope of our understanding, and suggests a more forward-looking, adaptive approach to knowledge recombination research.

3.6.3 Limitations

In presenting our findings, we recognize a number of limitations that underpin our research. Foremost, the extent to which our results can be generalized is circumscribed due to our focus on a single industry: nuclear power technology. This sector offers a distinct technological context for delving into the role of trajectory integration, particularly given its clear technological lineages, the rigorous design limitations imposed by antecedent technology, and the extensive knowledge requirements imperative for effective recombination.

It should be acknowledged, however, that these attributes are not uniformly present or applicable across diverse technological domains. There may exist nuanced interactions between trajectory integration and other knowledge recombination processes in different domains. As a result, the prominence or applicability of trajectory integration could vary, being potentially less pertinent or manifesting differently in these other domains. Thus, while our research provides valuable insights, readers should consider domain-specific characteristics when generalizing or applying our findings.

Secondly, our theoretical framework includes a pivotal assumption: the premise that knowledge components are utilized in a specified manner during knowledge recombination. Our approach revolves around externally observable patterns and does not delve deeply into the intricate, endogenous cognitive processes that transpire within inventors' minds during recombination. Our framework's lack of integration with cognitive models rooted in psychology, which might have provided a richer understanding of the cognitive dynamics at play. Additionally, we have employed insights from laboratory or natural experiments that could have lent a more empirical dimension to our study. As a result, while our research offers a systematic observation of knowledge recombination processes and their outcomes, it stops short of deducing causal relationships, especially those related to cognitive underpinnings.

While our observational study provides a structured understanding of knowledge recombination in the context of trajectory integration, it should be recognized that our conclusions might not readily extend or be generalizable to the broader cognitive mechanisms that underlie knowledge recombination—simply because we do not postulate or present those mechanisms. Future research endeavors might consider bridging this gap by integrating more comprehensive cognitive models and experimental methodologies.

Third, patent data faces many challenges as an effective means to proxy invention mechanisms. Based on patent data, we make a strong assumption about how these components are recombined. As there are innumerable ways to recombine a given set of components, we assume that the links between components (as reflected in their citations) capture core structures related to how knowledge recombination occurs. Thus, our study is limited to the assumption that patent citations reflect knowledge flows that operate as the core mechanism of knowledge recombination.

3.6.4 Conclusion

We have argued that extant literature would benefit from an improved understanding of knowledge components and knowledge recombination's dynamic characteristics. We defined the concept of trajectory integration and hypothesized that it predicts a positive relationship to technological impact. We argue inventions along a trajectory undergo evolutionary changes, sometimes improving and other times regressing, due to the cognitive limitations of inventors. Trajectory integration enhances inventors' understanding of technological developments, helping them make informed decisions about which features to include or exclude, leading to more functionally superior inventions.

We further hypothesized that trajectory integration positively moderates technological distance. Technological domains encapsulate related technologies with similar functions, while technological distance represents the dissimilarity between these domains, complicating the process of recombination due to inventors' bounded rationality. Trajectory integration, by offering shared patterns of inventive problem-solving, can ease the challenges posed by recombining distant components, turning inventions into bridges between disparate domains.

We use patent data on nuclear energy technology to test these hypotheses. Our empirical results support our hypotheses. The initial results provide an interesting new link between the literature on technological trajectories and knowledge recombination, thereby expanding how both trajectories and recombination may be studied for several reasons.

Firstly, it bridges the gap between technological trajectories and knowledge recombination, showing a robust connection and suggesting potential research areas on how knowledge recombination interacts with competition across multiple trajectories. Secondly, the study highlights the importance of consolidation in driving technological change, arguing that consolidation plays as crucial a role as disruption in promoting innovation. This notion challenges the prevalent emphasis on disruption, calling for a deeper exploration of knowledge consolidation processes. Thirdly, the research underscores the dynamic characteristics of knowledge, emphasizing the evolutionary nature of knowledge and its implications for both theoretical and applied strategies. However, the study has limitations: its focus on nuclear power technology may limit the generalizability across different domains; it does not delve deeply into the cognitive processes of inventors; and it heavily relies on patent data, assuming patent citations reflect the core mechanism of knowledge recombination.

Chapter 4

On and On and On:

Knowledge interdependence enables technological domain growth

Solo-authored

ABSTRACT

This study explores the impact of how interconnected knowledge within a specific technological field, or domain, influences the growth and innovation of that domain. We propose two ideas: (1) the more interconnected the knowledge within a domain, the faster the domain grows, and (2) a higher degree of interconnectedness within a domain pushes inventors to create more innovative solutions. Our analysis examines green technology patents filed between 1924 and 2012. The findings reveal that interdependence within a domain drives its growth but does not necessarily lead to increased novelty. This study contributes to our understanding of how the structure of knowledge within a domain affects the invention process, highlights the benefits of highly interdependent knowledge, and emphasizes the importance of considering the connections within domain knowledge when examining innovation.

4.1 Introduction

Understanding sources of inventions is important, as new technology plays a critical role in driving long-term economic progress and enhancing societal well-being. Inventions belong to one or several technological domains—groups of technologies with similar purposes, functions, or uses—such as wind power or solar power generation technologies (Rosenkopf & Nerkar, 2001; Nemet & Johnson, 2012; Keijl et al., 2016). The growth and novelty rates of these domains vary, with some domains experiencing rapid growth, such as biotechnology, and others growing more slowly, like traditional incandescent lighting technology (Abernathy & Utterback, 1978; Carnabuci & Bruggeman, 2009). Furthermore, domain growth differs in terms of the rate of inventions that substantially enhance the domain's technological state of the art, i.e., domain novelty (Strumsky & Lobo, 2015; Verhoeven, Bakker & Veugelers, 2016). Many factors drive domain growth and novelty, such as the degree of complementarity and interconnectivity between domains (Carnabuci, 2010; Carnabuci, 2013). To understand domains' capacity for technological advancement, it is critical to understand their characteristics.

Recent scholarly attention has examined *domain knowledge structures* (Baumann, Schmidt & Stieglitz, 2019; Persoon, Bekkers & Alkemade, 2021;). Inventions within a domain represent knowledge and develop the domain's knowledge structure reflected in interdependencies between these inventions (MacCormack, Rusnak & Baldwin, 2006; Carnabuci & Bruggeman, 2009; Rahmandad, 2019; Ganco et al., 2020).[37] However, the extent of this interdependence varies considerably across domains. For example, the pharmaceutical domain exhibits high interdependence among inventions, with effective therapies depending on complex relationships between

[37] Knowledge components are "any fundamental bits of knowledge or matter that inventors might use to build inventions" (Fleming & Sorenson, 2004: 910). Knowledge interdependence "[…] arises when a [component] significantly affects the contribution of one or more other [component] to the functionality of a [component]. When [components] are interdependent, a change in one may require the adjustment, inclusion, or replacement of others for a [component] to remain effective." (Sorenson et al., 2006: 995).

compounds, molecular targets, and treatment approaches (Henderson & Cockburn, 1994; Rothaermel & Boeker, 2008), while bicycle technology demonstrates low interdependence, e.g., the brakes and steering are—thankfully—not interdependent (Bijker, 1997). While some scholars have started to consider interdependence as a feature of domains (Rahmandad, 2019; Baumann et al., 2019), they have not yet investigated the relationship between knowledge interdependence on domain growth and novelty.

In this study, we investigate the relationship between differences in domain knowledge interdependence (DKI) and domain growth and novelty. To this aim, we adopt a knowledge recombination perspective, which regards how inventors search for and use knowledge for invention (Fleming, 2001; Xiao et al., 2020). Interdependencies shape the landscape over which knowledge combination occurs (Adner & Kapoor, 2010; Raveendran, et al., 2020). When inventors successfully create or combine knowledge interdependencies in new inventions, they shape domains' knowledge structures to benefit the foundation for future advancements (Rosenberg, 1979; Ahuja & Katila, 2001; Kapoor & Adner, 2007). As interdependencies emerge, they facilitate domain growth and novelty (Murmann & Frenken, 2006; Rahmandad, 2019; Ganco et al., 2020). Interdependencies present inventors with challenges in knowledge recombination, but also opportunities to create new benefits (Ulrich, 1995; Fleming & Sorenson, 2001). By examining interdependence, we identify mechanisms impacting domain growth and novelty, offering insights to promote high-growth technological domains and advance state-of-the-art across various fields.

