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The Dynamic Geographies of the Knowledge Economy in Germany:
Where do firms & workers locate?

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Danksagung

Diese publikationsbasierte Dissertation ist während meiner Zeit als wissenschaftlicher Mitarbeiter am Lehrstuhl für Raumentwicklung an der Technischen Universität München entstanden. Diese Arbeit wäre nicht ohne die zahlreiche Unterstützung und Freiheit, die mir gewährt wurden, möglich gewesen. Ein besonderer Dank gilt dabei den Personen, die mich während dieser Zeit fachlich wie persönlich begleitet haben.

Zu Beginn möchte ich mich deshalb bei Prof. Alain Thierstein bedanken, meinem Doktorvater und Erstbetreuer dieser Arbeit. Das Thema dieser Dissertation, hier vor allem der relationale Denk- und Arbeitsansatz und die Wissensökonomie, wurden durch ihn maßgeblich geprägt. Darüber hinaus stand Prof. Thierstein über all die Jahre mit fachübergreifender Expertise stets an meiner Seite. Ich bedanke mich auch bei meiner Zweitbetreuerin Prof. Bing Zhu von der TU München für Ihre fachliche Expertise.

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Summary

This dissertation addresses the fundamental question: *'Do jobs follow people, or do people follow jobs?'* Set against the backdrop of Germany's dynamic and evolving knowledge economy over the past two decades, this dissertation examines where, how, and why firms and so-called knowledge workers locate from spatial, relational, and economic perspectives. To answer the question of causality, three sub-questions were formulated, each of which serves as the title of a corresponding publication: 'Where do knowledge-intensive firms locate?'; 'The contribution of knowledge-intensive firms to employment growth' and 'Where do knowledge workers locate in Germany?' To enable this approach, an extensive review of the literature and methodological analysis is carried out at the beginning. The resulting conceptual framework introduces the topic and key concepts on proximity, firms, workers, locational choice, knowledge work, and the methods applied.

Through a multi-faceted approach that uses advanced methods including Exponential Random Graph Modeling (ERGM), Granger causality testing, and origin-destination data analysis, this dissertation reveals the complex relational interdependencies between firm location decisions, regional employment growth, and knowledge worker mobility. In this context, this dissertation focuses on knowledge-intensive firms assigned to four distinct knowledge bases: analytical high-tech, synthetic high-tech, synthetic Advanced Producer Services (APS), and symbolic APS. This dissertation draws on extensive datasets covering firm locations, firm networks, and detailed employment changes. It also highlights how other factors, such as the various forms of proximity, transportation infrastructure, the presence of universities, and connectivity – both physical and non-physical – can influence the spatial distribution of knowledge-intensive economic activity. Since the data used has been standardized, and all data covers the same time period and spatial extent, so-called functional urban areas (FUAs), common conclusions can be drawn. Thus, this dissertation shows how the knowledge economy contributes to regional economic development, emphasizing that growth is not uniform in space but varies significantly, depending on the type of knowledge involved. The analysis of relocation patterns of knowledge workers offers additional insights since the results are spatialized.

Through its published work, especially in the European context, this dissertation makes significant contributions to academic research and policymakers. In its present form, it comprehensively addresses the spatial, relational, and economic complexities of knowledge-intensive activities.

Zusammenfassung

Diese Dissertation befasst sich mit der grundlegenden Frage: *Folgen Arbeitsplätze den Menschen oder folgen Menschen den Arbeitsplätzen?* Vor dem Hintergrund der dynamischen und sich in den letzten zwei Jahrzehnten immer weiter entwickelnden Wissensökonomie in Deutschland wird in dieser Dissertation untersucht, wo, wie und warum sich Unternehmen und so genannte Wissensarbeiter:innen aus räumlicher, relationaler und wirtschaftlicher Sicht ansiedeln.

Zur Beantwortung der oben beschriebenen Frage der Kausalität wurden drei Teilfragen formuliert, die jeweils als Titel einer entsprechenden Veröffentlichung dienen: *Wo siedeln sich wissensintensive Unternehmen an? Der Beitrag von wissensintensiven Unternehmen zum Beschäftigungswachstum* und *Wo siedeln sich Wissensarbeiter:innen in Deutschland an?* Um diesen Ansatz zu ermöglichen, wird zu Beginn eine umfangreiche Literatur- und Methodenanalyse durchgeführt. Der sich daraus ergebende konzeptionelle Rahmen führt in das Thema und die Schlüsselkonzepte zu räumlicher Nähe, Unternehmen, Arbeitnehmer:innen, Standortwahl und Wissensarbeit sowie mit den angewandten Methoden.

Mithilfe eines vielschichtigen Ansatzes, der fortschrittliche Methoden wie Exponential Random Graph Modeling (ERGM), Granger-Kausalitätstests und die Analyse von Herkunfts- und Zielortdaten verwendet, werden in dieser Dissertation die komplexen wechselseitigen Abhängigkeiten zwischen Standortentscheidungen von Unternehmen, regionalem Beschäftigungswachstum und der Mobilität von Wissensarbeiter:innen aufgezeigt. In diesem Zusammenhang konzentriert sich diese Dissertation auf wissensintensive Unternehmen, die vier verschiedenen Wissensbasen zugeordnet werden: analytische Hochtechnologie, synthetische Hochtechnologie, synthetische *Advanced Producer Services* (unternehmensnahe Dienstleistungen, APS) und symbolische APS. Diese Dissertation stützt sich auf umfangreiche Datensätze, die Firmenstandorte, Firmennetzwerke und detaillierte Beschäftigungsveränderungen abdecken. Sie zeigt auch auf, wie andere Faktoren wie die verschiedenen Formen der Nähe, die Verkehrsinfrastruktur, das Vorhandensein von Universitäten und die – physische und nicht-physische – Konnektivität die räumliche Verteilung der wissensintensiven Wirtschaftstätigkeit beeinflussen können. Da die verwendeten Daten standardisiert wurden und alle Daten denselben Zeitraum und dieselbe räumliche Ausdehnung, die sogenannten *functional urban areas* (funktional städtische Räume, FUA), abdecken, können gemeinsame Schlussfolgerungen gezogen werden. So zeigt diese Dissertation, wie die wissensbasierte Wirtschaft zur regionalen Wirtschaftsentwicklung beiträgt, wobei

hervorgehoben wird, dass das Wachstum räumlich nicht einheitlich ist, sondern je nach Art des beteiligten Wissens erheblich variiert. Die Analyse der Verlagerungsmuster von Wissensarbeiter:innen bietet zusätzliche Erkenntnisse, da die Ergebnisse verräumlicht sind.

Mit ihren wissenschaftlichen Veröffentlichungen, insbesondere im europäischen Kontext, leistet diese Dissertation einen wichtigen Beitrag zur akademischen Forschung und für politische Entscheidungsträger:innen. In der hier vorliegenden Form als kumulative Dissertation befasst sie sich zudem umfassend mit den räumlichen, relationalen und wirtschaftlichen Komplexitäten wissensintensiver Tätigkeiten und spannt dabei einen thematischen Rahmen, der das Werk als kohärent Ganzes lesbar macht.

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List of Abbreviations

AI ... *artificial intelligence*

APS ... *Advanced Producer Services*

BA ... *Bundesagentur für Arbeit (Federal Employment Agency)*

BBSR . *Bundesinstitut für Bau-, Stadt- und Raumforschung (Federal Institute for Research on Building, Urban Affairs and Spatial Development*

BeH ... *Beschäftigtenhistorik (Employment History Panel)*

BHP ... *Betriebs-Historik-Panel (Establishment History Panel)*

CM ... *Carlino-Mills*

CORE ... *commercial office real estate*

DFG ... *Deutsche Forschungsgemeinschaft (German Research Foundation)*

EEG ... *Evolutionary Economic Geography*

ERGM ... *Exponential Random Graph Model*

ESPON ... *European Spatial Planning Observation Network*

EU ... *European Union*

FUA ... *Functional Urban Area*

GaWC ... *Globalization and World Cities*

GIS ... *Geographic Information System*

IAB ... *Institut für Arbeitsmarkt- und Berufsforschung (Institute for Employment Research)*

ICT ... *Information and Communication Technology*

ID ... *Identifier*

INM ... *Interlocking Network Model*

LAU ... *local administrative unit*

MAR ... *Marshall-Arrow-Romer*

NUTS ... *Nomenclature des unités territoriales statistiques*

OD ... *Origin-Destination*

OECD ... Organisation de coopération et de développement économiques

R&D ... *Research & Development*

SAOM ... *Stochastic Actor-Oriented Model*

SDSM .... *Stochastic degree sequence model*

SIAB............... *Stichprobe der Integrierten Arbeitsmarktbiografien (Sample of Integrated Labour Market Biographies)*

SNF.. *Schweizerischer Nationalfonds (Swiss National Science Foundation)*

STEM... *Science, Technology, Engineering, and Mathematics*

WZ .... *Wirtschaftszweige*

Declaration of AI Use in the Writing Process

The author of this dissertation used DeepL and Grammarly to review the grammar and spelling of the written text. The author fully accepts responsibility for any errors.

Preface

Three peer-reviewed publications are included in this document. These publications are listed below:

Heidinger, M., Wenner, F., Sager, S., Sussmann, P., & Thierstein, A. (2023). Where do knowledge-intensive firms locate in Germany?—An explanatory framework using exponential random graph modeling. *Review of Regional Research*. https://doi.org/10.1007/s10037-023-00183-8.

Heidinger, M., Fuchs, M., & Thierstein, A. (2024). The contribution of knowledge-intensive firms to employment growth: A Granger causality approach for German regions. *Regional Studies, Regional Science*, *11*(1), 103–121. https://doi.org/10.1080/21681376.2024.2312186.

Heidinger, M., Fuchs, M., & Thierstein, A. (2025). Where do knowledge workers locate in Germany? A case study using employment relocation data in the German knowledge economy from 2012 to 2021. *Raumforschung Und Raumordnung | Spatial Research and Planning*. https://doi.org/10.14512/rur.3084.

Since publishers often have varying citation style requirements, these have been standardized to ensure a smooth and consistent reading experience throughout the document. Each of these publications includes its own dedicated list of references. In addition, the numbering of figures, tables, and equations has been streamlined by introducing a consecutive numbering system that ensures clear identification throughout the document. However, some works are written in British English, others in American English.

1 Introduction

The Organisation de coopération et de développement économiques estimates that urbanization continues to accelerate globally, with the urban population expected to reach 55% by 2050. This reflects a growing concentration of both economic and social activity in urban areas (OECD & European Commission, 2020, p. 3). While this trend has been evident for years, another form of restructuring can be observed, particularly in advanced economies like Germany, which is not quite as well known: the concentration of firms and employment in a smaller number of cities worldwide (Castells, 2011; Friedmann, 1986; Krätke, 2007; Sassen, 2001). So, what is driving this trend? Although there are various reasons for this, the central factor that binds them all together – and is also a key element in this dissertation – is the increasing dependence on and use of knowledge as *the* crucial resource for firms.

Knowledge has become a cornerstone for firms, forming the basis for innovation, fostering economic success, and driving growth in an increasingly competitive global environment (Bathelt & Glückler, 2011, p. 196; Vissers & Dankbaar, 2013). It has been instrumental in shifting economies away from industrial models towards knowledge-based approaches (Bathelt & Glückler, 2003, p. 1). However, this change is not just a local phenomenon but is closely linked to the general global shift from manufacturing to advanced service-oriented economies. The increasing globalization of value chains has outsourced production processes to regions with lower labor costs, creating a new global division of labor. In this landscape, knowledge-intensive work has emerged (Tippel et al., 2017).

In contrast to 'traditional' resources like raw materials, which have always been and continue to be important for industrial economies, knowledge is not a readily available commodity that can be extracted, used, and processed. Instead, it is a complex, multi-layered construct formed through iterative processes of social interaction, learning, and exchange (Cooke et al., 2007, p. 46). Unlike physical assets, it is not divisible but instead grows indefinitely (Storper & Scott, 2009, p. 148). Knowledge can also be consumed by multiple actors simultaneously, such as in firms or by workers, without being depleted (Hidalgo, 2024). In fact, and this may be one of the most important aspects of knowledge, it is essential to consume it and combine it with other knowledge, as this is the only way to create new knowledge (Cooke et al., 2007, p. 51). Therefore, knowledge must be constantly acquired, integrated, and applied by firms that want to drive their innovation and maintain a competitive advantage (Bathelt & Glückler, 2011, p. 63). Despite all this, knowledge is diverse and varies considerably in its nature, quality, and usefulness, which is why not all knowledge is the same and cannot be effectively used by all firms in the same way.

This variability makes it crucial for firms to identify and leverage the 'right' knowledge sources, which they find in the form of a highly qualified workforce (Asheim & Gertler, 2006). For instance, knowledge-intensive industries like biotechnology, finance, or engineering are all highly dependent on scientists, engineers, or consultants, to name a few (Thierstein et al., 2009, p. 63). As a result, these employees are characterized by a high level of education and possess the corresponding analytical and communicative skills, but also creativity (Florida, 2003; van Oort et al., 2003). It is this group, often referred to as knowledge workers, that drives innovation through problem-solving, scientific work, and the application of creative solutions in firms (Asheim & Gertler, 2006; Florida, 2003; Storper & Scott, 2009). Thus, their knowledge is highly specialized, or as Hidalgo (2024) puts it, 'non-fungible.' As a result, knowledge workers, like any other resource, are unevenly distributed in space (Storper & Scott, 2009, p. 148). Knowledge workers tend to feel most comfortable where there is a lot of interaction, i.e., in urban areas. These offer diverse cultural amenities, a high quality of life, and a high level of education (Carlino & Saiz, 2019; Florida, 2003). Therefore, firms must locate to such areas to gain access to these fitting knowledge resources (Bathelt & Glückler, 2011). However, it is equally important to recognize that knowledge workers themselves are mobile and adapt to changing market dynamics, often relocating for job opportunities, professional networks, or personal connections (Tippel et al., 2017).

In fact, a growing concentration of knowledge-intensive work can be observed in large cities (Adler & Florida, 2020; Balland et al., 2020; Bassens & van Meeteren, 2015; Simmie, 2003). Florida (2005) famously described this phenomenon as 'the world is spiky,' meaning that innovation is highly concentrated in specific locations (Balland et al., 2020; Sassen, 2020). One of the main reasons for this is that knowledge-based firms use localized resources and extend their reach globally through multiple branches and locations, often in different countries. As a result, cities are increasingly acting as nodes in the global flows of not only goods but also capital and knowledge within these networks of firm locations (Castells, 2011; Sassen, 2001). However, the position of a city in this network of cities is shaped by a mix of physical and non-physical factors (Castells, 2011, p. 443). Hard location factors, like the number of universities and research institutions, high GDP, taxes, and accessibility through public transportation infrastructure, such as airports and railway stations, are essential, although their relative importance varies across knowledge-intensive industries (Conventz & Thierstein, 2014; Florida et al., 2015; Roesler & Broekel, 2017; Wenner & Thierstein, 2021).

Consequently, the locations of both firms and employment come to the fore of regional and economic sciences, an interrelationship that has long intrigued regional and economic scholars (e.g., Chen & Rosenthal, 2008; Storper, 2010; Storper & Scott, 2009). This dynamic poses a real chicken-and-egg dilemma: do jobs follow people, or do people follow jobs? More specifically, do firms choose regions that already have an appropriately skilled workforce, or are workers drawn to regions where a wide range of firms are already established? Or do they prefer regions where similarly positioned firms are located? Alternatively, could there be an entirely different process at work? As this introduction has already shown, there is growing evidence of a bidirectional influence: firms choose to locate in cities and regions with a fitting workforce, while workers, in turn, are attracted to cities and regions with the right firms and work opportunities.

But how can knowledge-intensive firms be defined and delineated? Are there differences in where they are located? Who are the knowledge workers who bring this specific knowledge with them, how can they be distinguished, and where do they locate? Can they contribute to employment growth? These questions are at the heart of this dissertation, which examines knowledge-intensive firms and their employment, with a focus on the locations of multi-branch, multi-locational firms. By employing a relational approach, the focus is placed on the complex relationship between firm locations and the locations of knowledge-intensive employment. This dissertation pursues three key objectives to address this complexity: first, to analyze where knowledge-intensive firms locate in Germany; second, to examine whether knowledge-intensive employment drives employment growth or vice versa; and third, to explore the location patterns of knowledge workers in Germany. The studies in this dissertation are set in the German context and focus on 186 functional urban areas (FUAs). This dissertation is based on three related datasets, which were analyzed using three methods: 1) a self-collected, relational dataset of 480 multi-branch, multi-location firms and their locations in Germany. This dataset acts as the cornerstone of this dissertation, as it offers insights and empirical evidence on how and where knowledge-intensive firms adjust their spatial division of labor to leverage appropriate knowledge sources. They do this by continuously optimizing the strategic location of activities in the value chain across multiple locations. This increases the firms' efficiency both within and outside over time.

2) This dataset was expanded into a panel dataset that tracks all firm locations from 1999 to 2021 in collaboration with the Institute for Employment Research (IAB). 3) In addition, the employment per year, firm location, and FUA were generated. These datasets made adopting both a relational and a dynamic geographical approach possible in the studies. The structure of this dissertation is organized as follows.

Chapter 2 introduces the conceptual framework of this dissertation and provides a concise literature review that systematically reassesses the state of research in a historical context. The chapter outlines key literature on agglomeration and network economies, knowledge, knowledge generation, knowledge exchange, the different forms of proximity required for this, firm location decisions, and knowledge employment dynamics. This review culminates in the identification of research gaps, the formulation of research questions and presentation of hypotheses.

Given the dissertation's reliance on extensive data and analytical methods, Chapter 3 describes the data generation process and briefly introduces the methods used. It focuses on three primary data sources: self-collected data, extended firm data using official records, and official employment data for each firm. Then, the spatial extent and the three applied methods are introduced. Because the studies rely on a variety of data sources, this chapter also explains the approaches used to compile and regenerate the necessary datasets. A more comprehensive discussion of each methodology follows in the subsequent chapters.

To examine the formulated research question, Chapter 4 employs network analysis on the collected network of locations of knowledge-intensive firms in Germany grouped in knowledge bases. Each firm location is assigned to the corresponding FUA in which it is located. The study used exponential random graph modeling and firm networks of multi-branch, multi-location firms in Germany. Various FUA-specific and relational features were constructed or collected to understand how physical and non-physical factors influence these firm networks. These include factors like the presence of an airport or train station, travel time between FUAs, and the presence of larger cities within a FUA, all of which may impact the observed networks. The results are presented and discussed using a summary table of parameter estimates.

Chapter 5 examines whether employment in knowledge-intensive firms influences total employment in Germany (or vice versa). This chapter aims to contribute to the growing literature on causality studies and add further knowledge to the research question. Therefore, this study is conducted using Granger causality tests. It uses the self-developed time series dataset on knowledge-intensive employment (see Section 3.3) and classifies employment into APS, high-tech, and total employment. This chapter tests whether the change in total employment has affected the change in the absolute number of knowledge-intensive workers and vice versa. The study is set up in a two-step framework, first testing the relationship at the global level (i.e., for the whole of Germany) and, in the second step, at the local level (i.e., for each of the 186 FUAs in Germany). The results from the second step are visualized and discussed using maps.

Chapter 6 examines the relocation patterns of knowledge-intensive workers in Germany. The study conducts a comprehensive analysis, tracking the origin and destination of each worker of a dataset of firms that relocated between 2011 and 2021. Each knowledge worker is categorized into one of four knowledge bases and included in the dataset if they relocated between FUAs during the observation period. This classification helps explain how firms create and utilize knowledge in their innovation process and allows them to differentiate workers' relocation patterns. The relocations are aggregated into ties between FUAs, highlighting ties that are relationally close but geographically distant. The results are presented and discussed through maps that reveal distinct relocation patterns across FUAs. These three chapters, i.e., studies have been published or accepted for publication in peer-reviewed journals.

Chapter 7 summarizes the main findings from the previous three chapters, encompassing the key publications. It discusses and interprets the results within the context of the overall conceptual framework and the relevant literature presented in Chapter 2. This chapter also discusses the results in relation to the initial research questions outlined in Section 2.5.

The dissertation concludes with Chapter 8, which provides a comprehensive summary of the findings and reflects on the results. Additionally, this chapter addresses methodological limitations and potential issues, highlights implications for current research, proposes approaches to tackle unresolved questions, and suggests avenues for future research. The following **Figure 1** provides an overview of the dissertation's structure.

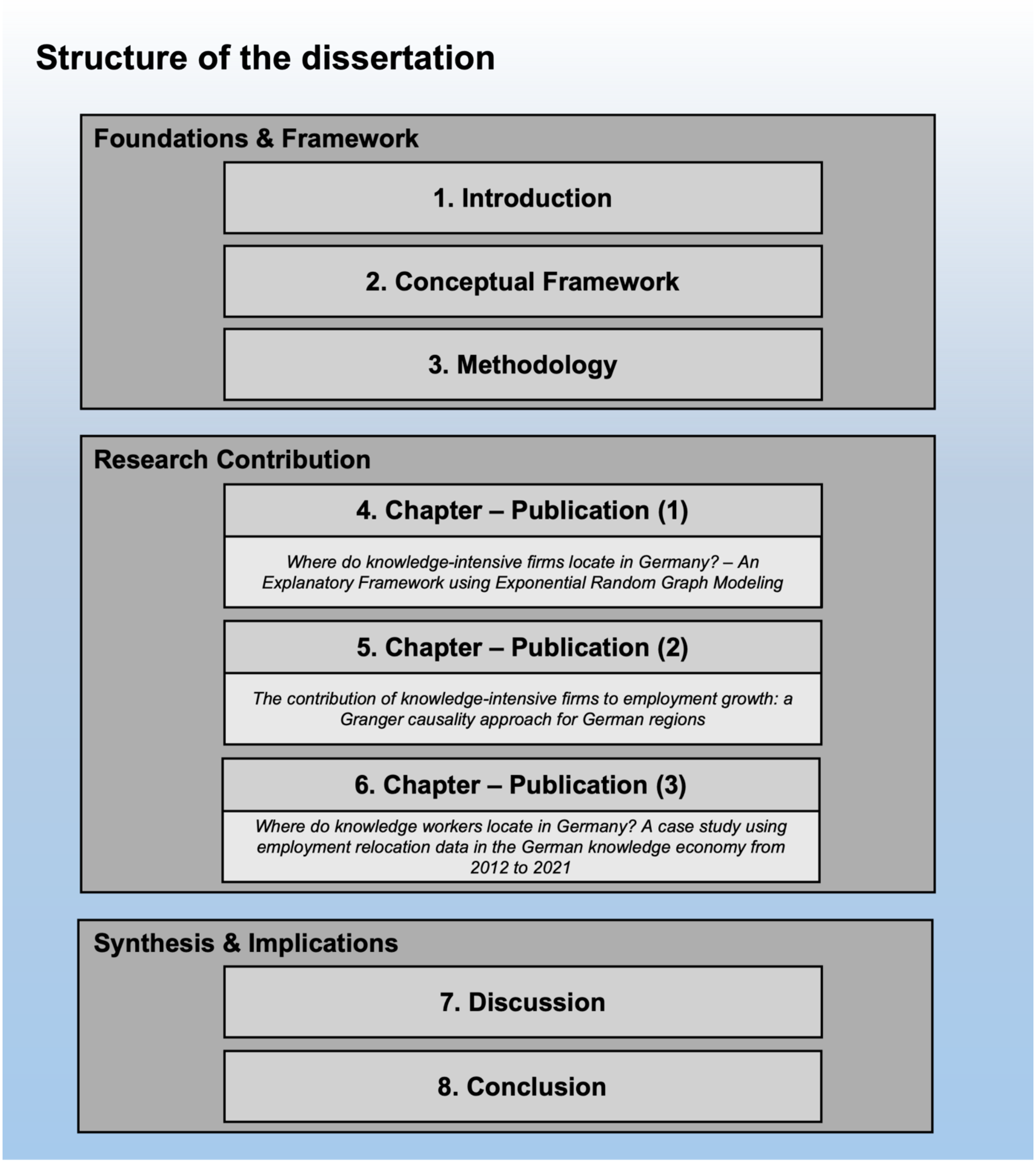

Figure 1 Structure of the dissertation. Own illustration.

2 Conceptual Framework

As the introduction has shown, knowledge production is a complex, multifaceted process that involves multiple actors, with human activity and interactions at its core. Historically, three key elements – cities, firms, and employment – have converged in knowledge production. This chapter offers a historical and scientific overview of the concepts of proximity, knowledge, firm locations, and employment, exploring how cities and regions contribute to knowledge creation and why their role in knowledge production is essential.

2.1 From Agglomeration to Proximity

2.1.1 FROM LOCALIZATION ECONOMIES

For centuries, economic activities typically took place near natural resources to produce goods and develop new products. However, this shifted in the late 19th to early 20th century due to industrialization processes in Europe, leading to the eventual rise of urban areas as new economic centers. Two seminal works, Adna F. Weber's *'The Growth of Cities'* (1899) and Alfred Marshall's *'Principles of Economics,'* (1920) pioneered the theoretical debate about where and why this economic growth occurred in light of the Industrial Revolution.

Industrialization introduced new, highly standardized production and manufacturing processes, allowing firms to mass-produce goods. However, to further reduce production costs, the growing manufacturing facilities had to increase their production output, an economic effect that Marshall (1920) referred to as (firm-)internal economies or broader 'economies of scale.' Consequently, these firms became increasingly reliant on additional labor, prompting workers to relocate from nearby rural areas in search of economic opportunities, which led to the creation of a substantial workforce in these newly developed industrial urban areas. In turn, the labor pools were beneficial for competing and collaborating firms, who also wanted to gain access to local markets and other suppliers (Diodato et al., 2018, p. 2).

Marshall (1920) described this process of emerging concentrations and clusters of firms and workers in urban areas as 'external economies.' These external advantages, often referred to as 'localization economies,' which remain beneficial today, have produced additional productivity benefits, alongside labor pool sharing and proximity to both customers and suppliers (Diodato et al., 2018). They also lead to reduced transportation costs through the construction of transportation, such as roads and railways, and other technical infrastructure.

Most importantly, such external advantages facilitate knowledge exchange between firms, which further decrease production cost by improving goods and processes through (un-)intended "*sharing, matching, and learning*" (Duranton & Puga, 2004, p. 2066) of knowledge and information between firms of the same industry (Glaeser & Gottlieb, 2009; Neffke, 2009; Storper & Venables, 2004). In short, economies of scale can be attributed to internal cost-saving and output-increasing factors of firms. Localization economies, often called 'Marshallian externalities,' describe all the external benefits that arise when industries cluster together (Neffke, 2009, p. 23).

2.1.2 TOWARD UNDERSTANDING URBAN EXTERNALITIES

Now, these thought processes and economic theories are not just a construct of the past or the European industrialization era but have been adopted, expanded, and tested globally over the last century. Jane Jacobs (1969), for example, defined the advantages or benefits of firms locating in cities with a diverse industrial base (Neffke, 2009, p. 25). Jacobs emphasized that a diverse local market opens up the possibility of inter-industry knowledge exchange and can lead to innovation. In contrast, the Marshall-Arrow-Romer (MAR) externalities (Arrow, 1962; Marshall, 1920; Romer, 1986), building on Marshallian externalities, highlight the benefits of industry specialization within a region (Beaudry & Schiffauerova, 2009; Neffke, Henning, Boschma, et al., 2011). While Jacobs (1969) argues that a diverse local market is more resilient against external shocks, produces new inter-industry knowledge, and comes up with new product combinations (Neffke, Henning, Boschma, et al., 2011). Literature on MAR externalities, on the other hand, posits that a strong, specialized local industry can also sustain itself. Such regions can attract highly specialized workers and other highly specialized suppliers and customers, thereby further reducing transportation costs and enhancing productivity (ibid.). The advantage of a highly specialized region is that workers are more likely to be protected from firm or demand uncertainty (note the difference to industry uncertainty in Jacobs' externalities) because of the large, relatively homogenous employment pools (Beaudry & Schiffauerova, 2009). Both MAR and Jacobs's externalities can be summarized as urbanization externalities.

Generally, urbanization externalities bring both advantages and disadvantages (Neffke, 2009, p. 26). The benefits of urbanization externalities usually arise in large cities (Neffke, Henning, Boschma, et al., 2011, p. 50). This is because large cities or metropolitan areas often provide access to large markets, have a large pool of highly educated workers and employees, house universities or other research institutions, and provide business service opportunities (Neffke, Henning, Boschma, et al., 2011, p. 52). Access to non-local markets is typically offered through a high-quality transportation infrastructure, such as an airport or high-speed railway station (ibid.). The logical disadvantages are the high cost of living, traffic and congestion problems, longer commute times, high land prices, housing shortages, and expensive labor costs (Neffke, Henning, Boschma, et al., 2011). Glaeser and Gottlieb (2009, p. 31) summarize that urbanization economies operating across industries are called agglomeration economies. This highlights the prominent link in the literature between urbanization and Jacob's externalities, as large cities typically host a diverse mix of industries rather than one highly specialized industry (Beaudry & Schiffauerova, 2009, p. 2). Lastly, Porter (1990) proposed to focus on the competitive aspect when firms co-locate in a region or city (the so-called Porter externalities): Firms in the same or similar industry compete for the same inputs, such as local resources or highly skilled workers (Neffke, 2009, p. 27).

In reality, localization and urbanization externalities are not exclusive concepts but go hand in hand. Duranton and Puga (2004, p. 2078), for example, argue that innovation benefits from a diverse environment, but specialization processes take over. Firms thus benefit from being in an economic setting that is a mix of competing and other firms and actors; however, over time, workers become more and more specialized in what they do, ultimately leading to a more specialized region (ibid.). Stimson (2022, p. 101) summarizes these externalities as follows: localization externalities affect the individual firm through the industry to which it belongs, while urbanization externalities arise from the size of the city or region, which in turn affects the firm. These individual theories, building blocks, come together to form what are referred to as so-called agglomeration economies.

2.1.3 DEFINING AND CONTEXTUALIZING AGGLOMERATION ECONOMIES

In general, agglomeration economies help us understand why and where certain firms locate. They have also been identified as the drivers of growth of mega-cities and large city regions (Camagni et al., 2016, p. 133). However, there is by no means only one singular definition for agglomeration economies, hence making a general valid definition difficult (Parr, 2002b, p. 152).

Parr (2002a, 2002b) understands two conceptual approaches to a definition: external and internal agglomeration effects. While the former is relevant for understanding the economic environment of a city or region that influences a firm's performance, such as the localization and urbanization economies introduced earlier (Parr, 2002b), the latter, referenced as 'internal economies of scale,' (Parr, 2002a, p. 718) is relevant for the individual firm. Parr (2002a) defines three important dimensions for the individual firm to save costs. First, economies of scale, as introduced earlier, thus reduce cost by increasing production output. Second, economies of scope diversify the production output by producing two or more different products simultaneously, thus decreasing the cost of operation. Third, economies of complexity: These economies arise when a firm engages and manages the different stages of production independently, which leads to a decrease in cost due to the ability to better coordinate processes (Parr, 2002a, p. 718). Obviously, each of these firm-internal economies is not dependent on economic concentration. However, Parr (2002a, p. 718) argues that a firm significantly benefits if external agglomeration effects are at play, e.g., by being close to customers. Van Meeteren et al. (2016) summarize that all of these theories contribute to the fact that large cities offer advantages for the firms located within these cities. In short, it is important to understand which perspective a researcher wants to take to study agglomeration effects, be it that of the firm or that of the location/ region/ city. Parr (2002b, p. 166) argues that all of these different agglomeration economies can coexist at the same time.