Our first hypothesis proposes that domain knowledge interdependence drives domain growth by enhancing the benefits and simplicity of knowledge recombination, enabling more inventions to be created and ultimately driving domain growth (Murmann & Frenken, 2006; Baumann et al., 2019; Ganco et al., 2020). Our second hypothesis is that DKI drives domain novelty by compelling inventors to devise innovative solutions satisfying complex structural conditions, resulting in more unique and divergent inventions (Siggelkow & Levinthal, 2003; Ethiraj & Levinthal, 2004).

Using a sample of patents filed in all 638 green domains in the 1924–2012 period (1 578 762 patents reflected in 36,506 domain-year observations), we test for the role of DKI in generating domain growth and novelty. The results indicate that interdependence drives domain growth, while there is mixed evidence of a relationship between interdependence and domain novelty. Although our main analysis supports the notion that DKI drives domain novelty, this relationship seems to reverse in post hoc analysis, suggesting that more complex or nuanced dynamics may be at play.

Our findings contribute to the literature in three ways. First, we contribute to the domain growth and novelty literature by emphasizing the importance of domains' internal knowledge structures in the inventive process (Carnabuci, 2010; Pichler, Lafond & Farmer, 2020). We argue domains are not just component characteristics within recombination (e.g., Ahuja & Lampert, 2001; Yayavaram & Ahuja, 2008), but contexts where knowledge recombination occurs. Domains are evolving knowledge foundations for future inventions, which both build upon and shape these domains (Simon, 1956; Levinthal & March, 1981). Second, our research expands interdependence studies by uncovering the benefits of high interdependence, contrasting with prior emphasis on low interdependence advantages, such as in notebook computers (Pil & Cohen, 2006; Campagnolo & Camuffo, 2010).[38] This nuanced perspective on interdependence may have implications at individual or firm levels (Yayavaram & Ahuja, 2008), offering a more comprehensive view of innovation. Third, our study enriches knowledge recombination literature (Savino et al., 2017; Xiao et al., 2022) by underlining the influence of domain knowledge structures on recombination (Rahmandad, 2019; Ganco et al., 2020), in contrast to previous research focused on cross-domain recombinatory search (Fleming, 2001; Rosenkopf & Nerkar, 2001).

[38] Pil & Cohen (2006) and Campagnolo & Camuffo (2010) both demonstrate that low interdependence reduces complexity in assembly and design and allows for more efficient problem-solving, thereby providing an edge in an industry where rapid innovation and product updates are critical. However, our research reveals the potential advantages of high interdependence, lends support to the traditional perspective that low interdependence is always beneficial.

4.2 Theoretical background

4.2.1 Knowledge recombination

Inventions are a major source of economic value and competitive advantage (Porter, 1985; Ahuja & Lampert, 2001). They result from knowledge recombination, the process characterized by how and where inventors search for knowledge components (Kogut & Zander, 1992; Grant, 1996; Fleming, 2001). Because the theory of knowledge recombination is based upon cognitive theories of search-based problem solving (e.g., bounded rationality) (Newell & Simon, 1972; March, 1991), knowledge recombination research often focuses on patterns in knowledge search, such as search across different domains (Rosenkopf & Nerkar, 2001; Xiao et al., 2022).

Inventors' search spans many types of domains, including geographical (Capaldo et al., 2017), temporal (Kok et al., 2019), organizational (Brennecke et al., 2021), and technological domains (Caner et al., 2017). A technological domain (hereafter simply *domain*) is a group of technologies that share a similar purpose, function, or use (Anderson & Tushman, 1990; Rosenkopf & Nerkar, 2001). Inventors and firms vary in their use of domain knowledge, such as in the number of domains combined (Schoenmakers & Duyster, 2010), familiarity with given domains (Yayavaram & Ahuja, 2008), and the distance between domains used (Keijl et al., 2016; Nemet & Johnson, 2012). For example, modern wind turbines combine traditional windmill turbine technology (one domain) with airfoil technology from aircraft wings (another domain) to generate more power (Manwell, McGowan & Rogers, 2010). The resulting technology reflects a *lift-based* rather than a *drag-based* design.

4.2.2 Domain growth and novelty

Domains vary not only in their rate of growth but also in domain novelty, i.e., how much inventions within a domain advance the technological state-of-the-art (Dahlin & Behrens, 2005; Verhoeven et al., 2016; Strumsky & Lobo, 2015). Domain growth and novelty depend on how well inventors can understand the domain and think of ways to add new inventions to it (Huenteler et al., 2016). Extant research suggests that inventors who explore various knowledge domains and integrate previously unconnected elements generate novel inventions that challenge existing paradigms and advance technology (Schoenmakers & Duysters, 2010; Uzzi et al., 2013). Understanding domains includes understanding their internal characteristics and the interrelationships between domains.

Domains exhibit varying relationships with other domains, with some sharing numerous traits while others are distinctly unique and contrasting (Carnabuci et al., 2015; Kovács et al., 2021). These differences manifest in complementarity, competitiveness, and connectivity between domains (Rosenberg, 1979; Ahuja & Katila, 2001; Carnabuci, 2011), as evidenced by the frequency of joint usages with other domains (Yayavaram & Ahuja, 2008). High connectivity between domains can lead to rapid growth in one domain, stimulating growth in another (Carnabuci, 2010; Pichler et al., 2020). Connectivity and complementarity also facilitate knowledge brokering, enabling recombination, and enhancing growth potential (Carnabuci & Bruggeman, 2009; Carnabuci, 2013).

Domain characteristics, such as size, scope, degree of overlap, and diversity, also play a crucial role in shaping their growth potential (Weitzman, 1998; Carnabuci, 2011). Larger domains offer more opportunities for knowledge recombination and growth (Weitzman, 1998). Broad-scope domains have extensive connections with other domains, which can influence each other's activity (Stuart & Podolny, 1996; Nemet & Johnson, 2012). This is especially true if connected domains are extensively overlapped, larger, and have rapid growth (Carnabuci & Bruggeman, 2009; Pichler et al., 2020). Similarly, broad-scope domains tend to have higher potential for novel invention, while narrow-scope domains facilitate less novel invention (Stuart & Podolny, 1996; Rosenkopf & Nerkar, 2001). Diversity regards the variety, detail, and granularity of knowledge components within a domain, impacting the potential for fine-tuned inventions (Fleming & Sorenson, 2004; Carnabuci, 2011). More diverse domains may be adaptable to a greater range of different applications and environments (Ardito, Petruzzelli & Albino, 2016), whereas less diverse, more specialized, narrowly focused domains may have higher potential for invention in specific areas and purposes (Brusoni, Prencipe & Pavitt, 2001; Fixson & Park, 2008; Dibiaggio & Nasiriyar, 2009). Thus, understanding a domain's individual characteristics is critical for understanding its capacity for change.

Indeed, research shows that inventors' abilities are significantly influenced by their knowledge environment, such as in institutional and network contexts (Hargadon & Douglas, 2001; Fleming et al., 2007). Knowledge networks facilitate access to diverse sources, allowing inventors to bridge structural gaps and fostering domain novelty through breakthrough ideas and enhanced innovation potential (Fleming & Sorenson, 2004; Schillebeeckx et al., 2021). As domains constitute the knowledge context within which inventions emerge, understanding a domain's internal knowledge structures is vital for understanding its capacity for growth and novelty.

4.2.3 The role of interdependence

Interdependence is components' functional dependence on specific structural connections, which can alter or disable components' functions when changed (Ulrich, 1995; Fleming & Sorenson, 2001).

Prior research has mostly focused on the challenges facing inventors conducting a single, isolated step of knowledge recombination (Henderson & Clark, 1990; Caner et al., 2017). Extant literature highlights that knowledge interdependence entails a tradeoff between knowledge recombination difficulty (which is not desirable) and invention benefits (i.e., utility, which is desirable) in this individual step (Fleming & Sorenson, 2001; Murmann & Frenken, 2006; Chen, Kaul & Wu, 2019).[39]

[39] Through effects on knowledge recombination, knowledge interdependence can affect invention and technological growth (Fleming & Sorenson, 2001; Murmann & Frenken, 2006; Dosi & Nelson, 2010; Adner & Kapoor, 2010; Caner, Cohen & Pil, 2017). By restricting functional abilities, knowledge interdependencies may affect firm operations (Brahm, Parmigiani & Tarziján, 2021), knowledge accumulation (Dutrénit, 2000;

On one hand, interdependence makes recombination more difficult because as interdependencies aggregate, increased interdependence among knowledge components necessitates inventors meeting structural conditions to enable successful recombination (Fleming, 2001; MacCormack et al., 2006; Arthur, 2007), which can potentially make the invention more challenging due to complexity (Murmann & Frenken, 2006).

On the other hand, interdependence can enable significant benefits. Invention involves recombining knowledge about components' functions to create novel or improved functions, which provide utility (Saviotti & Metcalfe, 1984; Ulrich, 1995; Arthur, 2007; Arthur, 2009). Often, these new or improved functions emerge only when components are interdependently structured (Ulrich, 1995; Henderson & Clark, 1990; Murmann & Frenken, 2006; Arthur, 2007; Arthur, 2009). For example, an inventor knows how a hammer and a crowbar each function and interdependently combine these functions in a carpenter's hammer. The carpenter hammer's additional utility emerges with interdependence, as the claw balances the hammer strike, and the hammerhead reduces the metal needed for the claw.

Given these difficulties and benefits, interdependence has been treated primarily as a problem of balancing trade-offs in individual inventions. For example, army tank technology optimizes trade-offs between firepower, armor protection, and battlefield mobility (e.g., heavy armor and guns reduce speed). As Castaldi, Fontana, and Nuvolari (2009: 552) write, "Indeed, tanks are not simple bundles of technical characteristics. In each design, technical characteristics are interrelated with each other to form what Saviotti and Metcalfe (1984) define as the 'internal structure of the technology'." At the invention level, balancing and optimizing interdependence's trade-offs is achieved by moderate levels of interdependence (Fleming & Sorenson, 2001; Pil & Cohen, 2006; Fixson & Park, 2008; Chen et al., 2019). Thus, moderate interdependence has been shown to optimize performance for single

Davis & Aggarwal, 2020), and interfirm coordination or competition in innovation activities (Brusoni et al., 2001; Adner & Kapoor, 2010; Howard, Withers & Tihanyi, 2017; Chen, Kaul & Wu, 2019).

instances of knowledge recombination (Fleming & Sorenson, 2001; Chen et al., 2019).

However, this single-invention perspective ignores the cumulative effect of a domain's overall interdependence. The above approach treats domains as characteristics of individual components instead of the environmental context within—or foundational knowledge structures upon—which new inventions are built. On the contrary, domains differ in the way inventions cumulatively build upon each other to benefit knowledge recombination (Adner & Kapoor, 2010; Kim, Yoon & Lee, 2020). For example, the pharmaceutical industry often exhibits high interdependence, where new drugs frequently build upon existing research and prior discoveries (Henderson & Cockburn, 1994; Rothaermel & Boeker, 2008; Keijl et al., 2016). This interconnected nature of chemical compounds forms the foundation for future inventions within the domain, bolstering efficiency, innovation, and adaptability, thereby fostering a conducive environment for future recombination as interdependencies accumulate.

A domain's knowledge is reflected in its constituent inventions or knowledge components and the network of connections between those knowledge components. As inventions recombine and build upon previous ones, they can create interdependencies between them (Baumann et al., 2019; Ganco et al., 2020; Rahmandad, 2019). Domains can have lower interdependence, where inventions rely on fewer prior inventions within the same domain (Arthur, 2009; Kneeland et al., 2020). For example, bicycle technology reflects low interdependence (Bijker, 1997).

The cumulative structure of domain knowledge is related to, but distinct from, the size of the domain. Differences in interdependencies mean domains differ in connective density (i.e., dispersion), with some exhibiting densely organized interdependencies, while others display more dispersed interdependencies and loosely connected domain knowledge components (Rahmandad, 2019; Persoon, Bekkers & Alkemade, 2020; Persoon, 2021). As Persoon, Bekkers, and Alkemade (2021: 1092) astutely note, "Although the size of [these technological domains] is substantial, this does not necessarily imply that the underlying knowledge structure is cumulative: A pile of stones is different from a stone wall, and some walls are higher than others." Thus, domains can have higher interdependence, where inventions typically build on many previous inventions from the same domain (Hargadon & Sutton, 1997; Kapoor & Adner, 2007; Kim et al., 2020).

4.2.4 Relevance to knowledge recombination

Although inventors explore both within and across domains to develop inventions, these new inventions may introduce new interdependencies that subsequently shape the landscape (Rahmandad, 2019; Baumann et al., 2019; Ganco et al., 2020). We contend that differences in DKI can influence future technological development, where a domain's overall knowledge interdependence fosters comprehension, recombination, and enhanced domain growth and novelty, with highly developed domain knowledge structures resulting in increasing returns to scale and accelerated invention (Persoon et al., 2021; Persoon, 2021). By influencing the accumulation of knowledge structures, additional interdependence has a direct impact on future technological development (Murmann & Frenken, 2006; Corredoira & Banerjee, 2015).

We believe that such advantages are due to how domain knowledge components are organized to enable future knowledge recombination. For instance, consider the task of memorizing a sequence of characters such as "P H D M D R S V P C E O I H O P" (Pinker, 2015: 68), where each character denotes a distinct knowledge component. This task can be simplified by organizing the information into interdependent clusters, such as "PHD MD RSVP CEO IHOP", which represent recognizable groupings of letters. For example, by combining the letters P, H, and D, we form the abbreviation 'PhD'. This structure can be further consolidated, resulting in a single coherent unit: "The Ph.D. and the M.D. RSVP'd to the CEO of IHOP". As interdependence increases, knowledge components become embedded, leading to the formation of a new, overarching knowledge structure (Simon, 1962; Sanchez & Mahoney, 1996; MacCormack et al., 2006; Kovács et al., 2021). This structure not only preserves the original meaning of individual components but also incorporates new contextual features and overall significance (Caner et al., 2017; Ganco et al., 2020). Similarly, we argue the knowledge structure of a domain can affect inventors' ability to contribute to that domain's growth and novelty.

4.3 Hypotheses

4.3.1 Hypothesis one – domain growth

We propose that interdependence fosters domain growth by 1) enhancing the benefits accessible to knowledge recombination; and 2) simplifying future knowledge recombination.

First, interdependence enhances benefits accessible to future recombination. Knowledge components exhibit varying degrees of compatibility or enhancement of each other's functions (Carnabuci, 2010; Dibiaggio et al., 2014). Interdependence functionally connects components through a structural dependence to enhance their performance, and these performance benefits exist in response to this structural connection (Usher, 1954; Ulrich, 1995; Henderson & Clark, 1990). If one component performs better, so does the dependent component. Due to these performance dependencies, when three or more components interdependently connect, their performance benefits indirectly extend to all connected components, amplifying the cluster's collective performance (Ulrich, 1995; Rahmandad, 2019; Ganco et al., 2020). The resulting component benefits future knowledge recombination. Additionally, this state of increased interdependence provides a novel context in which inventors can identify new opportunities.

For example, in cases of high interdependence, such as the turbojet engine, components collaboratively enhance their functions, leading to greater fuel efficiency at high cruising speeds compared to prop engines (Liew et al., 2006). This interdependence provided a new context for extensive subsequent beneficial knowledge recombination within the domain of aircraft engine technology. Inventors working in this space would have new architectures with which to work and new opportunities to identify.

Conversely, inventions with low interdependence involve reconfiguring existing components without significantly altering overall performance. As a result, the foundational potential for future recombination remains unchanged (Sanchez & Mahoney, 1996; Baldwin, MacCormack & Rusnak, 2014). For instance, incremental advancements in smartphone design often focus on rearranging features rather than creating substantial interdependence between components. As Ulrich (1995: p. 432) writes, "local performance characteristics can be optimized through a [low-interdependence] architecture, but global performance characteristics can only be optimized through a [high-interdependence] structure." Additionally, if the overall knowledge structure and context remain the same, then inventors are limited in their approach, as many opportunities to optimize this context may have been exhausted. In this fashion, interdependence provides greater benefits to knowledge recombination and enables more invention within the domain.