So far, spatial scales or distances have not been a major focus of the theoretical debate, except for, for example, Jacobs (1969), who mentions that large cities are fertile for firms (Neffke, 2009, p. 25). Rozenblat (2010) argues that agglomeration economies are applied at an intra-urban scale, thus meso or city level. But do these effects occur, or more specifically, apply to all sectors and distances alike? What is the extent of an agglomeration, then? According to Rosenthal and Strange (2020), the spatial scale of an agglomeration is "*fairly far*" (p. 29), as most studies used the metropolitan or regional scale as the spatial scale of analysis. Van Meeteren et al. (2016) also take the 'regional perspective' and argue that different spatial scales are needed for the different mechanisms and processes at play within an agglomeration. For example, according to Duranton and Overman (2005), localization economies, i.e., industrial clustering, occur at distances of less than 50 km. Van Meeteren et al. (2016) also indicate that labor market pooling is highly dependent on workers' commuting patterns; thus, a functional rather than an administrative delineation of the agglomeration is needed. This is consistent with the findings of Rosenthal and Strange (2020), who tested agglomeration effects at three spatial scales (regional, neighborhood, and building level) using employment data for a study area on the East Coast of the United States. At the regional level, the authors find that while employment is highly concentrated in urban centers, firm productivity is not, which aligns with previous research on city size and productivity (Rosenthal & Strange, 2020, p. 32). The paper further suggests that industries cluster in the same neighborhood at the neighborhood level, thus being close to each other, highlighting the importance of in-person interactions (p. 40). Finally, at the building level, the paper finds that areas that exhibit industrial clustering at the neighborhood level are not clusters per se but rather are concentrated in individual buildings (p. 41). Rosenthal and Strange (2020) thus surmise that agglomeration effects appear at all spatial scales considered, but the strongest at regional and neighborhood levels, with knowledge and information exchange operating at a smaller spatial scale (i.e., at the neighborhood or building level) than labor market pooling, which appears to extend well into the regional level. In summary, this paper is embedded in the existing scientific knowledge since different types of agglomeration economies play out at different spatial scales, as van Meeteren et al. (2016) previously stated.

2.1.4 FROM PROXIMITY TO A MULTIDIMENSIONAL VIEW OF PROXIMITIES

Discussing the exchange of knowledge and information across spatial scales raises questions about what the term 'proximity' really describes, how proximity can be defined, and why proximity is relevant to knowledge transfer. Interestingly, Stimson (2022, p. 98) notes that one of the first applications of the term 'proximity' in the context of regional economics was by Martin Beckmann (1968, p. 10), who proposed that in a theoretical economic market setting where prices are constant everywhere, the optimal price is influenced by proximity to economic factors such as customers or competitors. In fact, most of the literature on regional economics during this period focused exclusively on firm and industry concentration, using the concepts of agglomeration or localization economies (Stimson, 2022, p. 98).

The most common approach to proximity is the geographical or spatial perspective towards proximity since it is measurable, observable, and reproducible. According to Capello (2022), spatial proximity and agglomeration economies go hand in hand since both concepts combine two essential strands of regional research: regional economics and location theory (p. 445). And it makes sense: As a firm, proximity significantly reduces transportation costs by being located close to business partners, competing firms, or, in general, markets. Camagni et al. (2016, p. 136) note that "*Proximity is by definition linked to the geographical dimension of* *agglomeration and interaction effects: if information and transportation costs were nil, in the absence of scale economies there would be no reason to concentrate activities. In this sense, agglomeration economies are 'proximity economies"*. In short, it is economically advantageous to be spatially concentrated, at least sectorally.

Through the introduction of theories and models on urbanization and localization economies in the early 1970s, the term spatial proximity was extended with a gradual meaning, slowly shifting the focus on the definition and meaning of 'space' in the context of spatial proximity (Capello, 2022, p. 446). The previously assumed, or potentially simplified, 'space' as a uniform construct was more a theoretical concept than what was observed in reality: a diverse space where economic growth, decline, and stagnation are often close together (Capello & Nijkamp, 2009, p. 5). The 1970s and 1980s were also a time when the first advanced economies emerged, i.e., manufacturing and industry were relocated and replaced by service-oriented economies (Stimson, 2022, p. 99). Firms began to enter closer collaborations with local research institutions to become more innovative (Capello, 2022, p. 446), ultimately leading to the emergence of a small number of highly innovative, high-tech-oriented regions around the globe (Stimson, 2022, p. 99).

To understand why such regions perform better than other regions of similar size and economic structure, the literature has increasingly shifted its focus from geographical proximity to other forms of proximity, such as 'relational' proximity (Capello, 2022, p. 448). In Boschma (2005), this proximity is referred to as 'social proximity' and described as "*socially embedded relations between agents at the micro-level*" (p. 66). Boschma (2005) further notes that relationships "*between actors are socially embedded [...] based on friendship, kinship and experience*" (p. 66). Relational proximity can be defined as the "*interaction and cooperativeness among local agents, the source of collective learning processes and socialization to the risk of innovation*" (Capello & Nijkamp, 2009, p. 6). It therefore focuses on dynamic social relationships between actors in a specific region. Capello (2022, p. 449) summarizes that relational proximity is based on stable connections and interactions between local economic actors, such as customers and suppliers, and is based on trust and loyalty (Capello & Nijkamp, 2009; Stimson, 2022). Understanding the relationships between actors, or whether there are any at all, helped to explain why certain regions are more innovative than others (Capello & Nijkamp, 2009, p. 6). In the early 2000s, the concept of 'relational proximity' was also applied to the network-related approach to cities, where cities are seen as relational spaces (Lüthi & Thierstein, 2009, p. 10; Pike, 2007). Although this definition has not been widely adopted, it is worth noting here because this dissertation's underlying concept of cities as interconnected networks is a key foundation.

Boschma (2005, p. 68) defines three additional dimensions of proximity: institutional, organizational, and cognitive. Starting with institutional proximity, Boschma (2005) describes it as the institutional framework consisting of formal institutions, such as laws and rules, and informal institutions, such as local norms and habits. Further, Boschma (2005) argues that institutional proximity is a "*common language*" (p. 68) among economic actors that reduces uncertainty, lowers transaction costs, and enables interactive learning. Additionally, Balland et al. (2022, p. 76) define institutional proximity as a resulting process due to collaboration, which increases over time.

"*Organised proximity*" (Capello, 2022, p. 449) or organizational proximity is defined by Boschma (2005) "*as the extent to which relations are shared in an organizational arrangement, either within or between organizations*" (p. 65). Capello (2022, p. 450) argues that organizational proximity is a highly subjective construct of how each actor interprets their closeness to other actors. It can therefore be described as a "*continuous scale going from autonomy to control*" (Broekel & Boschma, 2012, p. 4). Broekel and Boschma (2012) emphasize the importance of distinguishing between profit and non-profit organizations; while non-profit organizations, such as universities, often collaborate with other non-profit organizations, profit organizations, such as firms, tend not to share their knowledge with other organizations, such as competitors. According to Boschma (2005, p. 65), organizational proximity or closeness between actors with similar routines is beneficial for sharing knowledge, mutual learning, and, thus, innovation.

Lastly, cognitive proximity refers to the conditions under which actors cooperate and therefore synthesize new knowledge (Capello, 2022, p. 452). Boschma (2005, p. 63) argues that firms, thus actors, usually search for new knowledge in close 'proximity' to their existing knowledge. Similar to organizational proximity, two similar actors or firms may run the risk of being 'too close' and therefore not leveraging the collaboration effectively (Broekel & Boschma, 2012, p. 3). In accordance with the limitations of proximity, Boschma (2005, p. 72) warns of the potential for locked-in processes when local actors are *too close* and thus hinder the exchange of new knowledge, which has later been described as the 'proximity paradox' (Broekel & Boschma, 2012).

In 2003, Gertler (2003) asked which of these proximities matters the most. Hence, various studies, especially in the Evolutionary Economic Geography (EEG) literature, have focused on the application, differentiation, and interaction of the forms of proximity on different spatial scales (Balland, Boschma, et al., 2022; Boschma & Frenken, 2018). Balland (2012), for example, found that geographical and non-geographical proximities tend to be positively correlated, essentially confirming the literature on institutional proximities, as introduced above. Boschma and Frenken (2010) confirm the theoretical basis of Boschma (2005) on proximity, finding that although actors who are close to each other cooperate more, the outcome or benefit is not as high as one would expect because of the similarity of the actors, i.e., the presence of locked-in processes.

Now, of course, interaction and communication do not only happen at a local or geographically proximate distance. Globalization and digitalization processes have greatly reduced the cost of transportation, so much so that one can ask whether proximity *still* matters. With digital Information and Communication Technologies (ICT) now prominent and accessible everywhere, the rationale for co-locate seems less compelling. Historically, cities were defined and characterized by their size and dominance over the surrounding hinterland (Neal, 2010, p. 2196). However, the emergence of city networks has shifted this perspective. Fundamental works by the likes of Castells (1996) captured the emerging paradigm of city networks by viewing cities as integral parts of economic networks.

Castells' discussion was embedded in an era when the emerging Internet and the expansion of fast transportation systems, such as high-speed railways or flights, made it easier to transport information and goods globally (Rozenblat, 2010; van Meeteren, Neal, et al., 2016). Castells (1996, 2020, p. 245) argues that cities form interconnected networks at different spatial scales, functioning as hubs and nodes in these networks. Castells (1996, 2020, p. 244) further describes the nodes as the 'space of places,' the locality where people work and live, so to speak. The network dynamics, however, are referred to as 'spaces of flows' (Castells, 2020, pp. 244–245), emphasizing the role of cities in the global exchange of resources, information, and capital investment.

Capello (2000) also discussed the increasing networking of cities and regions and offered an attempt to conceptualize network externalities for 'city networks'. In general, network externalities arise when the benefit of a good increases with the number of other users using the same good or network, with a typical example being the telephone infrastructure (Katz & Shapiro, 1985; van Meeteren, Neal, et al., 2016). In the context of 'city networks,' they are assumed to arise through the increasing connectivity of a city to the network. Thus, the better a city is connected, the better the urban performance of that city is sought to be (Capello, 2000, p. 1936). Van Meeteren et al. (2016) have addressed the conceptual issue of network externalities and agglomeration externalities through a network analysis of a sample of firm networks. The presented approach proposes an interpretation of network and agglomeration externalities as a complementary continuum. Similarly, Bentlage et al. (2013) find that multi-locational firms that operate on a global scale combine the advantages of agglomeration and network externalities by using the "*uneven supply of physical infrastructure*" (p. 56) to their advantage. Stimson (2022, p. 103) summarizes that while ICTs do bring positive effects through the network of innovators, physical proximity may be an essential element in exchanging knowledge.

Table 1 Evolution of the term proximity. Adapted from Capello (2022, p. 446).

Underlying theory	Type of proximity	Key elements	Time
Agglomeration economies	Spatial/ Geographical proximity	Labor pooling, reduction of transportation cost through co-locating	1960s
Urbanization and localization economies	Relational proximity (social-based)	Trust	1980s
	Organised/ Organizational proximity	Similar organization structures	1990s
	Institutional proximity	Framework of norms and rules	
	Cognitive proximity	Having a similar understanding of concepts	
Network economies	Relational proximity (network-based)	Using ICTs & fast transportation infrastructure to identify, implement and exchange distant knowledge	2000s

The forms of proximity presented here are critical to understanding how knowledge is shared across space. In short, proximity fosters trust among actors, shapes an institutional framework of common laws and norms, and facilitates access to a shared labor pool (Boschma, 2005; Eriksson, 2011; Storper & Venables, 2004). Thus, there is broad agreement in the literature that geographic proximity matters and that an urban environment, such as a city or a metropolitan region, is a fertile environment for knowledge exchange, since it is here that the various forms of proximity are most likely to occur (Rammer et al., 2020). **Table 1** summarizes the evolution of the various proximities just presented. The next section will examine the aspects of knowledge in more detail.

2.2 Toward a Framework for Differentiating Knowledge

2.2.1 KEY DEFINITIONS OF KNOWLEDGE

The previous section laid out the theoretical foundation for this dissertation. It gave reasons why an urban setting is important for the innovation process in firms. This chapter section is on the process of sharing, combining, and creating knowledge, which is an essential element in knowledge-intensive firms.

To understand *how* knowledge is shared between two (or more) actors, it is first necessary to define *what* the term ‘knowledge’ encompasses. In the economic context, information, routine, or practice helps the receiving end, usually a firm, institution, or person, to improve its processes or products. Thus, it is a key element in creating innovation and an important driver of economic growth and development (Cooke et al., 2007, p. 26; Howells, 2002, p. 871). Cooke et al. (2007) state the importance of distinguishing between information and knowledge. The authors describe knowledge as a “*cognitive capacity which empowers its possessors with the capacity for intellectual and manual action*” (p. 29). According to Howells (2002), knowledge is a “*dynamic framework or structure from which information can be stored, processed and understood*” (p. 872). Conversely, information is a passive asset of pre-structured data that can be reproduced indefinitely but always requires knowledge to understand, decipher, or apply (Cooke et al., 2007, p. 29).

Michael Polanyi’s (1958) seminal work on knowledge opened the discussion of how knowledge can be distinguished by discussing the terms tacit and codified knowledge. Polanyi (1958) also saw tacit and codified knowledge as a continuum rather than two distinct types of knowledge, where both forms of knowledge are needed to interpret one another (Simmie, 2003, p. 610). The term tacit knowledge is typically described as 'know-that' or 'know-how' (Gertler, 2003). Knowledge can therefore not be "*easily transmitted*" (Howells, 2002, p. 872) between actors, appears intrinsic, and is often associated with 'learning by doing' (Arrow, 1962; Gertler, 2003; Howells, 2002). Vissers and Dankbaar (2013) call tacit knowledge a "*vague and ambiguous term*" (p. 717), thus not definable or observable. Examples of tacit knowledge are swimming, cooking, or handicraft (Cooke et al., 2007, p. 29). The term codified or explicit knowledge, on the other hand, is associated with the exact opposite; it can be easily shared, exchanged, and replicated, is formal, and thus can be written down in manuals or blueprints (Simmie, 2003, p. 611). Storper and Venables (2004, p. 367) argue that the ongoing transformation of complex tasks, many of which once relied on tacit knowledge, into routine tasks leads to the codification of information. This process ultimately results in the creation of codified knowledge.

2.2.2 METHODS OF KNOWLEDGE SHARING

Building on the discussion on geographic proximity, researchers aim to understand how knowledge gets shared effectively. Feldman and Audretsch (1999, p. 410), for example, argue that new knowledge is shared when two actors are geographically proximate, but the spatial extent of where and how far it spreads is limited. This is in line with Storper and Venables (2004, p. 351) and Vissers and Dankbaar (2013, p. 717), who argue that face-to-face contacts are highly important, but the probability of sharing knowledge depends on a given local or regional relational proximity (that is, trust or loyalty (Capello & Nijkamp, 2009), see also Subsection 2.1.4). Bathelt et al. (2004) refer to the process of information sharing and communication between actors, "*created by face-to-face contacts, co-presence and co-location of people and firms within the same industry and place or region*" (p. 38), as 'local buzz'. However, this would also imply that the likelihood of a face-to-face encounter in an unfamiliar setting for both actors, such as a different city or country, reduces knowledge sharing.

Using employment relocation data, Eriksson (2011) found that neither too little nor too much proximity is beneficial for knowledge sharing between manufacturing units and knowledge-intensive services in Sweden (p. 133). While these findings might appear inconclusive at first, they highlight the inverted U-shaped relationship between the cognitive distance of related actors and performance, as defined by Nooteboom et al. (2007). This relationship can be broken down into four dimensions that benefit knowledge sharing (Eriksson, 2011, p. 146): Close spatial proximity and similar knowledge are ineffective in promoting effective sharing, but this dynamic changes over longer distances. Conversely, dissimilar knowledge is beneficial in close, spatial proximity but less effective over long distances. Frenken et al. (2007) used a different approach and compared related and unrelated industries to other regional factors, such as economic and employment growth in urban areas. Frenken et al. (2007, p. 696) found that knowledge sharing in related industries significantly affects employment growth in urban areas, while unrelated industries even have a negative influence. Thus, a diverse industrial base is more important than urban density per se, effectively agreeing that Jacobs' externalities are important drivers of growth. In summary, knowledge sharing generally occurs when two (or more) actors are in proximity, both spatially and cognitively, but also through the use of ICT. This is particularly true for urban areas because here, the density, size, and economic and social diversity are given to maximize knowledge sharing (Bathelt & Glückler, 2018, p. 184).