Second, greater interdependence simplifies future knowledge recombination by consolidating components into a cohesive, single component (Siggelkow & Levinthal, 2003; Kovács et al., 2021). While recombining multiple interdependencies is challenging, a realized invention entails interdependent components have been successfully combined. The interdependencies need not be decomposed, as a successful combination is now available. Contrary to common assumptions in knowledge recombination studies (Fleming & Sorenson, 2001; Murmann & Frenken, 2006), the new component need not be continually reduced to antecedent interdependencies. This simplified component becomes a starting point for future knowledge recombination (Ghosh et al., 2014; Cohendet & Meyer-Krahmer, 2001), mitigating complexities previously associated with recombining multiple interdependencies (Fleming & Sorenson, 2001; Ghosh et al., 2014). For example, in the domain of semiconductor lithography, interdependent components have been successfully clustered and bound to develop advanced technologies (Kapoor & Adner, 2007; Dibiaggio et al., 2014).

By enhancing the foundation for subsequent developments (Rosenberg, 1979; Huenteler et al., 2016), interdependence shifts the recombinant search landscape, facilitating innovation and simplifying recombination for inventors (Yan, Zhang & Guan, 2019; Ganco et al., 2020). This process allows for development of more interdependencies, the accumulation of benefits attributable to interdependent connections, and fosters domain growth. In summary, domain interdependence drives technological domain growth by enhancing components' benefits and simplifying recombination difficulties, promoting domain growth.

Hypothesis 1: DKI is positively associated with domain growth.

4.3.2 Hypothesis two – domain novelty

We propose that DKI drives domain novelty by compelling inventors to devise innovative solutions that satisfy complex structural conditions, resulting in more novel inventions.

During knowledge recombination, the functions of components combine to produce the overall technological function and application of the resulting invention (Usher, 1954; Arthur, 2007; Arthur, 2009). Addressing the complexities and challenges that arise from multiple interdependencies is a difficult task due to the structural conditions they create (Fleming & Sorenson, 2001; Brusoni & Prencipe, 2011). To overcome these challenges, inventors must develop innovative solutions that satisfy the complex structural conditions (Fixson & Park, 2008).

Greater interdependence encourages inventors to push beyond conventional boundaries and explore alternative ideas in uncharted territories (Sorenson, Rivkin & Fleming, 2006; Chen et al., 2019) whether new inventions build upon previous ones within the same domain. For example, in the field of renewable energy, the high interdependence between energy storage, generation, and transmission technologies necessitates inventive designs to optimize their synergistic performance, leading to novel inventions such as integrated smart grid systems and hybrid energy storage solutions (Lund et al., 2017). In contrast, domains with low interdependence, such as mechanical engineering, are less likely to produce unique components because the component functions can be easily separated and individually modified, reducing the need for innovative structural organization and novel approaches to invention (Simon, 1962; Von Hippel, 1990).

As interdependence further increases, the overall structural design of technologies tends to diverge due to the need for yet more novel solutions that can navigate and satisfy the multiple constraints imposed by the complex interplay of interdependent components (Henderson & Clark, 1990; Ethiraj & Levinthal, 2004). This divergence in structural design results in an increase in domain novelty as inventors think beyond conventional boundaries and develop inventive solutions to address the intricate web of interdependencies (Fleming & Sorenson, 2004; Gupta, Smith & Shalley, 2006). As a result, in highly interdependent domains like biotechnology, combining unique components often results in groundbreaking innovations (Rothaermel & Hill, 2005; Newell et al., 2008). For example, CRISPR-Cas9 gene-editing technology—a transformative invention—utilizes the Cas9 protein derived from bacterial immune systems and a guide RNA sequence from molecular biology and genetics to target specific regions of DNA (Doudna & Charpentier, 2014). Conversely, in low-interdependence scenarios, the overall structural design of technologies remains consistent, allowing inventors to focus on incremental modifications to constituent modules (Schilling & Steensma, 2001; Baldwin & Clark, 2010; Karim & Kaul, 2015). For instance, in the smartphone industry, low interdependence between hardware and software components enables designers to make small, iterative changes without drastically altering the overall structure. For these reasons, we hypothesize that DKI increases domain novelty.

Hypothesis 2: DKI is positively associated with domain novelty.

4.4 Methods

4.4.1 Empirical context

In this study, we focus our empirical investigation on green technologies. Green technologies are environmentally sound technologies and are defined by The United Nations Environmental Program as those which protect the environment, are less polluting, use resources more sustainably, recycle more of their wastes and products, and handle residual waste in a more acceptable manner than the technologies for which they were substitutes (United Nations, 1992). Examples include clean energy production, like solar panels, pollution reduction technology, water treatment technology, electric vehicles, and sustainable materials.

Prior research highlights the significance of knowledge accumulation in green technology development (Huenteler et al., 2016; Conti et al., 2018; Persoon, Bekkers & Alkemade, 2020). Green technology domains, exhibiting varying interdependence levels, serve as fertile testing grounds for our hypotheses. For instance, wind technology demonstrates high interdependence between blade technology and components like the rotor, gearbox, and generator, necessitating precise coordination for optimized efficiency (Manwell, et al., 2010). Similarly, bioenergy balances feedstock production, transportation, and energy distribution (Naik et al., 2010), while smart grid technology requires seamless coordination of interconnected components (Fang et al., 2011). Studying these rapidly growing domains enables examination of the relationship between knowledge interdependence, domain growth, and novelty, informing strategies for promoting high-growth technological domains and advancing state-of-the-art across various fields.

4.4.2 Data

We rely on patent data from the European Patent Office's patent database, PATSTAT, which provides high-quality, aggregated patent data from all offices internationally. A community of practice in innovation research has used patent data to model knowledge flows, knowledge recombination, and other processes related to invention (Corsino, Mariani & Torrisi, 2019; Jaffe & De Rassenfosse, 2017). As mentioned above, domain-level knowledge structures emerge from the accumulation of interdependencies at the invention level. Using patents as a proxy for capturing knowledge structures is advantageous because they provide detailed information on technological advancements and their connections, facilitating large-scale analysis (Hall, et al., 2001; Griliches, 1990). Moreover, patents represent codified knowledge, allowing for the systematic identification of technological interdependencies and the analysis of knowledge diffusion patterns (Narin, Hamilton & Olivastro, 1997). This approach makes our study accessible and engaging to a broader audience, emphasizing the value of patent data in understanding the more generalized knowledge mechanisms.

To understand the characteristics of knowledge at the domain level, it is crucial to first analyze the knowledge characteristics of individual inventions. A patent application is a formal request submitted to a patent office for the protection of an invention. Each patent office has its own set of requirements and procedures, which means that inventors might need to submit multiple patent applications in different offices to secure protection in various regions.

A patent family, on the other hand, is a group of related patent applications that protect the same invention in multiple jurisdictions. By aggregating data from all patent applications within a patent family, we can access comprehensive information about a specific invention (Arts et al., 2013). To accurately identify the invention-level data, we gather and compile all the patent application data within each patent family. In other words, the family-level data reflect each invention's data.

To represent domains, we aggregate invention data according to the International Patent Classification (IPC) subclass (4-digit) classification, as is common to represent domains in extant literature (Savino et al., 2017; Carnabuci, 2010). This enables us to effectively characterize and understand the knowledge attributes of individual inventions, which in turn helps us to analyze and categorize domain-level knowledge characteristics. Depending on the variable at hand, we additionally aggregate data to reflect the state of a specific domain at a particular year (domain-year observations).

Additionally, very small or nascent domains reflect a small handful of inventions. To focus on knowledge dynamics in more normal-sized domains—as well as remove outlier effects—we remove observations where the domain size is less than 10. After cleaning our data, our sample reflects approximately 1.5 million green inventions and 638 green domains across a period of 88 years, from 1924 to 2012. The total number of domain-year observations is 36 506 domain-year observations.

4.4.3 Dependent Variables

a) Growth

Where domain *d* has a total of *n* accumulated inventions at year *t*, we measure growth as the number of inventions that are generated in the following year (*t+1*) (Carnabuci & Bruggeman, 2009; Carnabuci, 2010). In other words, the number of new patent families (inventions) that use a specific IPC code (representing one green domain) and filed, in terms of priority date, in the following year.

b) Novelty

To operationalize domain novelty, we first require a method of identifying whether a given invention is technologically novel (Strumsky & Lobo, 2015; Arts & Veugelers, 2015; Verhoeven et al., 2016). The core thrust of many approaches to assessing novelty consider new or infrequent combinations of unique domains in a patent. Verhoeven et al. (2016) introduce two patent-based indicators: novelty in recombination, which assesses an invention's innovativeness in combining components and principles, and novelty in knowledge domains, which measures the degree to which an invention utilizes previously untapped domains. These measures focus on whether technological domains have been previously combined, where novel combinations entail the inventions are deemed technologically novel.

Building on the approaches of Verhoeven et al. (2016) and Strumsky and Lobo (2015), we assess an invention's technological novelty by examining whether it combines previously uncombined technological domains. To measure this, we:

1. Create a list of domain combinations for each invention.
2. Generate a list of historical domain combinations for every year and domain.

Using these lists, we can determine if any combination has occurred before. We utilize 4-digit IPC codes as proxies for technological domains. For each invention, we identify all associated domains and list every pairwise combination of these domains. If any pair is novel—i.e., not found on the historical lists—the invention is considered novel. To create historical domain pair lists, we apply several constraints:

1. We limit our historical lists to domain pairs from inventions within the same domain. This constraint is applied to characterize the effect of each domain's unique knowledge structure on novelty. Since domain knowledge structures provide the foundation for future invention and reflect the current state-of-the-art, we focus on novelty relative to a given domain's knowledge structure.
2. We use a 10-year time window to constrain our historical domain pair lists, acknowledging that knowledge structures evolve. This evolution affects both the context in which knowledge is used and the sources of knowledge components (Nemet & Johnson, 2012).

By limiting our analysis to inventions within the focal domain and those emerging within a 10-year rolling window, we can generate a list of all unique domain pairs on all inventions and determine if an invention is novel.[40] Once we have measured whether each invention is defined as novel, we then, as with growth, count the number of inventions that occur in a domain in a given year that are novel (*Novel Growth*). This enables us to closely follow our estimates of overall growth using negative binomial regressions with estimates of novel growth. This measure's validity aligns with prior literature (Strumsky & Lobo, 2015; Verhoeven et al., 2016) and is adjusted to reliably reflect our theoretical approach.

4.4.4 Independent Variable: DKI

In this study, DKI is the key independent variable, which captures the intricate relationships among different knowledge components within an invention (Persoon et al., 2021; Ganco et al., 2020). For each year, we calculate DKI as the ratio of citations that exist in a domain to the number of inventions in that domain.

DKI is quantified by considering both unidirectional dependence, as represented by the number of backward citations (Fleming & Sorenson, 2001; Sorenson et al., 2006; Wang et al., 2014), and the potential for new unidirectional and bidirectional interdependence arising from the co-occurrence of components within an invention (Yayavaram & Ahuja, 2008; Baldwin et al., 2014; Hur & Oh, 2021). By accounting for these two aspects, this proxy measure enables a more comprehensive understanding of how inventions rely on past knowledge and the potential for forming new interdependencies within the domain (Hargadon & Sutton, 1997; Arthur, 2007).[41]

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[40] For example, if an invention includes IPC codes A10A, B20B, and C30C, then the following domain pairs exist for this invention: A10A-B20B, B20B-C30C, A10A-C30C. To develop our historical list, suppose our constraints entail we have 100 prior inventions in the last 10 years and inside the focal domain. On these 100 inventions, A10A-B20B and B20B-C30C pairs both occur, but not A10A-C30C. Therefore, the invention is considered technologically novel.

[41] Three network diagrams of the DKI of wind energy in 1950, 1975, and 2000 are presented in Appendix A.

For our primary analysis, we operationalize DKI using the citation-to-invention ratio (i.e., edge-to-node ratio, in network terms). Although the average backward citation count has been used to measure different phenomena (Griliches, 1990; Hall et al., 2001), it does not necessarily reflect the overall number of connections and inventions in a domain, as inventions can share common antecedents, facilitating the development of numerous connections with fewer additional inventions.

Determining a measure for Domain Knowledge Interdependence (DKI) proved complex. Initially, modularity network measures were considered, which identify node clusters and gauge interrelationships by a technique called fast label propagation (Traag & Šubelj, 2023), but this approach inadequately captured multilevel interdependence. Clustering coefficients and betweenness or closeness centrality measures were also examined (Wang et al., 2014; Yan et al., 2019; Hur & Oh, 2021), but proved ineffective with sparse patent citation networks or in capturing interdependence.

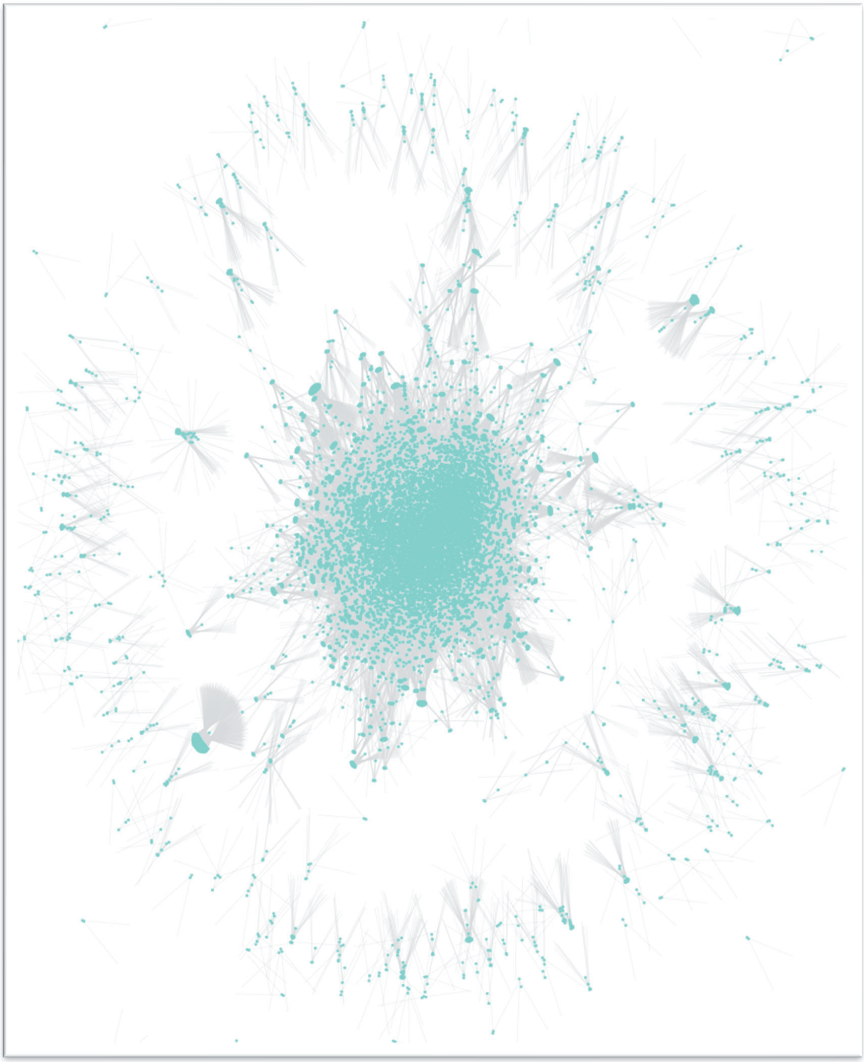
Paper 3, Figure 1 – DKI of Wind, 1950

Size	DKI
2 270	1.09

Paper 3, Figure 2 – Wind Domain Knowledge, 1975

Size	DKI
3 272	1.10

Paper 3, Figure 3 – Wind Domain Knowledge, 2000



Size	DKI
16 193	1.87

4.4.5 Control Variables

To enhance the internal validity and robustness of our findings, we account for potential confounding factors that could impact the dependent variable, domain growth and knowledge interdependence, by including control variables established in prior research (Carnabuci & Bruggeman, 2009; Carnabuci, 2011; Persoon et al., 2021). We control for various attributes of domains and their inventions. The control variables considered are domain size, scope, overlap, diversity, as well as year and domain fixed effects.