Now, the very simplistic question arises as to why physical proximity still matters in knowledge exchange when ICTs have made it quite easy to share knowledge globally. The answer is short: because both tacit and codified knowledge forms are needed and occur in local spillover processes (Bathelt et al., 2004). Tacit knowledge is typically shared through face-to-face interactions, whereas codified knowledge tends to be more universally accessible and omnipresent (Bathelt et al., 2004, p. 32). Hidalgo (2024) argues that knowledge is non-fungible, meaning that replacing one tacit knowledge resource with another does not produce the same results. Simmie (2003, p. 612) summarizes various ways in which tacit knowledge is exchanged: through job change or relocation, technology diffusion, and research and development (R&D) collaboration with other firms. Codified forms of knowledge exchange are typically associated with formal contracts or collaborations with research institutions, such as universities or laboratories, and are achieved through the funding of university chairs, the employment of student workers, or other forms of formalized links (Howells, 2002, p. 87). Therefore, tacit knowledge is typically associated with spatial or geographical proximity (Asheim & Gertler, 2006; Bathelt et al., 2004; Gertler, 2003; Growe, 2019). Simmie (2003) argues that codified knowledge also depends on distance. This is because, while the scope, extent, or quality of codified knowledge may not decrease with distance, the ability to decode it decreases in the absence of tacit knowledge (Simmie, 2003, p. 611). In this context, Ibert and Kujath (2011, p. 29) highlight the need for relational proximity between two actors. Finally, Asheim et al. (2011) summarize that the dichotomy of tacit and codified knowledge is too narrow to understand how knowledge and innovation work. In summary, the types of knowledge used and shared vary greatly across industries and firms and shouldn't be distinguished in a 'simple' dichotomy.

2.2.3 EXPLORING THE KNOWLEDGE BASE APPROACH

The knowledge creation process generally involves a complex interplay between highly specific forms of knowledge, both tacit and codified (Asheim, 2007, p. 224). Simmie (2003, p. 613), for example, describes that industries that rely more on scientific, thus codified knowledge, such as the pharmaceutical industry, are less likely to be involved in localized spillovers than those that rely more on tacit knowledge. In such industrial settings, the knowledge creation is based on rational decisions and formal workflows rather than 'learning by doing' (Asheim, 2007, p. 225; Gertler, 2003). This is why Asheim and Gertler (2006) and Asheim (2007) aimed to define a more differentiated framework to understand the knowledge creation process, the so-called knowledge base approach (Moodysson et al., 2008, p. 1040). The knowledge base approach builds on the basis of knowledge that the various industries and sectors are based on or rely on (Asheim & Gertler, 2006, p. 294). Asheim and Gertler initially distinguished between two types of knowledge bases, 'analytical' and 'synthetic' knowledge, which are based on different combinations of tacit or codified knowledge but also differ in terms of qualifications, challenges, or path dependencies (Asheim & Gertler, 2006, p. 295). However, this was later extended to three knowledge bases: science-based or analytical knowledge, engineering-based or synthetic knowledge, and creativity-based or 'symbolic' knowledge (Asheim, 2007, p. 225). An approach that goes in the same direction is given by Cooke et al. (2007, p. 30), who argue that knowledge is exchanged between actors who share, or are part of, the same knowledge community, in which typically new knowledge is created. The authors further emphasize that these knowledge communities can exist at different spatial and cognitive scales, ranging from departments in firms to the locations of firms, up to the scale of cities, and at which scale different knowledge communities coexist and interact with each other (ibid.).

As the name suggests, the science-based or analytical knowledge base plays a crucial role in economic activities that rely heavily on scientific knowledge (Asheim & Gertler, 2006, p. 296). Industries classified with an analytical knowledge base rely on R&D, either in-house or in collaboration with universities or research institutions (Asheim, 2007, p. 225; Asheim & Gertler, 2006, p. 296). Knowledge is typically received and created in codified form, i.e., scientific studies, patents, or other standardized procedures (Asheim, 2007, p. 225; Simmie, 2003, p. 613). According to Asheim (2007, p. 225), the jobs that process this information require specific analytical skills, often acquired in universities or other research-related activities. Even though industries or firms in this knowledge base are highly dependent on codified knowledge, tacit knowledge is also needed to process or explain certain routines in the knowledge-creation process (Asheim & Gertler, 2006, p. 296; Gertler, 2003). Lastly, the innovation process in this knowledge base is assumed to be new products, thus the most radical of all three knowledge bases (Asheim & Coenen, 2005; Asheim & Gertler, 2006).

On the other hand, synthetic knowledge applies and combines existing knowledge to innovate (Asheim & Gertler, 2006, p. 295). Asheim (2007) argues that there is often a "*need to solve specific problems that emerge in interaction with clients and suppliers*" (p. 225). This effectively describes the process of knowledge creation in the synthetic knowledge base, as knowledge is synthesized through knowledge exchange (thus interaction) between actors. In general, a higher degree of tacit knowledge is involved, due to interaction with clients and suppliers, but also new knowledge learned at the workplace and interdisciplinary work (Asheim & Gertler, 2006, p. 295). In-house R&D and collaborations are less important (Asheim, 2007, p. 225). This knowledge base is assumed to incorporate the innovation process through existing product improvements (Asheim & Coenen, 2005; Asheim & Gertler, 2006). Finally, Asheim (2007, p. 226) argues that the jobs are more practical than analytical, skills-based.

Finally, the symbolic, or creativity-based, knowledge base recombines existing knowledge in creative and inventive ways to create new knowledge but also to innovate as a firm (Asheim, 2007, p. 227). Asheim (2007, p. 226) argues that this knowledge base has the strongest embeddedness in society and culture. Asheim and Hansen (2009) later specify that, in order to use this 'symbolic' knowledge in innovation processes, the actor has to "*be there*" (p. 432). Thus, typical examples are cultural, advertising, and other 'design-oriented' industries (Asheim, 2007). Asheim and Hansen (2009, pp. 430–431) argue that this knowledge base relies the most on highly specific, tacit knowledge, thus on face-to-face interaction. In this knowledge base, the "*know-who*" (Cooke et al., 2007, p. 60), therefore knowing local actors, rules, and dependencies, has a higher importance than the 'know-how' of the synthetic knowledge base, for example. The authors argue that the application and understanding of the aesthetic, rather than the cognitive, is in the foreground (Asheim & Hansen, 2009). The knowledge is 'typically' received and transmitted in various aesthetic forms, such as designs, texts, thoughts, or pictures (Asheim, 2007, p. 226). Finally, Grillitsch et al. (2017, p. 4) argue that the innovation process in this knowledge base is embedded in short-term projects, with frequent changes in collaboration with predominantly local actors. This is an important distinction from the other two knowledge bases, where collaborations or research projects span longer time periods.

Similar to the dichotomous classification introduced by Polanyi (1958), the question arises as to the spatial context in which the knowledge exchange takes place in each of the three knowledge bases. Asheim and Gertler (2006, p. 297) found that the exchange of analytical knowledge, even though heavily reliant on codified knowledge, thus formalized information that is theoretically available ubiquitously, is heavily localized. The authors summarize that firms in this knowledge base mainly tend to form local working relationships and collaborations with other local firms in the same knowledge base, mainly because newly generated knowledge is highly localized, so it is first shared with, or spills over to, local actors, i.e., other local scientists. This is consistent with the findings of Simmie (2003, p. 611), who argues that codified knowledge is best decoded or understood in close geographic proximity to the source. According to Asheim and Gertler (2006), knowledge exchange and spillovers are less localized in the synthetic knowledge base than in the analytical knowledge base. This is because, in the former, continuous collaboration with both local and non-local clients and suppliers facilitates a wider spread of knowledge exchanges. Asheim et al. (2016) argue that symbolic knowledge is the "*most sticky*" (p. 8) of all three knowledge bases, meaning that it relies the most on tacit knowledge and an understanding of the local cultural setting. According to Asheim and Hansen (2009), this locality is usually found in a "*diverse and urban*" (p. 432) setting, which is typically associated with cities such as New York City.

The knowledge base approach does face scientific criticism for being oversimplistic in its assumptions, as it groups different, diverse industries into a single knowledge base. Additionally, it is criticized for lacking a temporal or dynamic component, limiting its ability to capture the evolving relationships between industries over time (Boschma, 2018; Manniche et al., 2017; Wagner & Growe, 2023, p. 4).

2.3 The Emerging Knowledge Economy

2.3.1 DEFINING THE KNOWLEDGE ECONOMY

It is now evident from the previous sections that knowledge plays an important role in driving firms' innovation processes. Nowadays, firms no longer compete only with local or regional competitors; globalization has shifted competition to a global scale (Cooke et al., 2007, p. 26). At the same time, economies are increasingly moving away from manufacturing toward advanced service-oriented economies in a process called "*informationalization*" (Hall & Pain, 2006, p. 4) because of the availability and usability of telecommunication services (Sassen, 2020, p. 615), as discussed in the previous section. This increasing pressure is forcing firms to constantly re-evaluate their location choices and increase their innovation output to remain competitive on a global stage (Hall & Pain, 2006, p. 4). Studying and understanding these changes in the global division of labor, the restructuring of spatial configurations, and the rise of knowledge-intensive industries has resulted in a growing body of literature on the knowledge economy.

Over the years, various definitions and options to delimit the knowledge economy have been proposed. One prominent definition by the OECD defines economies as 'knowledge-based' if they are "*directly based on the production, distribution, and use of knowledge and information*" (OECD, 1996, p. 7). Van Oort et al. (2009, p. 860), however, argue that this definition is too narrow and consider two additional aspects to be important in knowledge economies: innovation capital and investment in human capital.

At this point, it is important to note that although the terms 'knowledge economy' and 'knowledge-based economy' are often used interchangeably, they have slightly different meanings and origins (Cooke & Leydesdorff, 2006, p. 5). The former, rooted in Schumpeter's (1934) work, refers to large firms being drivers of innovation and new knowledge creation (Cooke et al., 2007, p. 52). The latter is embedded in a more contemporary systemic discussion that is needed from a governmental perspective to develop appropriate policies (Cooke & Leydesdorff, 2006, p. 7). According to Cooke et al. (2007, p. 26), the knowledge economy refers to the ongoing shift towards more knowledge-intensive activities, in which economic growth and productivity increasingly depend on highly skilled and educated workers rather than on natural resources. Economic growth and productivity are generated in the knowledge economy by creating, applying, and sharing science-based knowledge. Following Cooke et al. (2007, p. 27), this definition can be divided into four approaches to the knowledge economy. First, there has been an increase in investment in creating, understanding, and interpreting new knowledge, e.g., through education, new tech, or R&D. In this context, it is important to mention the importance of universities and other research organizations in the knowledge economy, as they not only train researchers and future employees but also serve as a place for the transfer of new knowledge (Cooke et al., 2007, p. 54). Second, there has been a growth in knowledge-intensive services and firms that use "*knowledge as a product*" (Cooke et al., 2007, p. 27) to help solve problems or improve processes with their customers or suppliers by synthesizing knowledge (Asheim & Gertler, 2006, p. 295). Third, universally accessible and easily shareable codified knowledge is an essential element in R&D-intensive industries that rely on scientific, codified knowledge, such as biotechnology or pharmaceutical engineering (Bathelt et al., 2004; Simmie, 2003). And fourth, improvements in ICT make it much easier to share, manage, and combine different knowledge resources (Cooke et al., 2007, p. 27). A more concise definition is given by Lüthi et al. (2011), who define the knowledge economy as "*that part of the economy, in which highly specialized knowledge and skills are strategically combined from different parts of the value chain in order to create innovations and sustain competitive advantage*" (p. 162-163). Therefore, the focus is on the continuous process of acquiring and recombining specific knowledge to remain innovative and competitive as a firm (Lüthi et al., 2011, p. 163).

The presented definitions show that the knowledge economy is a complex framework of various knowledge sources, knowledge bases, and knowledge communities (Cooke et al., 2007, p. 56). This raises the question of which firms and economic sectors comprise the knowledge economy, which will be outlined in the following.

So far, some key elements and industries of the knowledge economy have already been mentioned, such as the increase in R&D activities or an increasingly service-oriented economy (Bathelt et al., 2004; Cooke et al., 2007; Simmie, 2003; Stimson, 2022). Hall and Pain (2006, p. 4) state that one specific feature of the knowledge economy is the emergence of advanced producer services (APS). APS can be described as "*a cluster of activities that provide specialized services, embodying professional knowledge and processing specialized information, to other service sectors. Such knowledge intensive services, provided by specialist consultancies, are a central feature of the new post-industrial economy, reflecting an acceleration of technological change based especially on micro-electronics, information and computer technology, new materials and biotechnology*" (Hall & Pain, 2006, p. 4). According to Wood (2002, p. 5) and Hall and Pain (2006, p. 4), key areas of APS, thus APS firms, are management and administration, production, research, human resources, information and communications, and marketing. Castells (2011) is more specific than Wood (2002) and defines a second major group of knowledge-intensive industries alongside APS: high-tech manufacturing, thus R&D-intensive industries (Castells, 2011, p. 409). According to Castells (2011), these groups "*can be reduced to knowledge generation and information flows*" (p. 409) and therefore define the knowledge economy.

2.3.2 SHIFTING PERSPECTIVES: FROM LOCALITY TO RELATIONALITY

This subsection provides a more comprehensive understanding of relationality, which was briefly introduced in Subsection 2.1.4, as it emerges from the global restructuring of economies. Globalization has contributed to the formation of global city networks, primarily shaped by knowledge-intensive firms' spatial and economic behavior. Two seminal works in this context are John Friedmann's *'The World City Hypothesis'* (1986) and Saskia Sassen's *'The Global City'* (2001). Friedmann (1986) emphasized that globalization processes lead to the integration of cities into the world economy, thus creating a global hierarchy of cities and urban areas that are all interconnected in a global network of cities (Hall & Pain, 2006, p. 6; Krätke, 2014, p. 122). According to Sassen (2001, pp. 90–91), a key factor of globalization is the global dispersion of economic activities in financial services, as well as in other business and consulting sectors. Paradoxically, however, this dispersal leads to a growing concentration of important firm-internal or 'central functions' in selected, so-called 'global cities' (Sassen, 2020, p. 616). These global cities are agglomerations of highly specialized firms that house a number of headquarters and other leading producer-service firms that not only command and control the global network of increasingly dispersed firm locations but also determine where and how knowledge is shared, used, and created (Bathelt & Glückler, 2011; Castells, 2011; Hall & Pain, 2006; Sassen, 2001, 2020). Typical examples of such leading global cities, particularly in finance, consulting, and business services, are New York City, London, and Tokyo (Hall & Pain, 2006, p. 13). Bathelt and Glückler (2011, pp. 114–115) note that centrality and connectivity to other cities in the global network of cities are limited to the central city and not the metropolitan region surrounding it, even though relations exist as well. There has also been criticism that not much has been said about other cities that are also important for other economic activities (Castells, 2011; Hall & Pain, 2006; Neal, 2017; Taylor, 2004). It should be noted that Castells (2011, p. 417) argues that high-tech manufacturing firms were the first to practice the globalized (re-)location strategy as described by Friedmann (1986) and Sassen (2001). Whether it was APS firms or high-tech manufacturing that started to implement globalized firm networks in their firm-international organization strategy is beyond the scope of this dissertation. Still, it does highlight that both APS and high-tech firms are part of, and needed in, the knowledge economy (Krätke, 2014; Lüthi et al., 2013, p. 163).