Domain size, which is associated with growth and innovation, is controlled for as larger domains typically possess more knowledge components for recombination (Weitzman, 1998; Carnabuci, 2013). *Size* is operationalized as the cumulative number of individual inventions within a domain. Domain scope represents the breadth of connections to other domains and can influence the ability to access and recombine knowledge (Cohen & Levinthal, 1990). Broad-*scope* domains (i.e., those high in scope) connect with many other domains, such that knowledge recombination in those domains is more dependent on the activity in connected domains (March, 1991; Stuart & Podolny, 1996; Nemet & Johnson, 2012). We control for scope, measured as one minus the number of inventions in a domain divided by the number of domain IPC codes occurring on those inventions. This ratio captures the extent to which a domain's inventions involve co-occurring domains.

Similarly, *overlap* regards the degree to which a domain shares a high proportion of its inventions with other domains, but additionally includes the individual shared proportions and sizes of connected domains (Carnabuci, 2010; Pichler et al., 2020). To calculate overlap, we employ the Jaccard index for each domain connected to a given focal domain. This is defined as the quantity of patents held by both domains divided by the patents held by either domain. To account for the size of the connected domains, we compute the logarithm of each connected domain's size. Subsequently, the Jaccard index of each domain is multiplied by the logarithm of that domain's size, yielding an approximation of that domain's overlap influence. By summing all overlap influence scores, we obtain the yearly overlap for the focal domain.

Knowledge diversity within a domain, signifying the balanced distribution of knowledge across its citations, influences the potential for innovation and growth in the domain (Trajtenberg et al., 1997; Nemet & Johnson, 2012). Accounting for this diversity, we determine the frequency of each connected domain's appearances on the focal domain's patents, giving a frequency count for all connected domains. In alignment with innovation management literature, we calculate diversity using the Herfindahl-Hirschman Index (HHI), defined as one minus the HHI score derived from these counts.

Given that we are estimating performance variables with respect to domains over time, we use both entity and time fixed effects.[42] To control for unobserved heterogeneity and potential time-varying biases, we include year and domain fixed effects with clustered standard errors. We treat each domain and year as dummy variables, reporting year but not domain in our descriptive statistics.

4.4.6 Analysis

Domain growth is a non-negative count variable (integer) with an over-dispersed distribution, i.e., its variance exceeds the mean. While Poisson regressions are commonly used to model count variables, Poisson models assume the distribution of variance equals the mean. The negative binomial distribution is a discrete distribution of observed successes in a series of independent Bernoulli trials and can be thought of as a Poisson distribution with parameter λ, a random variable with a Gamma distribution (Hilbe,

[42] By fixed effects, I mean that these effects are constant across years of the same domain. In a growth model with random intercepts k_i and the fixed slopes b_i for individuals *i* generates parallel lines, we estimate growth *y* of *i* at time *t* as $y_{it} = k_i + b_{it}$ (Kreft & De Leeuw, 1998).

2011).[43] Where the distribution of such count variables reflects variances exceeding the mean, a negative binomial regression is appropriate. To accommodate growth's overdispersion, we use negative binomial regressions to estimate growth. Novelty is similarly distributed, and so we also use negative binomial regressions to estimate novelty in our main analysis. Our statistical approach involves high-dimensional fixed effects, which span multiple domains and years.

4.5 Results

4.5.1 Descriptive statistics

Below our descriptive statistics are displayed in table 1.

[43] A Gamma distribution is a continuous probability function with three parameters, shape ψ, rate δ, and the Gamma function Γ, and regards the expected waiting time for a random event, a rate which converts—in our case—to an expected number of inventions per year.

Paper 3, Table 1 – Descriptive Statistics

Variable	Min	Mean	Max	StdDev	Skewness	Kurtosis	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Growth	0	437.52	87564	2227.99	17.87	468.62	1.00							
2. Novelty	0	52.08	2248	118.92	6.54	63.96	0.74	1.00						
3. DKI	0.50	1.05	5.26	0.28	2.94	19.06	0.50	0.57	1.00					
4. Size	10	6825.78	972 063	31198.08	12.60	210.96	0.86	0.73	0.52	1.00				
5. Scope	0.02	0.62	0.93	0.15	-1.91	3.70	-0.06	-0.04	-0.03	-0.10	1.00			
6. Overlap	0.01	2.55	19.92	2.31	1.86	4.55	0.42	0.67	0.60	0.44	0.20	1.00		
7. Diversity	0.00	0.91	0.99	0.08	-2.90	12.46	0.05	0.12	0.13	0.06	0.16	0.17	1.00	
8. Year	1924	1980.14	2012	20.37	-0.30	-0.87	0.16	0.28	0.52	0.19	0.48	0.45	0.34	1.00

Notes: Table 1 displays descriptive statistics for 36 506 domain-year observations from 1924-2012. It includes variables like Growth, Novelty, DKI, Size, Scope, Overlap, and Diversity, presenting measures like mean, median, standard deviation, and range. Growth and Size show high skewness, indicating a right tail. Significant correlations are noted, including Growth and Size (0.86) and Novelty and Overlap (0.67).

There are 36 506 domain-year dyad observations of which all variables are measured. Our sample therefore excluded years in which calculating these variables would be impossible, such as when the domain did not exist in the previous year. Our sample therefore spans years 1924 to 2012.

4.5.2 Main results

Our primary findings are presented in the section below. Model 1 serves as a baseline, providing an estimate of Domain Growth. This allows us to examine the effect of DKI, representing DKI, on Growth in Model 2. Likewise, Model 3 offers a baseline estimate for Novel Growth, while Model 4 supplements this with DKI. Our primary results are displayed below in Table 2.

Paper 3, Table 2 – Main results

	Model 1 Growth	Model 2 Growth	Model 3 Novelty	Model 4 Novelty
DKI		0.778*** [0.030]		0.427*** [0.025]
Size	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
Scope	-3.745*** [0.085]	-3.834*** [0.085]	-1.076*** [0.074]	-1.119*** [0.074]
Overlap	0.347*** [0.004]	0.309*** [0.004]	0.184*** [0.003]	0.163*** [0.003]
Diversity	-0.122 [0.086]	0.059 [0.086]	0.661*** [0.077]	0.759*** [0.077]
Domain Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
AIC	347 082.582	346 560.698	265 219.02	265 072.547
BIC	353 180.834	352 667.454	271 317.271	271 179.303
Log Likelihood	-172 824.291	-172 562.349	-131 892.51	-131 818.273
McFadden R2	0.837	0.84	0.897	0.898
Observations	36 506	36 506	36 506	36 506

Notes: Table 2 presents results from four models. Model 1 analyzes Domain Growth, and Model 2 introduces the Domain Knowledge Interdependence (DKI) effects. Models 3 and 4 explore Novel Growth, with Model 4 adding DKI. Coefficients, with errors in brackets, signify DKI's positive influence on growth in Models 2 and 4. AIC, BIC, and LRT values confirm a better fit for Models 2 and 4 over Models 1 and 3. All models account for Domain and Year Fixed Effects, with a consistent observation count of 36 506.

The empirical findings support our hypotheses. In Models 2 and 4 the statistically significant positive coefficient of DKI indicates its positive association with both domain growth and novelty. More specifically, Model 2 demonstrates a marked enhancement in goodness-of-fit measures in comparison to Model 1. This is illustrated by the lower values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) and higher values of the Likelihood Ratio Test (LRT) in Models 2 and 4, both of which suggest better model fit than 1 and 3, respectively.

4.5.3 Post hoc analysis

We conducted several post hoc analyses. First, we conduct sensitivity checks by altering the time windows and year ranges of our sample. Second, we check for nonlinear relationships between DKI and growth and novelty. Third, we conduct a robustness test using alternative operationalizations of our dependent variables. Fourth, we explore the relative importance of consolidating interdependence versus ongoing disruption in driving domain growth and novelty by decomposing the consolidation-disruption index into separate consolidation and disruption measures.

4.5.4 Sensitivity tests

In our first post hoc analysis, we conducted a series of sensitivity tests to scrutinize the robustness of our primary findings. This step is essential to ensure the stability of our results under different conditions, including varying time windows, year ranges, and domain sizes. These adjustments help establish whether our primary findings are robust to changes in data aggregation periods and gauge the sensitivity of our results to temporal effects.

We resampled our data across different year ranges. This step aimed to verify the robustness of our primary results across different temporal ranges. We applied 5-, 10-, and 20-year rolling time windows from 1924 to 2012 and found that our hypothesized relationships between DKI and domain growth and novelty disappear if the time windows are limited to many rolling windows that fall before 1950. However, the numbers of inventions and citations were very small in domains before 1950. In other words, little domain knowledge exists. While the hypothesized effects disappear, we attribute this to the fact that little domain knowledge exists to capture effects.

However, after 1950 we also found that the primary relationships tend to disappear if using 5-year time windows. This may be because DKI captures accumulating interdependence across longer periods, and so smaller time windows do not appropriately measure DKI. Accordingly, our results remain robust from around 1950 onwards across almost all 10-year and all 20-year time windows.

Next, we re-operationalized our independent and dependent variables to check for robustness across varying time windows. First, we re-operationalized novelty to remove the 10-year time window limiting whether an IPC code pair-dyad had previously appeared.[44] Furthermore, we checked whether removing all small domain sizes—which entail many novel inventions because the domain is new—and large domain sizes (e.g., only sampling domains in sizes from 500 to 10 000 inventions). Our results remained robust across all these changes to novelty. For DKI, we added a time window to limit relevant domain knowledge to a 10-year prior period. Our primary results exhibited resilience across differing temporal specifications, year ranges, and domain size ranges.

To determine whether autoregressive temporal effects were driving our primary relationships (e.g., high previous-year novelty drives current-year growth) we included the previous year's growth and novelty scores as controls. Our results remain robust across various combinations of controlling for previous year growth, novelty, percentage growth, and percentage novel.

4.5.5 Alternate dependent variables

We conducted a robustness check and adopted alternative operationalizations of our dependent variables to achieve scale independence and gain a more comprehensive understanding of the relationships between our independent and dependent variables. This approach ensures robustness

[44] Though this only decreased the number of inventions considered "novel" by 16%.

by converting our dependent variables to scale-invariant outcomes, considering the bounded nature of many of our independent variables (ranging, for example, from 0 to 1). Specifically, for the operationalization of domain growth, we measure the relative increase in size as a percentage of growth instead of using a count variable, allowing us to utilize linear regressions for estimation and normalize the growth percentage values by taking their logarithm. Additionally, in re-operationalizing novelty, we determine the percentage of novel inventions in a domain's growth and estimate it using both Beta regressions and linear regressions for comprehensive analysis.

Paper 2, Table 3 – Continuous DV Results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Growth (OLS)	Growth (OLS)	Novel (OLS)	Novel (OLS)	Novel (Beta)	Novel (Beta)
DKI		0.409*** [0.025]		-0.112*** [0.006]		-0.537*** [0.030]
Size	-0.000*** [0.000]	-0.000*** [0.000]	0.000*** [0.000]	0.000*** [0.000]	0.000*** [0.000]	0.000*** [0.000]
Scope	2.352*** [0.071]	2.291*** [0.071]	0.686*** [0.018]	0.702*** [0.018]	3.224*** [0.085]	3.270*** [0.084]
Overlap	-0.000 [0.003]	-0.019*** [0.003]	-0.050*** [0.001]	-0.045*** [0.001]	-0.231*** [0.004]	-0.207*** [0.004]
Diversity	0.881*** [0.073]	0.973*** [0.072]	0.251*** [0.019]	0.226*** [0.019]	1.118*** [0.082]	1.019*** [0.082]
Domain Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
AIC	42343.094	42070.353	-37970.924	-38280.401	-41023.823	-41346.687
BIC	48039.169	47774.719	-32274.849	-32576.035	-35228.253	-35542.826
Log Likelihood	-20484.547	-20347.177	19672.462	19828.201	21210.91	21373.343
R2	0.465	0.470	0.693	0.696	n/a	n/a
Adjusted R2	0.452	0.457	0.686	0.689	n/a	n/a
Observations	29 473	29 473	29 473	29 473	29 473	29 473

Notes: This table presents the results of linear regression models examining the relationship between DKI and the dependent variables, Log (Growth %) and Novelty. Model pairs (1 & 2, 3 & 4, 5 & 6) apply different specifications, with every second model (2, 4, 6) introducing the DKI variable. The effect of DKI on Log (Growth %) is positive and significant, while its effect on Novelty, operationalized as OLS, is negative and significant. Size, Overlap, and Diversity are also included as control variables. All models control for both Domain and Year fixed effects.

The outcome of this robustness test is mixed. We find a positive effect on novel growth in our primary analysis, but not the propensity in this post hoc test. However, this does not necessarily disconfirm our hypothesis. Our findings demonstrate that DKI to *a greater quantity of novel inventions* but also increases the domain's orientation towards non-novel inventions. It may be that the effect on growth is simply much stronger and, given the relative proportion of novel versus non-novel inventions, appears to reduce the proportion of novelty.

4.6 Discussion & conclusion

4.6.1 A new view of domain knowledge

This study highlights the critical role of DKI in stimulating technological domain growth and novelty. Our findings contribute to the existing literature on knowledge recombination (Levinthal, 1997; Ahuja, 2000; Ahuja & Katila, 2001; Fleming, 2001). Drawing on the theoretical foundations of knowledge recombination and interdependence (Simon, 1962; Nelson & Winter, 1982; Newell & Simon, 1972), our findings emphasize the significance of DKI in shaping the growth of technological domains. Varying levels of interdependence within different domains contribute to differences in growth rates and domain novelty (Carnabuci & Bruggeman, 2009; Persoon et al., 2021). High levels of interdependence foster a dense network of interrelated knowledge components, facilitating knowledge exchange and cross-fertilization, which promotes domain growth (Fleming & Sorenson, 2001; Wang et al., 2014).

The results regarding the relationship between interdependence and domain novelty are complex and suggest a more nuanced interaction than initially hypothesized (Levinthal & March, 1981; Kovács et al., 2021). In contrast, low levels of interdependence enable inventors to explore diverse paths and assemble knowledge components in novel ways, leading to higher levels of domain novelty (Rothaermel & Boeker, 2008). It is conceivable that while interdependence encourages inventors to develop unique and divergent solutions, it may simultaneously impose constraints that limit the attainable novelty (Levinthal, 1997). Alternatively, these mixed results may reflect unconsidered contextual factors, such as the social, economic, and regulatory environments that surround the invention process (Abernathy & Utterback, 1978; Carnabuci & Bruggeman, 2009).

More generally, our findings challenge a general and intuitive notion in knowledge recombination literature: that more flexibility—more modular and more easily recombined—structures benefit invention and technological change. This may be true for individual inventors, where lower interdependence makes recombination easier. In the long run and broader technological contexts (such as domains), interdependence may profile the foundation for future invention. In some sense, interdependence may generate the "fertile ground" within which the seeds of future invention may take root.

4.6.2 Theoretical implications and future research

Our study makes several important contributions to the literature. We contribute to the literature on domain growth, technological novelty, the role of interdependence, and knowledge recombination.

First, we contribute to the domain growth literature by emphasizing the importance of domain knowledge structures, particularly interdependence, as a key driver of domain growth (Carnabuci, 2011; Carnabuci, 2013; Carnabuci & Bruggeman, 2009). Prior studies have highlighted how structural interdependencies shape performance in diverse high-level contexts, including organizational (Rahmandad, 2019; Raveendran, et al., 2020), industry (Kapoor & Adner, 2007), and economic contexts (Rosenberg, 1979). Extending this analysis to a domain context, our work reveals a significant interdependence-performance relationship. Given the importance of overall technological advancement in domains for societal well-being and economic progress, understanding the factors that drive domain growth is essential.

These findings emphasize opportunities to further explore and define intricacies in domain knowledge structure relationships. For instance, while earlier research has shown that swift technological advancement influences the structure of accumulating knowledge (Persoon et al., 2020; Persoon et al., 2021), our findings suggest a reciprocal relationship: the accumulation of knowledge structures can, in turn, predict a domain's rate of advancement. There may exist nonlinear feedback effects warranting further study, and our findings serve as a springboard for additional investigations into the sources of overall technological domain advancement.