Bathelt and Glückler (2011, p. 115) argue that the relational perspective is the logical extension of (local) agglomeration theories. It complements local externalities with network externalities of cities through the connection to other cities in the global city network (Bathelt & Glückler, 2018, p. 184). Thus, a highly connected city offers firms the opportunity to not only interact with local actors but also with extra-local partners or clients (ibid.). It combines and draws on existing research on relational and physical proximity and aims to understand and identify where firms locate or concentrate by studying firm networks and relationships and interactions between firms, economic actors, and other organizations (Bathelt & Cohendet, 2014, p. 870; Ibert, 2011, p. 65). Bathelt and Glückler (2018, p. 180) further argue that economic actors are embedded in certain networks, institutional contexts, and processes. These conditions influence where firms choose to locate or open new locations, ultimately creating new knowledge. In Bathelt and Glückler (2011, p. 131), two key components in the global knowledge creation are highlighted: local buzz and global (or trans-local) pipelines. In essence, firms need spatial proximity to other firms, thus concentrations of firms or clusters in cities, to foster knowledge exchange and spillovers from local markets. Asheim and Gertler (2006) highlight that local buzz not only attracts knowledge-intensive firms but also highly educated workers. This is because a global city, such as New York City, as identified by Friedmann (1986) and Sassen (2001), offers "*a critical mass*" (Asheim & Gertler, 2006, p. 298) of employment, firms, suppliers, and headquarters in related industries and fields (Castells, 2011, p. 415). Therefore, according to Asheim and Gertler (2006, p. 298), the most central global cities have the most knowledge-intensive employment. However, it is equally important for firms to be embedded in trans-local partnerships to gain access to external, often new, knowledge (Bathelt & Glückler, 2011, p. 137). Without such external knowledge resources, there is a risk of becoming locked-in, thus missing out on new information or technologies (Bathelt & Glückler, 2018, p. 182). The connectivity of a city in the global city network can be understood as a strategic access point to access localized knowledge and local partners and clients in other locations (Bathelt & Glückler, 2011, p. 196, 2018, p. 184).

At this point, it is important to reintroduce the knowledge base approach. Analytical high-tech firms generally create new knowledge, i.e., innovate locally, either in-house or through collaboration with local research institutions or universities. As a result, they are less dependent on extra-local knowledge resources. Synthetic APS firms, on the other hand, depend more on extra-local knowledge. This is because innovation in these firms occurs by synthesizing existing knowledge by combining existing knowledge in close proximity to clients and partners (Asheim & Gertler, 2006, p. 295). For these firms, it is crucial to constantly identify new clients and partners (such as manufacturing firms), thus tapping into new markets to stay competitive on the global scene (Bathelt & Glückler, 2011, p. 196, 2018, p. 184). Therefore, cities with higher connectivity and centrality increase the likelihood of firms finding such business opportunities in other cities (ibid.). However, the process of accessing localized knowledge resources through trans-local pipelines does not lead to an equal distribution of knowledge in space (Bathelt & Glückler, 2011; Kujath & Stein, 2011). Florida (2005) famously argues that the world is 'spiky,' meaning that knowledge-intensive firms and employment, i.e., the knowledge economy, are increasingly concentrated in a small number of cities and regions.

In summary, knowledge-intensive firms include both high-tech and APS firms. To remain competitive, their location strategies must draw on local and extra-local sources of knowledge, increasingly shaping the space that is observed.

2.4 Findings on the Locations of Knowledge-Intensive Firms & Workers

The following section presents research findings on the theoretical foundations discussed above, focusing on key and more recent studies. It emphasizes three main elements: knowledge-intensive firms, employment within them – so-called knowledge workers – and the geographic distribution of knowledge-intensive firms and their employees. Where appropriate, the analysis focuses specifically on the German knowledge economy. It also aims to identify open questions that require further research, which will be discussed in Section 2.5.

2.4.1 WHERE KNOWLEDGE-INTENSIVE FIRMS LOCATE

Research on knowledge-intensive firms can be loosely divided into two strands: location patterns and the relational approach. Both aim to explore where firms choose to locate, but integrating these perspectives simultaneously is challenging. The first strand presented here, location patterns, focuses on spatial factors, using spatial variables, (spatial) statistics, and geographic analysis to examine where and why firms cluster in cities or regions. In contrast, the relational or network-based approach uses social network analysis to examine how firms expand their networks and establish connections regionally and globally. The former is frequently studied in regional science. As mentioned in previous sections, universities and transportation networks are two key factors for firms to generate and share knowledge. Various literature, therefore, aims to understand the role and impact of universities (e.g., Arant et al., 2019; Audretsch & Stephan, 1996; Johnston & Wells, 2020; Roesler & Broekel, 2017). The literature agrees that access to transportation networks is also key since business travel facilitates knowledge exchange (e.g., Bentlage et al., 2014; Conventz & Thierstein, 2018; Coscia et al., 2020; Florida et al., 2015; Liu et al., 2013; Mukkala & Tervo, 2013; Neal, 2011b). Besides these hard location factors, literature shows that soft location factors, such as the environment or urban/ natural amenities, are increasingly important for firms that want to attract the best-fitting labor (e.g., Carlino & Saiz, 2019; Florida, 2003; Mulligan & Carruthers, 2011; Trip, 2007; Zandiatashbar & Hamidi, 2018).

Moving away from how knowledge is physically shared and transported, digital transformation within the knowledge creation process adds another layer of complexity. Formerly, APS firms have provided services to predominantly manufacturing firms worldwide (Bassens et al., 2024). Digitalization has transformed their service portfolios and contributed to the rise of big tech firms that have redefined the traditional value chain, where outputs now also include digital products (van Meeteren et al., 2022). These digital services, such as cloud-based collaboration platforms or machine learning services, are permeating how firms, especially APS firms, operate; it puts their location choices (back) in the spotlight (Bassens et al., 2024; Trincado-Munoz et al., 2023). Thus, Bassens et al. (2024) and Knoblauch & Löw (2024) both raise the question of whether the digital transformation, along with the impacts of the COVID-19 pandemic and recent geopolitical turmoil, has further influenced the global location choices of firms, a timeframe still too recent to be fully analyzed within the scope of this dissertation.

One specific strain of literature takes a dynamic approach, the Evolutionary Economic Geography (Boschma & Frenken, 2011). Frenken and Boschma (2007, p. 635) argue that this approach seeks to explain the (re-)location of firms and industries by examining their interconnectedness within regions and cities through networks. This is because such location choices are heavily embedded in path dependencies of previous firm locations, the presence of related industries, or the economic setting of a city or region (Boschma & Frenken, 2018; Frenken & Boschma, 2007). Therefore, studies in the field of EEG aim to understand not only how both the relatedness and variety of industries affect the economic success of regions but also why and how regions diversify (Boschma & Capone, 2015; Hidalgo et al., 2007; Neffke, Henning, & Boschma, 2011). While both the relatedness of industries and the diversity of regions are crucial, a recent and equally important dimension is the complexity of economic activities. In summary, the more advanced and sophisticated a product or service is, the greater the diversity of knowledge required to develop and manage the different knowledge resources (Hidalgo & Hausmann, 2009). Balland et al. (2020) and Balland and Rigby (2017) show that complex knowledge resources not only increasingly concentrate in urban areas but also scale with the degree of urbanization. Balland et al. (2022, p. 7) thus summarize that the probability of diversification is based on the existence of related activities (firms or sectors) in a region. At the same time, relatedness describes the 'proximity' of related activities (what firms do), which supports the probability of diversification. The third dimension, complexity, measures whether a region is situated in more sophisticated economic activities (Balland, Broekel, et al., 2022; Hidalgo, 2021).

On the other hand, and this is the second strand, the relational or network-based approach can be primarily attributed to the Globalization and World Cities (GaWC) research group led by Taylor (2004), which focuses on identifying and ranking world cities and uncovering important intercity relations of the global economy (Derudder & Taylor, 2018). Cities are viewed as nodes in a network of interconnected cities that compete and cooperate (Hall & Pain, 2006, p. 13). Because of their role in globalization processes as transmitters and synthesizers of knowledge, the focus is on specific APS firms, such as those in finance, insurance, or banking. Since this dissertation also applies the GaWC approach (see Chapter 4), relevant and recent findings are only briefly presented here. In short, the GaWC developed the so-called interlocking network model, which uses weighted data on firm locations and measures the connectivity between two or more cities (Pain et al., 2024, p. 7; Taylor, 2001, p. 186). Over the 20 years of its existence, the network-based 'connectivity' perspective on firms and cities has been continuously applied and extended in various contexts. Krätke (2014), for example, finds that different global cities top the rankings for manufacturing firms, highlighting the importance of studying both high-tech and APS firms. Pain et al. (2024) explore the relationship between commercial office real estate services (CORE), APS firms, and international capital flows using the interlocking network model. The authors find that cities that are part of both APS and CORE firm networks (i.e., host both an APS and a CORE firm location) can not only increase their capital flows between cities but also reduce the probability that there are no capital flows between cities (Pain et al., 2024, p. 17). On the other hand, Zachary Neal (e.g., 2010, 2013, 2017) tested and successfully extended the world city system with various network analysis tools and measures. Neal sought to determine whether more complex network analysis tools provide better insights into the formation of the world city network than simpler ones. He concluded that more complex tools, such as eigenvector centrality, don't necessarily provide better results. Therefore, he advocates either sticking with simpler, more interpretable measures or being clear about the specific benefits that justify using more complex measures (Neal, 2013, p. 1657). Zachary Neal also applied the stochastic degree sequence model (SDSM) to understand what the connectivity values of cities in the world city network mean, i.e., whether a 'high' value for a city corresponds to the best-available connectivity. He found that while certain cities with a high connectivity value are the best connected, in a theoretical world, it could be even higher. This suggests that firms do not simply concentrate in certain world cities but have individual strategies that shape the world we observe, and thus, more research on connectivity is needed (Neal, 2017, pp. 2873–2874). Neal et al. (2019) applied the SDSM approach to a sample of APS firms and their location networks for two points in time to predict whether these firms would alter their firm networks by expanding, contracting, or maintaining a presence. The authors find that the SDSM approach does yield good results in predicting future firm networks despite the lack of any other information about the firm (i.e., labor pool, size, age, or sector) (Neal et al., 2019, p. 17). Later, Neal et al. (2021b, 2021a) and Neal (2022) followed a recent trend of replacing the interlocking network model with bipartite projections to study world city networks (see Taylor and Derudder (2016) and Derudder (2021a)). The authors introduce the so-called ‘backbone’ approach, a tool for reducing complexity in dense networks. The backbone approach is explored in more detail in Chapter 4 and will not be discussed further here. These studies demonstrate that the world city network approach goes beyond the mere ‘connectivity’ value of cities, serving as a versatile foundation for a deeper understanding of firm and city networks.

2.4.2 WHERE KNOWLEDGE-INTENSIVE EMPLOYMENT LOCATES

Although employment is central to every firm because it facilitates the sharing and transport of various knowledge resources, the definition of employment has not been extensively discussed so far, particularly in knowledge-intensive sectors. As knowledge-intensive employment is one of the key focus areas of this dissertation, this section briefly introduces the most important and recent findings regarding the definition and location of knowledge workers.

Knowledge-intensive employment, or in short, knowledge workers, involves highly skilled individuals who possess tacit knowledge and thus perform non-routine tasks, making them essential to firms in the knowledge economy (Harrigan et al., 2021; Storper & Venables, 2004). Lee and Maurer (1997) argue that knowledge workers “*do not add value to the firm because of their labor per se; […] but they do add value to the firm because of what they know*” (p. 248). Florida (2005) famously describes these workers as the ‘creative class,’ though the term faced criticism. For instance, Krätke (2010) argues against lumping workers of different occupations and industries into a single ‘class.’ Thus, some lines of research focus on the underlying knowledge base to better understand knowledge workers (Asheim & Hansen, 2009; Grillitsch et al., 2017; Zhao et al., 2017). Asheim and Hansen (2009, p. 432), for example, summarize for the Finnish context that knowledge workers with a symbolic knowledge base tend to concentrate in city centers, a highly urban, culturally and socially diverse environment, while workers with a synthetic knowledge base prefer suburban areas. Workers with an analytical knowledge base are not so precise in their location choice, but a large city region seems to be an advantage. This is consistent with the findings of Grillitsch et al. (2017, p. 27) for Swedish regions, who argue that the knowledge base approach provides meaningful results to better understand the innovation process in firms. Zhao et al. (2017, p. 206) also applied the knowledge base approach for the German context, and studied location and commuting patterns of knowledge workers. The authors find that symbolic workers choose the most central locations and use public transportation, while synthetic workers tend to live in more peripheral areas but also rely on public transportation, and workers with an analytical knowledge base show a greater tendency to use active modes of transportation, such as bicycling, to commute.

Several studies focus on how relocation patterns and job mobility affect knowledge spillovers from knowledge workers (Breschi & Lissoni, 2005, 2009; Coscia et al., 2020). To clarify, 'relocation' is typically associated with moving to another city or country, while 'mobility' refers to switching jobs in general. Breschi and Lissoni (2009), for example, focused on relocation patterns and co-invention networks to understand tacit knowledge spillovers. The authors summarize that knowledge workers in the biotechnology, chemistry, and pharmaceutical sectors are less likely to relocate to other cities or regions, therefore 'unintentionally' localizing the knowledge spillovers. Research often describes this as the 'stickiness' of knowledge (Balland & Rigby, 2017, p. 2). Knowledge-intensive firms must, therefore, relocate or open subsidiaries to access these pools of highly skilled workers (Adler & Florida, 2020, p. 612; Storper & Scott, 2009). Several studies have shown, however, that accessing these pools of highly skilled workers comes with a premium of both wage levels and land or rent prices for firms (Adler & Florida, 2020; Serafinelli, 2019; Tambe & Hitt, 2014). Tambe and Hitt (2014, pp. 352–353) find that, specifically, firms in the IT sector benefit from knowledge spillovers through knowledge worker mobility, with an estimated production growth of about 20%, but highlight that some firms have to pay a wage premium to retain their workers. Deng et al. (2022), on the other hand, focus on relocation and wage expectations of workers. The authors find that geographic job changes, that is, relocating to another city, tend to result in higher wages, while occupational or industry changes result in lower wages. In addition, personal preferences and local knowledge also play a role, but research on this is scarce (Niedomysl & Hansen, 2010; Tippel et al., 2017). Tippel et al. (2017, p. 104) focus on worker relocations using the German example of Frankfurt and find that while hard factors such as income play a role in the relocation of knowledge workers, established social networks often limit their job search to areas in close spatial proximity to these networks. The authors also distinguish between 'internal' and international migrants: the former prioritizes local factors, while the latter focuses more on regional and national factors due to limited knowledge of specific locations.

Typically, workers express their knowledge and type of work with a certain skillset that has either been learned on the job, while doing, or through various forms of studying. This makes it rather difficult for a firm to replace one worker with another (Hidalgo, 2024). For obvious reasons, it is therefore not easy to assign specific skills to one worker, let alone scale such research to make general statements. This is why various research studies have focused not only on the spatial behavior of workers (i.e., where they are located) but also on the relatedness of different jobs and occupation types instead of certain skills (e.g., Cappelli et al., 2019; Ghosh & Grassi, 2020; Hane-Weijman et al., 2020; Neffke et al., 2024; Rehs & Fuchs, 2020). Neffke et al. (2024), for example, use occupations as a proxy for skills in order to study to what extent a job switch leads to a skill mismatch for both voluntary and involuntary job switches. The authors find that voluntary job switches lead to a higher difference in skills, thus learning. An involuntary job switch, i.e., losing a job, thus leads to a lower skill difference. Again, it is important to note that an occupation does not equate to a fixed set of skills, which is why this dissertation does not focus specifically on workers' skills. For instance, the rise of digital literacy (or digital know-how) driven by digital transformation influences the skills required, further blurring the boundaries between different occupations (Nadkarni & Prügl, 2021).

This section provided a brief overview of key and recent findings on both knowledge-intensive firms and their employment. It has also identified gaps and open questions in the research on both. The following section briefly summarizes the research gaps and questions to which this dissertation is intended to contribute.

2.5 Research Gaps & Research Questions

The previous sections have introduced and summarized research on firm location choices, the various roles of proximity in the knowledge-creation process, and knowledge-intensive employment. The literature review also identified important research gaps, underscoring the need for further research. This section will first present those gaps in research and then present the resulting three research questions (RQs). The research gaps are as follows:

1. *Only a limited number of studies have examined the firm-employment nexus, particularly within the German context.*

   Most of the existing literature focuses either on firms, their locations, and networks, or on employment, its distribution, and structural changes (e.g., changes and shifts in occupational composition). This is largely due to the scarcity of data linking firms directly to their employment (and vice versa). However, it can be argued that a new firm location may attract other firms and thus employment.

2. *Literature on firm location is often cross-sectional.*

   While research does include longitudinal studies on firm locations, specific subsets or samples, such as knowledge-intensive firms, are typically studied cross-sectorally. This makes tracking firm location closures, openings, or relocations challenging over time. Again, the core issue is the lack of publicly available, firm-specific location data, necessitating extensive data preparation or self-collection to address these gaps.

3. *Firm locations are mostly seen as singular entities.*

   Most studies on firm locations are cross-sectional or focus on specific regions or cities, often overlooking the underlying factors driving location choices. This is especially the case for multi-branch, multi-locational firms where a (new) location is opened, relocated, or closed based on the firm's internal requirements, location-specific characteristics, and decisions. However, precisely these decisions, which ultimately span a network of firm locations, illustrate how knowledge is generated and shared within a firm.

4. *A limited number of studies for the German context.*
   There is a US-oriented bias in APS firms, especially firms in tech, as most of them originate or have their headquarters there. This also leads to the majority of research focusing on the United States. For example, Florida's (2003) work on the 'Creative Class' has been repeatedly criticized for being inapplicable in the European context (Krätke, 2010; Tippel et al., 2017). A few exceptions exist in the European or Chinese context, but with a predominant focus on the largest cities.

5. *There is a lack of studies on worker mobility and relocations, especially in the German context.*
   Research on worker mobility or relocations often uses correlation or regression-type analyses, focusing primarily on changes at the 'target' destinations (i.e., regions or cities where workers are relocating). This leaves a critical blind spot: the origin of these workers and potential patterns in where they're relocating from. This gap is particularly evident in the German context, where strict data privacy regulations complicate tracking individual workers, further hindering a comprehensive understanding of migration flows.

Based on these five research gaps, the following three underlying research questions have been identified:

Research Question 1 **(RQ1):**	*How do knowledge-intensive firms establish their firm location networks, and what are the preferred locations in Germany?*
Research Question 2 **(RQ2):**	*Does employment in the knowledge economy induce employment growth or vice versa?*
Research Question 3 **(RQ3):**	*What are identifiable spatial patterns of relocations of knowledge workers in Germany, and has this changed over time?*

As highlighted in the introductory literature review, research on the German knowledge economy remains limited. This dissertation offers new insights into the relationality of knowledge-intensive firms and their employment patterns through a multiscalar perspective that integrates both spatial and temporal scales. A key challenge is the lack of publicly available data on employment and firm location, particularly in Germany. Hence, several economic geographers have called for the use of firm-level datasets to address underlying research questions more effectively (e.g., Abbasiharofteh et al., 2023; Duranton & Kerr, 2015).

To fill this gap, this dissertation contributes to the field by generating specific datasets for the knowledge economy in Germany, both at the firm and employment level, which are analyzed in relation to all three research questions.

The first Research Question (RQ1) bridges two perspectives often treated separately in the literature: the spatial and the relational dimensions. The spatial dimension describes where a firm opens a new location, such as a new subsidiary, plant, or R&D facility. As outlined in the previous section, a variety of factors can play a role, ranging from the number of jobs, universities, competing firms, or simply soft location factors such as the cultural environment. These location choices, however, introduce an often-overlooked dimension in this context, the relationality. The relational dimension is becoming increasingly important since locations can become relationally close (or proximate) yet spatially distant, e.g., through air traffic or digital ICTs. It is, therefore, crucial to understand how the chosen location and its spatial characteristics may influence where firms locate to maintain their network. In this context, two hypotheses are formulated. (1) Analytical and synthetic high-tech firms have a lower propensity for urban locations compared to the other knowledge bases, and (2) APS firms, in general, demonstrate a stronger preference for rail and air accessibility – while firms in synthetic high-tech show a stronger preference for road connectivity.

Research Question 2 (RQ2) sheds new light on another often-ignored perspective of temporal change. As indicated by the research gaps, much research has been conducted where firms or employment are located at a specific point in time, while not addressing the fact that these analyses are cross-sectional, meaning that they are valid only for when the data was collected. However, as the literature review has shown, firms locate where they find a fitting environment, and they may relocate when the requirements change. Such behavior, however, induces an influx of new labor since the newly created jobs must be filled. Here, two hypotheses can be formulated: (1) there is no overall causal relationship between knowledge-intensive employment and total employment growth and (2), there is no causal relationship between knowledge-intensive employment and total employment growth at the individual FUA level. Therefore, the underlying study follows a branch of research on the ‘jobs follow people’ or ‘people follow jobs’ discussion.

Research Question 3 (RQ3) focuses on relocation patterns of knowledge workers, exploring what networks of relocations of knowledge workers can be observed. Building on the findings of RQ2, RQ3 examines the ‘where’ – focusing on the origins and destinations of worker relocations. Incorporating the concepts of relationality and temporal dynamics introduced in RQ1 and RQ2, this research question also includes a temporal analysis using two time spans, 2012–2016 & 2016–2021, to determine whether the observed relocation patterns represent a permanent trend or a temporary occurrence. As Subsection 2.4.2 has already shown, initial assumptions can be made about this relocation behavior, which can be tested in a hypothesis: knowledge workers tend to relocate from smaller to larger urban areas, with relocation distance increasing toward larger urban areas. This approach aims to provide a deeper understanding and further differentiation of how knowledge worker relocations shape the economic structure of FUAs over time.

3 Methodology

This chapter offers a concise overview of the data and various methods used in the three studies, outlining the process by which the underlying data for this dissertation was generated. The data are based on several sources, which will be briefly presented. This dissertation was part of the interdisciplinary research project "*Knowledge-intensive firms, connectivity and spatial restructuring: dynamics and differences in Germany and Switzerland,*" funded by the German Research Foundation (DFG) and the Swiss National Science Foundation (SNF). This research project was designed as a long-term study and examined how the location of knowledge-intensive firms has restructured and changed the observable space and the functional-spatial urban hierarchies through their physical and non-physical networks between 2009 and 2019. The year 2009 was deliberately chosen, as it followed one of the most turbulent financial crises, triggered by the US housing market collapse, which led to a global economic downturn (Brunetti, 2012). Meanwhile, 2019 serves as a comparison point based on the assumption that a decade is sufficient to reveal significant changes in firm structure. This timeframe was also used to get a glimpse of how worker relocations have shaped the space. On average, workers stay in a job for less than ten years, and this tenure may be even shorter for knowledge workers (Statistisches Bundesamt (Destatis), 2024; Tambe & Hitt, 2014). Additional firm data and the corresponding employment data were generated in collaboration with the IAB between 2021 and 2023, as described in Section 3.1 & Section 3.3. Section 3.4 briefly presents the research design and the methods used. A more detailed discussion of the respective methodologies can be found in Chapters 4 to 6.

3.1 Firm Data

The dataset of firms used in this dissertation was selected based on the following criteria: (a) they are classified as knowledge-intensive, (b) they operate multiple branches and locations (i.e., firms with only a single location were excluded), and (c) they rank among the 30 largest in each subsector. It is important to note that the initial firm data generation process was significantly influenced by Lüthi (2011) to replicate the specific data structure of the first data collection in 2009.

Thus, in the first step, knowledge-intensive sectors must be defined. To define and select knowledge-intensive subsectors, this dissertation follows previous research in this field (e.g., Lüthi, 2011, p. 104; Thierstein et al., 2007, p. 29; Zhao, 2017, p. 52), which is based on the methodology of knowledge-intensive subsectors by Legler & Frietsch (2006). Both classifications aim to assess the competitiveness of advanced economies when their products and services compete on a global scale, thus focusing particularly on sectors that rely on creating knowledge to develop new products or knowledge-intensive services (2006, p. 5). Hence, Legler & Frietsch (2006, p. 5) define two highly aggregated groups of knowledge-intensive: those focused on developing and producing highly specialized goods and those providing knowledge-intensive services. The first group, the high-tech sector, relies heavily on technical expertise, continuous investment in R&D, and a highly skilled workforce to stay competitive on a global scale (Legler & Frietsch, 2006, p. 6). The second group encompasses the APS sector, where firms apply or develop new knowledge and link various industrial sectors by offering specialized services (ibid.). For the high-tech sector, the authors base their selection process of knowledge-intensive subsectors mainly on OECD data, in combination with other national data, such as patent applications, to measure the level of R&D and innovation in each sector (Legler & Frietsch, 2006). A subsector is considered knowledge-intensive if the R&D activities are above average (Legler & Frietsch, 2006, p. 8). In addition, a subsector is also considered if it has a high proportion of engineers or researchers (Legler & Frietsch, 2006, p. 9). APS subsectors are selected by the share of highly qualified workers, i.e., workers with a university degree, based on the EU Labour Force Survey and other national data for other countries (Legler & Frietsch, 2006, p. 12). This way, the authors developed a comprehensive list of knowledge-intensive subsectors based on the German Classification of Economic Activities (Wirtschaftszweige (WZ)). In contrast to Legler and Frietsch (2006) who selected the subsectors based on WZ2003, this dissertation's classification of knowledge-intensive subsectors is based on the current version, WZ2008. The final list of subsectors, nine in APS and seven in high-tech, used in this dissertation is compiled in the following table.

Table 2 Knowledge-intensive subsectors, the selected WZ 2008 codes in italics. Based on Legler and Frietsch (2006), Lüthi (2011).

Classification of subsectors	
Advanced Producer Services (APS)	**High-tech**
Accounting: *6920*	Automotive: *2910, 2932, 3011, 3020, 3030, 3091*
Advertising and media: *5811, 5812, 5813, 5814, 5819, 5911, 5920, 6010, 6020, 6931, 7311, 7312, 8230, 9003*	Chemical & pharmaceutical: *1910, 2013, 2014, 2016, 2017, 2020, 2041, 2051, 2053, 2059, 2110, 2120, 2211, 2219, 2319*
Banking and finance: *4110, 6411, 6419, 6430, 6491, 6492, 6499, 6611, 6612, 6619, 6030, 6810, 7740*	Computer hardware: *2620, 2823*
Design, architecture, and engineering: *7111, 7112, 7120, 7420*	Electronics: *2611, 2612, 2651, 2711, 2712, 2720, 2740, 2790, 2931, 3313, 3320*
Information and communication services: *3312, 5821, 5829, 6110, 6120, 6130, 6190, 6203, 6209, 6311, 6312, 9511*	Mechanical engineering: *2530, 2540, 2811, 2812, 2813, 2814, 2815, 2824, 2829, 2830, 2841, 2849, 2893, 2894, 2895, 2896, 2899, 3040*
Insurance: *6511, 6512, 6520, 6530*	Medical & optical instruments: *2660, 2670, 3250*
Law: *6910*	Telecommunications: *2630, 2640*
Management and IT consulting: *6201, 6202, 6831, 6832, 7010, 7021, 7022, 7320*	
3rd and 4th party logistics: *4950, 5010, 5020, 5110, 5121, 5122, 5222, 5223, 5229*	

In the second step, the top 30 firms in terms of employment were selected for each subsector, such as accounting or automotive. To find the top 30 firms, the Dun & Bradstreet[1] database (2019) was used. This database is one of the largest databases on firm, business & ownership information, including size, credit information, and business relationships. The WZ2008 codes associated with each subsector were used to identify the 30 largest firms in terms of employment. The decision to select only 30 firms per subsector is based on three key assumptions. First, this number is adequate to represent firms across Germany. Second, it adequately captures the division of labor within the German knowledge economy. Third, as noted above, the data generation process is consistent with the Lüthi (2011) methodology to replicate the data structure of this earlier study. In total, 270 individual APS firms and 210 individual high-tech firms were extracted. All firms are listed in the Appendix.

In this context, it is important to reiterate that a key assumption of this dissertation and the underlying research project is its focus on firms that operate multiple branches and in different locations. Unlike single-location firms, multi-branch, multi-locational firms need to continuously optimize their location strategies. Thus, their network of firm locations needs to respond to changing market conditions, to access fitting labor pools, and to remain competitive. Consequently, it can be assumed that these locations are carefully chosen according to the firms' needs since any change to the network of firm locations carries the risk of losing market share and lowering the return on investment. Thus, the underlying firm network exhibits a certain degree of spatial stability. This optimization process is a key strategy for multi-locational firms to maximize the overall value creation. In contrast, single-location firms do not face the same level of multi-locational risk and have more flexibility in relocating. For example, Lüthi et al. (2010, pp. 134–135) argue that knowledge creation within multi-branch, multi-locational firms is driven by the combination of intra-firm knowledge networks and the deliberate integration of extra-firm linkages with complementary, localized expertise and competencies, such as skills.

Semiautomated web-scraping methods were used in the third step to identify all firm locations for these 480 multi-branch, multi-locational firms worldwide, i.e., the headquarters and subsidiaries. This process used data from each firm's website presentation or published online information. A total of 42,661 APS firm locations, of which 26,710 are located in

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[1] Previosuly known as Hoppenstedt, later Bisnode, since 2021 Dun & Bradsreet.

Germany, and 16,708 high-tech firm locations, of which 2,904 are located in Germany, were collected. Each firm location was geo-referenced using Geographic Information Systems (GIS) such as QGIS or ArcGIS, summarizing a very precise location analysis of firms in the knowledge economy. The advantage of this method over a random sample of firms or secondary statistics is that it can reveal intra-firm networks, e.g., between subsidiaries or between headquarters and other intra-firm locations such as manufacturing plants. An overview of all self-collected and geo-referenced firm locations is shown in **Figure 3**. This approach was used in Chapter 4 and will be briefly introduced later.

In the fourth step, each firm and its corresponding subsector were assigned to one of four knowledge bases. This classification followed Zhao et al. (2017) and distinguishes between analytical, synthetic, and symbolic knowledge bases based on the seminal work of Asheim & Gertler (2006) and Asheim & Hansen (2009), as discussed in Subsection 2.2.3. Each subsector is then assigned to one of these three knowledge bases based on the knowledge base primarily used in that subsector. This results in four knowledge bases: Analytical High-tech, Synthetic High-tech, Synthetic APS, and Symbolic APS. Since the starting point of this classification is the process of how knowledge is created, mixed, shared, and used in a firm, it is not possible to combine an analytical knowledge base, i.e., highly abstract, scientific, and codified knowledge, with an appropriate subsector in APS, nor is it possible to combine a symbolic knowledge base, i.e., highly creative, design-based, and contextual knowledge, with an appropriate high-tech subsector (Asheim & Hansen, 2009, p. 430). The classification is compiled in the following table.

Table 3 Classification of subsectors in Knowledge Bases. Based on Zhao et al. (2017). Own illustration.

Classification of subsectors in Knowledge Bases		
Type of Knowledge Base	**Advanced Producer Services (APS)**	**High-tech**
Analytic		
		Chemical & pharmaceutical
		Medical & optical instruments
Synthetic		
	Accounting	Automotive
	Banking and Finance	Computer hardware
	Information and communication services	Electronics
	Insurance	Mechanical engineering
	Law	Telecommunications
	Management and IT consulting	
Symbolic		
	3rd and 4th party logistics	
	Advertising and media	
	Design, architecture, and engineering	

ENHANCED FIRM DATA IN COLLABORATION WITH IAB

Although the data on firm locations is comprehensive and provides a detailed, geo-referenced overview of the German knowledge economy, it is only a snapshot of firm locations at a specific point in time, namely 2019. To explore the research questions presented in Section 2.5, changes in the spatial distribution, the number, and location of firm locations must be highlighted. Therefore, in collaboration with the Institute for Employment Research (IAB), panel datasets on time series of firm locations and their respective employment in Germany have been constructed. The IAB has data on both firms and employment in Germany. Here, two datasets will be used: the Employment History Panel (BeH) and the Establishment History Panel (BHP). The IAB uses official employment data provided by the Federal Employment Agency (BA) for all employees who are subject to social security contributions and have worked in a firm for at least one day. Since the underlying BeH is an employment dataset, it will be discussed in more detail in Section 3.3.