Second, we contribute to the literature on technological novelty. Extant research has focused on defining, detecting, and measuring technological novelty (Arts & Veugelers, 2015; Verhoeven et al., 2016). Few studies have examined the sources of technological novelty (e.g., Strumsky & Lobo, 2015). Our findings on sources of domain novelty are complex and unclear. DKI increases growth and novelty but decreases the percentage of novel inventions. As such, the relationship between DKI and domain novelty requires further clarification. For example, a domain percentage of novel inventions negatively predicts the next year's percentage of novel inventions (coefficient -0.46), but this relation strongly inverts in the presence of DKI (coefficient 1.1). There may be some nonlinear dynamics between growth and novelty, where one influences the other (e.g., high novelty drives growth. By exploring the emergence of novel technologies in the same study at domain growth, we outline avenues for future research.

Third, our research significantly contributes to the existing interdependence studies by highlighting the often-overlooked benefits of high interdependence, a departure from previous studies that have primarily championed the merits of low interdependence in varied contexts (Pil & Cohen, 2006; Campagnolo & Camuffo, 2010). Our unique focus on the interdependencies inherent in knowledge adds a new dimension to the understanding of interdependence mechanisms, traditionally explored within organizational settings such as interdependence in team roles or task performance (Anderson et al., 2014; Raveendran et al., 2020). This nuanced perspective encourages a revisiting of previous findings regarding the influence of interdependence on inventor and firm performance (Siggelkow & Levinthal, 2003; Brahm, Parmigiani & Tarziján, 2021). The research implications of our findings point to strategic complexities of how interdependence may be used. Short-term costs associated with higher interdependence could be strategically considered as investments that yield greater rates of innovation in the long term. This study provides insight into the performance implications of interdependence and guides future research to explore how high interdependence can improve performance in various firm and inventor contexts.

Our fourth contribution advances the understanding of knowledge recombination literature (Savino et al., 2017; Xiao et al., 2022) by spotlighting the significance of dynamic domain knowledge structures on recombination (Ganco et al., 2020; Rahmandad, 2019). This distinguishes our paper from prior research centered on static cross-domain search spaces (Levinthal & March, 1981; Fleming, 2001; Fleming & Sorensen, 2001). Our research postulates that the evolution of domain knowledge interdependence can modify the landscape for knowledge recombination, thereby affecting the creation of new inventions.

Future research may more precisely investigate the role of domain knowledge structures in knowledge recombination processes. In highlighting the dynamic interplay of domain knowledge structures (as search spaces) and knowledge recombination, our study invites further inquiries into the relationships between these structures and pivotal factors in knowledge recombination. These factors include inventor collaboration networks, high-impact technologies, and innovation-focused firms (Yayavaram & Ahuja, 2008; Schillebeeckx et al., 2021). As such, our study advocates for a more comprehensive examination of the drivers influencing knowledge recombination.

4.6.3 Limitations

In our study, we acknowledge several limitations that necessitate further exploration in future research. First, by aggregating knowledge recombination mechanisms in our study, we might unintentionally conceal crucial and nuanced dynamics. Future research should probe the psychological and cognitive processes underpinning these mechanisms to gain a deeper comprehension of their existence and contribution to invention performance, domain growth, and novelty. Analysis at the domain level has limitations and should be complemented with analysis at the micro-foundations level of analysis. For instance, investigating how inventors navigate the challenges and opportunities presented by interdependent knowledge components within a domain could provide valuable insights (Rosenkopf & Nerkar, 2001; Raveendran et al., 2020).

Additionally, our study's exploratory nature has resulted in the formulation of broad hypotheses. For instance, we fail to specify the degree to which growth is attributable to interdependence (Garud et al., 2013; Raveendran et al., 2020). We also neglect to address the overarching phenomena of technological growth (Grant, 1996; Gupta et al., 2006). The concentration on technological domains without considering the role of individual inventors constitutes a significant shortcoming of our research. Subsequent studies should delve into these aspects in more detail, elucidating the role of interdependence and technological growth in the invention process.

Our methodological approach is observational in nature—examining broad patterns in invention—and so fundamentally provides descriptive findings rather than causal explanations. We do not conduct experiments with rigorous control groups but rather theorize about patterns in data. Moreover, we detect minor autoregressive effects, though our results remain robust when controlling for these effects. However, such effects may indicate more complex dynamics that we cannot control effectively. As a result, our study risks endogeneity and omitted variable biases. Future research could attempt to experimentally explore the factors that influence the relationship between DKI and invention outcomes, potentially using natural experiments. For example, examining the role of external factors, such as industry structure, market dynamics, and regulatory frameworks, in shaping interdependence and its effects would contribute to a more comprehensive understanding of the interplay between interdependence and novelty (Rothaermel & Hill, 2005; Ganco et al., 2020).

Furthermore, the temporal aspect of DKI deserves further attention. Conducting longitudinal studies that track the evolution of interdependencies within technological domains over time could provide insights into the dynamic nature of interdependence and its impact on growth and novelty (Newell et al., 2008; Sorenson et al., 2006). Examining how interdependencies form, evolve, and potentially dissolve within domains could illuminate the mechanisms underlying the interdependence-growth-novelty relationship.

It is important to note that although this study primarily focused on green patents, the insights gleaned may have broader applicability across different technological domains (Ardito et al., 2016). Further research is warranted to investigate the generalizability of these findings to other fields and to delve deeper into the mechanisms through which DKI impacts the invention process (Arthur, 2007; Capaldo et al., 2017). Expanding our understanding of DKI can shed light on the broader dynamics of technological innovation and knowledge creation.

Lastly, we encourage future studies to investigate the complex dynamics underlying the performance benefits associated with DKI. This entails examining the conditions and concurrent mechanisms that facilitate nesting's impact on invention outcomes (Ghosh et al., 2014; Kneeland et al., 2020). By doing so, future research can enhance the clarity and coherence of our findings while rendering complex concepts—such as DKI—more accessible and comprehensible for readers with diverse levels of familiarity with the topic. In conclusion, addressing these limitations and gaps in our study will contribute to a more robust and comprehensive understanding of the invention process, technological domains, and their interactive dynamics.

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Appendix 1 – Definitions

Bounded rationality – The cognitive theory of problem-solving underlying knowledge recombination and recombinant search; often characterized as heuristic search, means-ends search, and as search-based problem-solving (Simon, 1955; Simon, 1956; Newell & Simon, 1972).

Knowledge components – Units of knowledge or matter used by inventors to invent technology (Nelson & Winter, 1982; Kogut & Zander, 1992; Grant, 1996; Fleming & Sorenson, 2004).

Knowledge landscapes – The cognitive, search, and technological knowledge spaces that inventors search across to find recombinations of knowledge components (Levinthal, 1997; Carnabuci, 2011; Aharonson & Schilling, 2016; Chen, Kaul & Wu, 2019; Baumann, Schmidt & Stieglitz, 2019; Rahmandad, 2019; Ganco, Kapoor & Lee, 2020).

Knowledge recombination – How inventors search for and use knowledge components to invent technology (Schumpeter, 1934; Simon, 1955; Simon 1956; Newell & Simon, 1972; Levinthal & March 1981; March, 1991; Fleming, 2001; Xiao et al., 2022).

Interdependence – components' functional dependence on their structural connections, which can alter or disable their function if changed (Usher, 1954; Ulrich, 1995; Henderson & Clark, 1990; Fleming & Sorenson, 2001; Sorenson et al., 2006; Raveendran, Silvestri & Gulati, 2020).

Invention outcomes – The value or utility-related characteristics of inventions, such as the quantity, novelty, or impact of inventions (Fleming, 2001; Verhoeven, Bakker, & Veugelers, 2016; Xiao et al., 2022)

Trajectories – a sequentially interdependent group of technologies that progress over time, building upon each other's advancements (Dosi, 1982; Tushman & Anderson, 1986; Funk & Owen-Smith, 2017).

Technological Domain – a group of technologies that share a similar purpose, function, or use at a point in time (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Carnabuci & Bruggeman, 2009; Carnabuci, 2010).

Technological Domain Knowledge – All the knowledge components represented by the technologies belonging to a technological domain (Nelson & Winter, 1982; Carnabuci, 2011; Nemet & Johnson, 2012; Carnabuci, Operti & Kovács, 2015).

Technological Domain Knowledge structure – The network of a domain's knowledge components' interdependencies (Fleming & Sorenson, 2004; Sorenson, Rivkin & Fleming, 2006; Wang et al., 2014; Caner, Cohen & Pil, 2017; Yan, Zhang & Guan, 2019; Ganco, Kapoor & Lee, 2020; Raveendran et al., 2020; Persoon, 2021).