The BHP is an aggregated dataset based on the BeH (Ganzer et al., 2022, p. 28). As a starting point, it uses a so-called Establishment Identifier (ID), abbreviated as 'firm ID' in **Figure 2**. It tracks the aggregated number of employees, classified by gender, age, occupational status, qualification, and nationality, who are assigned to this Establishment ID and location (Ganzer et al., 2022, p. 37). The dataset is a panel that is updated on a reference date and contains data at the firm level from 1975. It includes information on firm size, economic sector, and location, covering all firm locations with at least one employee subject to social security contributions (for a detailed presentation of the dataset, including all available features, refer to Ganzer et al., 2022).

A matching dataset needs to be created to utilize and access both the BHP and BeH data. Therefore, the first step is to create a list of all geo-referenced firm locations identified in 2019, presented in Section 3.1, including their names, addresses, and assigned WZ2008 codes. This dataset of 29,614 identified firm locations was merged with the BHP via a record linkage and resulted in 17,234 uniquely identified firm locations based on the names, locations, and WZ2008 codes given. Although the record linkage process couldn't identify some firm locations in Germany, it has the advantage that each firm is now identifiable by the ID used at the IAB, thus making it possible to extract all information on all firm locations and branches between their first and last appearance. However, due to data protection regulations, this dataset only contains at least three firm locations per geographical unit. Besides this limitation, the constructed panel dataset uniquely tracks each firm and each of its locations in Germany from 1999 to 2021. 1999 is the year in which the current survey process was introduced (Ganzer et al., 2022, p. 29). Additionally, this ID can be used to extract information on all past and present employees who have or had a relationship with any of the firm's locations using the BeH. Each identified firm location is then assigned to a FUA, which will be introduced in the next section. **Figure 2** illustrates how all the different data sources about firms and their locations come together.

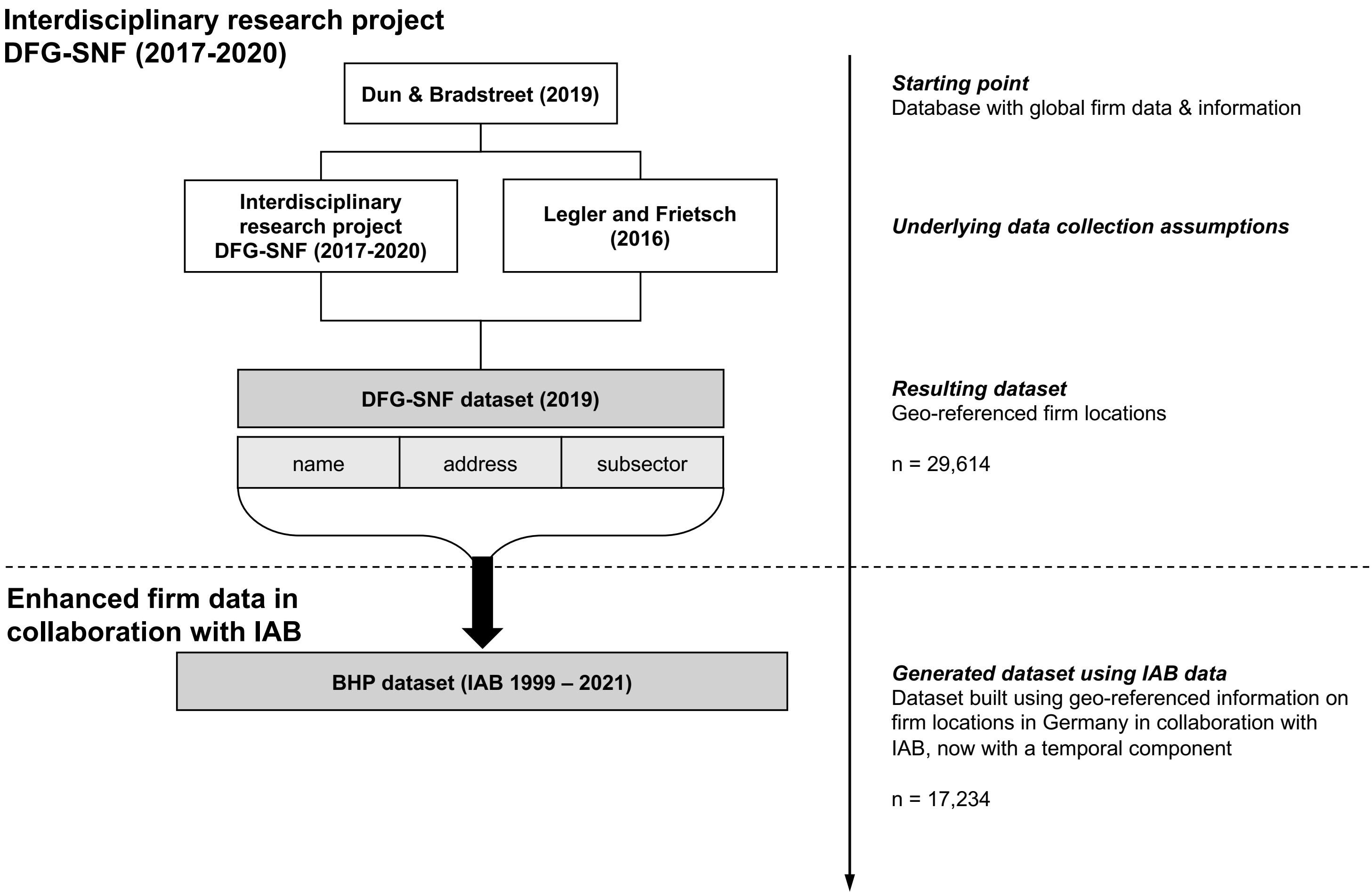

Figure 2 Firm data and how it was generated. Own illustration.

3.2 Spatial Framework

In this dissertation, all publications, i.e., chapters, are based on the same spatial unit. The spatial unit selected is the so-called functional urban area (FUA) concept, developed in the European Spatial Planning Observation Network (ESPON) research project 1.1.1 (ESPON, 2004). The research project delineates functional urban areas using different functional characteristics, such as population and transport, tourism, or knowledge function, to distinguish them (ESPON, 2004, p. 85). This is an important distinction from more commonly used hierarchical demarcations such as the 'Nomenclature des Unités Territoriales Statistiques' (NUTS) or Local Administrative Units (LAU), which are based on administrative boundaries and do not have a functional perspective. However, this perspective is a key element of FUAs in studying and understanding the functional division of labor between urban areas (ESPON, 2004, p. 109). Therefore, an FUA consists of two parts. In the German context, the urban center or core area has to have at least 15,000 inhabitants, but at least 50,000 inhabitants overall (ESPON, 2004, p. 24). Second, a catchment area surrounds this urban center (PUSH areas – Potential Urban Strategic Horizon) (ESPON, 2004, p. 124). These catchment areas must be economically integrated towards the urban center and are usually defined by a functional-spatial criterion, such as commuting or travel-to-work areas (ESPON, 2004, p. 4). ESPON defines the catchment areas with 45-minute isochrones, considering this area as a proxy for potential daily commuting patterns and the influence of the urban center on its surrounding areas (ESPON, 2004, p. 121; Rozenblat, 2020). This spatial construct, similar to planning regions, implies that knowledge transfer does not end at the borders of a city or district (Graf & Henning, 2009).

In this dissertation, FUAs are composed of different LAUs that cover the defined area, allowing for flexible data merging at the LAU level. Importantly, the 45-minute commuting areas are built regardless of national boundaries, which means that some FUAs extend into neighboring countries, while other border areas of Germany are not covered by an FUA of a German city (ibid.). Overall, 186 FUAs have been identified for Germany, as shown in **Figure 3**.

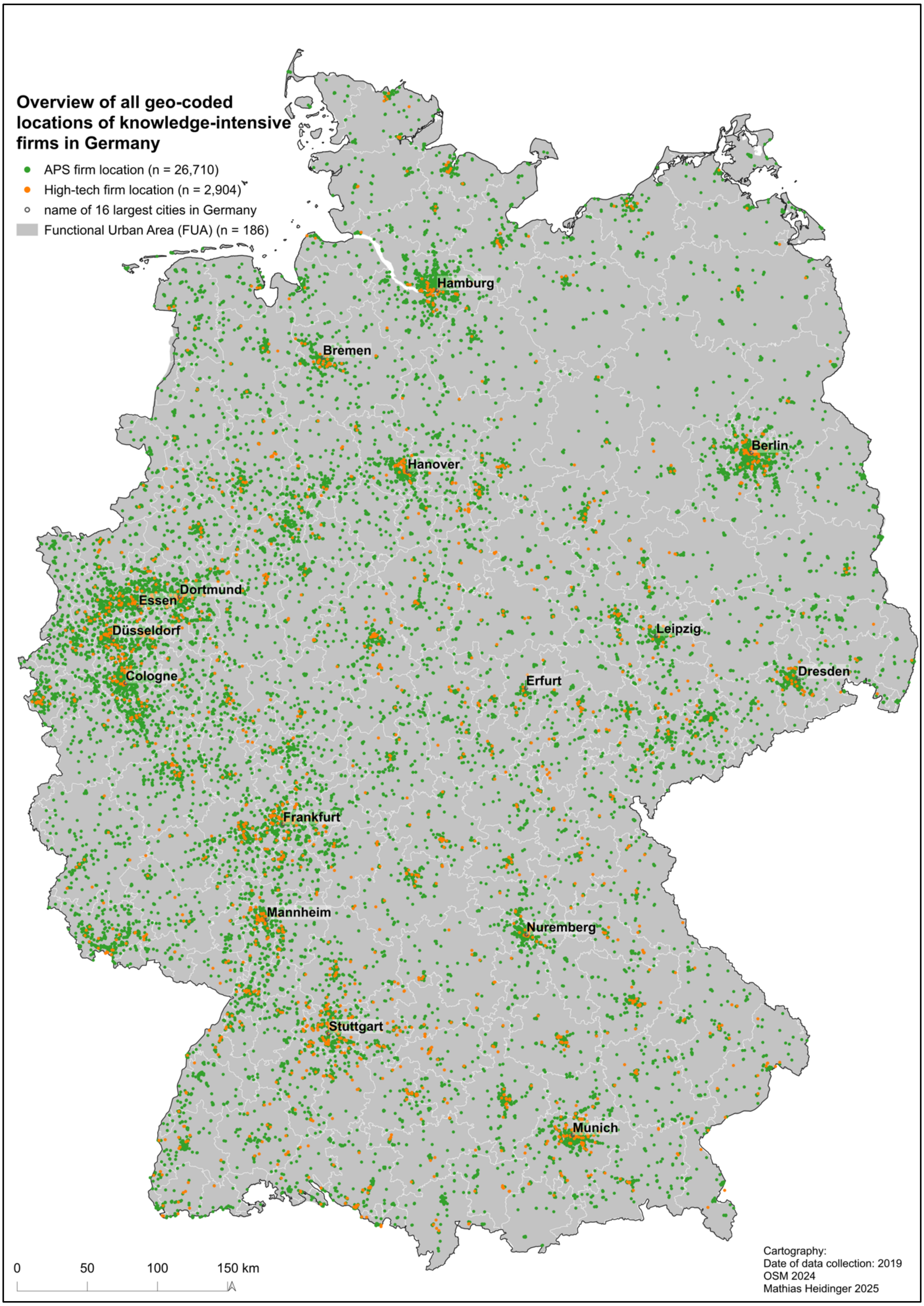

Figure 3 Overview of all geo-coded firm locations and FUAs in Germany. Own illustration.

While the spatial delineation of FUAs has limitations, especially at the micro level, i.e., where one cannot study the locations and movements of firms in districts and neighborhoods (as in Smętkowski et al. (2021), for example), the geo-referenced location of firms becomes less important when considering the macro level, where cities act as nodes in global urban systems (Rozenblat, 2022, p. 220). Instead of their geo-referenced locations, the interaction of firms as part of a city comes to the fore. Therefore, the FUA is considered a concise spatial construct in which the *actual* location of a firm is less important because the spatial proximity needed for interactions, information exchange, and knowledge generation is provided by the underlying commute area (Rozenblat, 2020).

It must be noted that the economic approach to the conceptualization of FUA introduces a form of spatial blurring through its aggregation process. This occurs by merging different LAUs and their distinct spatial features, such as the number of inhabitants or the built-up area, into one FUA. To overcome this problem, this dissertation adds an additional layer that reintroduces a spatial subdivision, following the urban, urban-rural, rural trichotomy developed by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) (2023). To do this, the BBSR classifies individual areas according to the following specifications: if at least 50% of its inhabitants live in a city of at least >20,000 inhabitants, but there must be at least one city of >100,000 present, and the total population density of that area is at least 300 inhabitants/km^2, then that area is classified as urban. An area is classified as urban-rural if at least 33% of its inhabitants live in a city of at least >20,000 inhabitants and the population density is between 150 and 300 inhabitants/km^2 or if there is at least one city of >100,000 inhabitants and the total population density is at least 100 inhabitants/km^2. An area is classified as rural; on the other hand, if less than 33% live in a city of at least >20,000 inhabitants and the population density is under 150 inhabitants/km^2. The trifold classification is available at the level of LAU, which is why the spatial expansions match the expansions of the FUAs. The process of generating the underlying employment data is discussed in the next section.

3.3 Employment Data

As described in Section 3.1, the IAB uses employment data provided and used by the German Federal Employment Agency. These data on individual employees in Germany are collected in the BeH dataset, which is based on reported employment data from health, pension, and unemployment insurance and goes back to 1975 and 1991 for East Germany, respectively. This means that the BeH covers all workforce, employees, trainees, and workers subject to compulsory social insurance, so students, the self-employed, and civil servants are not included in this dataset (Ganzer et al., 2022, p. 12). This shortcoming is less significant because this dissertation focuses on multi-branch, multi-locational firms, thus excluding self-employed individuals and civil servants. In short, the BeH contains all information about each individual employee, including gender, degree, date, and place of birth, the current workplace (the firm), place of work, and place of residence, and each new employment relationship with at least one day of work is recorded. It must be noted that this data is highly sensitive and can only be accessed in this form at the IAB directly.

Depending on the research question, this dissertation uses the BHP and BeH datasets to extract and aggregate knowledge-intensive employment. As a starting point, the panel dataset of merged and identified firm locations was used to extract all employees for each location aggregated from the BHP. These extracted employees were then aggregated into spatially aggregated sums per FUA and year. This limitation is based on the same data protection regulation as for firm locations, which is why this dataset only contains at least three workers per geographical unit, the FUA. In addition, a distinction was made between the four knowledge bases. Similar to the firm dataset constructed in Section 3.1, this dataset is in a panel structure and contains aggregated sums for all knowledge workers in the top 30 knowledge-intensive firms per knowledge base from 1999 to 2021 and is assigned to the spatial unit of the FUA. Due to its panel structure, this dataset was used in Chapter 5. The following table briefly summarizes the employment dataset of the top 30 knowledge-intensive firms per FUA for the years 2012 and 2021, in an aggregated form. The mean and total employment have slightly decreased, with a higher maximum, i.e., one FUA hosts more knowledge workers in 2021 than in 2012. Additionally, the median and 25th percentile have decreased. In short, the number of knowledge workers in the top 30 firms has slightly decreased overall, but increased and thus concentrated in the FUAs with the highest employment. This aspect will be discussed in more detail in the later chapters.

Table 4 Summary statistics of the employment in the top 30 knowledge-intensive firms. Own illustration.

Year	Min	Mean	StD	Max	Total	25%	Median	75%
2012	0	166.5	853.1	29,915	1,408,075	3	65	11
2021	0	160.0	839.7	32,362	1,385,459	0	59	10

For Chapter 6, another dataset on employment was constructed. This dataset consists of two time slices and is directly created from the BeH dataset. Since the underlying research question of Chapter 6 aims to study relocation patterns of knowledge workers, the dataset must be in the form of an origin-destination (OD) matrix. In theory, the so-called Integrated Labour Market Biographies (SIAB) serve a similar purpose but are a sample of the total workforce in Germany; therefore, it is not appropriate for this dissertation, but it served as a methodological reference (refer to Schmucker et al., 2023). Here, two points in time were selected for each of the two datasets: a) 2012 & 2016, and b) 2016 & 2021. Due to a reclassification of jobs in 2010 and 2011, many data and classification errors for these two years are missing. That is the sole reason why this dataset does not represent ten years or even beyond. Since the data generation process is the same for both datasets, the process is demonstrated using dataset a) as an example. The first step is to identify and extract information from the BeH on each knowledge worker who works or has worked in one of the top 30 knowledge-intensive firms, using the Establishment ID for firms and a unique ID for the workers. In this step, each worker was assigned to the appropriate knowledge base of the firm. The following assumptions were made to determine whether a knowledge worker has moved to another FUA. The unique ID of a knowledge worker has to appear at both times in the dataset. While this process excludes workers who may have started or ended employment with one of the multi-branch, multi-locational firms at the second time stamp, it provides a coherent, cohesive panel dataset for workers who actually relocated. The second step identifies whether a person has relocated to another FUA using the work location assigned to them in the BeH. In short, if the work location has changed between the two points in time, then this worker has relocated. A worker may relocate for various personal or job-related reasons, but this aspect is not considered. In short, the OD matrix includes where and in which knowledge base a worker has worked in the past but relocated to another FUA in the second time frame.

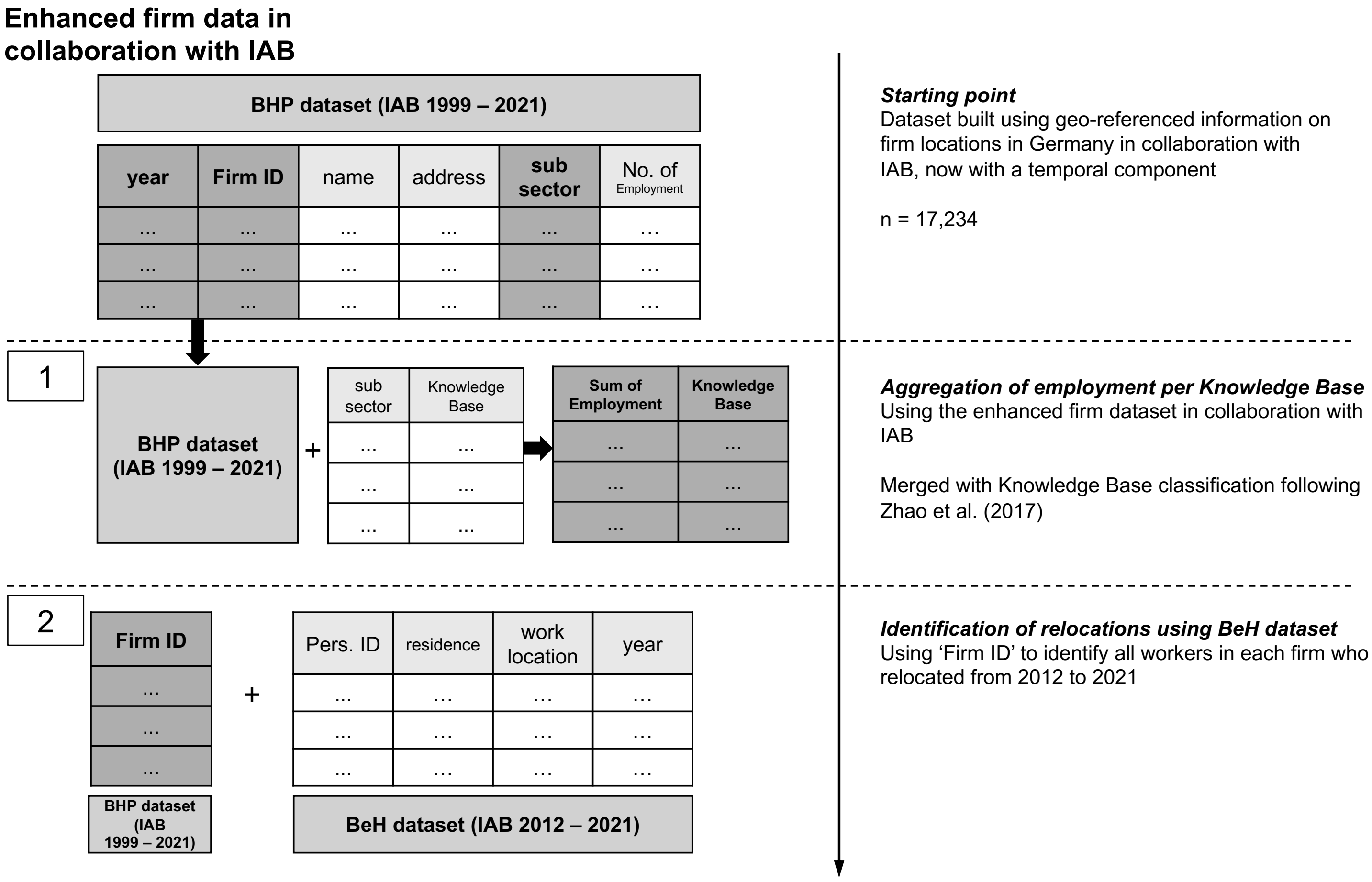

Figure 4 Employment data and how it was generated. Own illustration.

3.4 Research Methods

This section briefly overviews the various methods employed to address this dissertation's research questions and hypotheses in detail. Each method implemented is briefly described and contextualized. Network models and time series analysis were chosen because they reflect the relational approach and mutual conditionality of this dissertation. The selected methods complement the previous literature (e.g., Lüthi et al., 2011; Taylor et al., 2008; Wiese, 2015) and represent the logical next step in addressing the relationality between firm locations and knowledge-intensive employment. A more comprehensive explanation and discussion of their implementation can be found in the respective chapters. This section follows the same logical sequence as the underlying research data on firms and employment, as the data and methodology were developed and selected simultaneously.

3.4.1 NETWORK MODELING APPROACHES

Methods originally developed for social network analysis between humans or social actors have been enjoying great popularity outside this field for some time now due to their transferability to relational or, more broadly, network-related issues. Chapter 4 applies social network analysis to the relational firm dataset, described in Section 3.1. Social networks are composed of (social) actors, more commonly referred to as nodes, and their connections, also called relationships, ties, or edges, to other nodes (Rivera et al., 2010). Such ties can be either binary (e.g., the presence or absence of a tie) or valued, indicating stronger or weaker ties between actors (ibid.). This relational approach can also be applied to study how organizations, firms, or regions interact spatially and with each other, where the node is the individual firm location or region, and the tie is a relationship to other regions or firms. In this context, Peter Taylor (2004), in his seminal book on urban systems and world cities and the Globalization and World Cities (GaWC) research network, developed and applied the so-called Interlocking Network Model (INM) to not only study globalization processes through firm locations but also to identify the most important global cities. In this context, cities are the nodes in a global urban system of firms formed by APS firms (Taylor, 2001). Since each firm location in a city is assigned a value ranging from 0 (=no presence) to 5 (=headquarters), the resulting network is weighted, allowing for the possibility of ranking and thus studying ties. More important cities host and attract more firm locations while having more ties to other cities worldwide. The underlying *social* aspect here is that firms must communicate with firm locations in other cities, hence forming an economic relationship between the two cities (Taylor, 2001). Over time, the

INM model was applied and extended in various ways and contexts (Derudder, 2021b). For example, Rozenblat and Pumain (2007), Neal (2011a), Sigler and Martinus (2017) all extended the INM to apply centrality measures to identify central nodes (i.e., cities) in the world city network. Two other approaches that can foster the strength of the INM are exponential random graph modeling (ERGM) and stochastic actor-oriented modeling (SAOM). Block et al. (2019) summarize the differences between SOAM and ERGM by the formation of a tie between two actors. While the former introduces constraints such as time or resources that may hinder the formation of a tie, the latter does not (Block et al., 2019, p. 233). The SAOM was applied in Zöllner et al. (2020), while the latter was tested in, for example, Neal et al. (2021a). In Chapter 4, the dissertation adapts the approach using ERGM presented by Neal et al. (2021a) and extends it by analyzing how different spatial features (e.g., the presence of an airport) affect the probability of tie formation.

3.4.2 TIME SERIES ANALYSIS

Chapter 5, in particular, but also Chapter 6, deals with spatio-temporal change. Time series analysis is a constantly growing branch of research that is experiencing great popularity, especially with the increase in panel data collection towards longitudinal panel data.

Several different approaches have been developed using time series analysis, particularly in econometrics. Common approaches aim to identify trends, seasonal effects, and cycles, forecasting future trends, or assessing relationships between two different time series (for an introduction into time series analysis, refer to Baltagi, 2013; Becketti, 2013). Since this dissertation is specifically concerned with the question of causality: ‘Who follows whom?’ in the context of time series analysis, this translates to exploring how one time series affects another time series. Two approaches have been shown to produce good results: the so-called Carlino-Mills models and Granger causality tests. Both models test whether one observed time series can predict changes in another time series or vice versa. The Carlino-Mills (CM) model is named after Carlino and Mills (1987), who analyzed how regional job opportunities and wages influence population movement and economic growth in and across different areas. A drawback of the CM model has been highlighted by Hoogstra et al. (2017, p. 18), who argue that the CM model only operationalizes causality in one direction. In reality, developments can occur in both directions, even simultaneously, which is why Granger causality testing was used in Chapter 5. Granger causality, named after Granger (1969), uses two time series and tests them against each other to identify possible ‘Granger causal’ relationships. In other words, if one time series sees a significant change in values over time, this might have an effect on values in the second time series. In regional economics, Granger causality tests have been utilized in several contexts, such as between regions (core-periphery) in Finland (Tervo, 2009), whether air traffic causes regional growth (and vice versa) (Mukkala & Tervo, 2013), or the relationship between highly educated workers and other workers (Tervo, 2016).

3.4.3 VISUALIZING SPATIAL NETWORKS

The last methodology chosen in this dissertation is applied in Chapter 6. It focuses on how to visualize and interpret the relocation patterns of knowledge workers. Thus, Chapter 6 maps the OD matrix built in Section 3.3 using the 186 FUAs for Germany.

Visualizing and interpreting flows between regions is becoming increasingly challenging due to the increasing volume of flows and the growing complexity of interconnections between regions. In reality, readability is often no longer given (Wu et al., 2018). This is why research has put much thought into developing algorithms that simplify the output (e.g., Holten & Van Wijk, 2009; Hurter et al., 2012). Since these methods are a subset of network analysis, nodes and edges are the main focus of the study. The goal of these so-called graph bundling techniques or methods is that they usually aim to identify the most important nodes or edges in a network in large graphs with many nodes or ties (Becker et al., 1995). This leads to a loss of detail since edge bundling processes are always a tradeoff "*between clutter reduction and information loss*" (Zielasko et al., 2016, p. 7). As the name of these techniques already suggests, they often *bundle* nearby edges to reduce cluttering (Wu et al., 2018). In the context of this dissertation, the result would indicate to the reader that most workers relocate *only* between the largest FUAs, such as Munich, Frankfurt, and Berlin, largely due to a higher number of migrations to and from these larger FUAs, bundling neighboring relocation edges with them. Thus, the result would overlook these smaller, less weighted, neighboring FUAs in the migration dynamics for the sake of readability.

Therefore, this dissertation used two different grouping processes to improve the interpretability of the OD matrix. First, the data were normalized using the largest number of relocations of workers between two FUAs. Seven groups were then defined, ranging from < 0.01 to 0.9 relocations between two FUAs. In addition, the edges were color-coded using a color band according to the dominant direction of the number of moves. Second, a circular plot was developed following Gu et al. (2014). This plotting method provides a visually simplified yet profound and comprehensible way to understand large amounts of data. All FUAs are plotted on a circular ring and grouped by the BBSR classification, as shown above. Each FUA displays the absolute number of in- and out-relocations of employment to each other FUA. This approach allows the reader to easily grasp the absolute relocations in relation to other relocations, such as between urban and rural classified FUAs. However, one disadvantage, especially in a geographical context, is that the geographical spatialization of the relocation is lost. Only with effort can it be reconstructed whether, for example, relocations happened toward FUAs in spatial proximity. Hence why the maps were used as well. The procedures are described in more detail in Chapter 6.

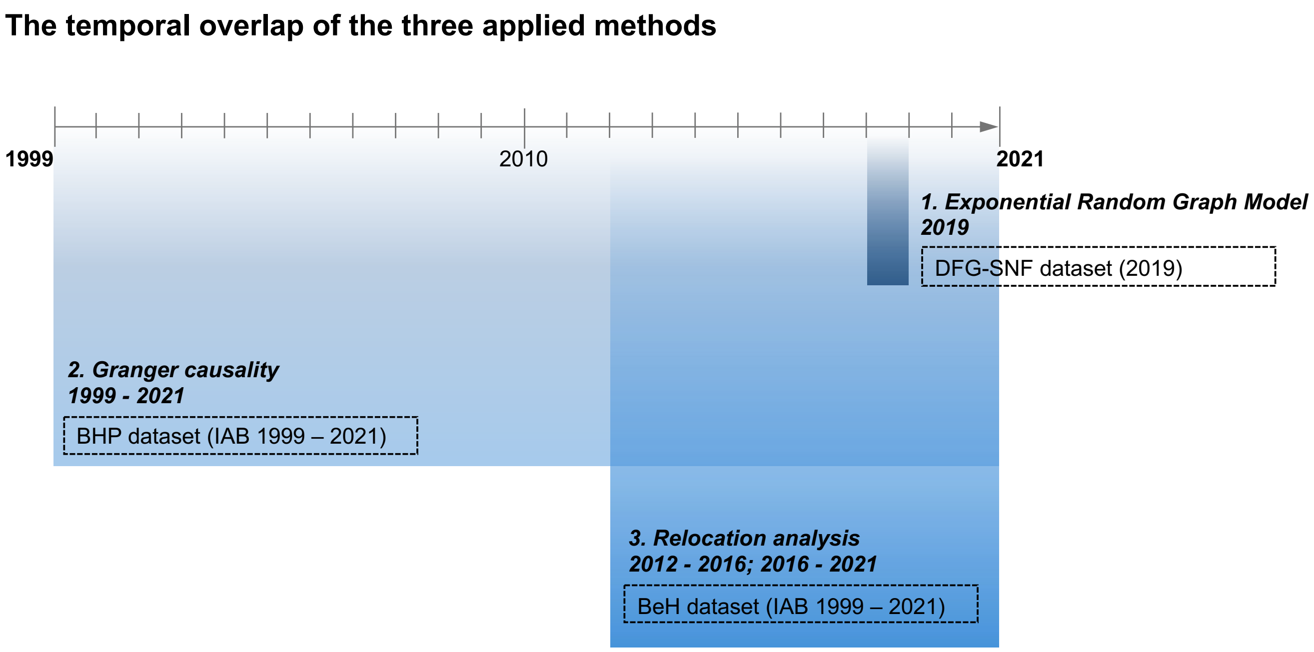

Figure 5 Methods used in this dissertation. Own illustration.

3.5 Chapter Overview

This publication-based dissertation is organized into three parts. Each of the three chapters starts with an introduction and summary of the conceptual background, which sets the scope of the chapter. Then, three studies are conducted to address the research gaps and questions presented in Section 2.5. Finally, the findings, issues, and challenges are discussed. **Table 5** outlines the structure of the following pages. The research questions are listed on the left, the hypotheses are listed in the middle column, and the methods & data applied for each chapter are briefly listed on the right. The structure is thus as follows.

Table 5 Overview of the assigned research questions, methodological approaches, and chapter numbers. Own illustration.

Research Question	Hypotheses	Methods & Data
RQ1	1. *"[…] we hypothesize that analytical and synthetic High-Tech firms have a lower propensity for urban locations than synthetic and symbolic APS firms."* (p. 87) 2. *"[…] APS firms, in general, demonstrate a stronger preference for rail and air accessibility, while among all High-Tech firms, those with a synthetic knowledge base show a stronger preference for road connectivity."* (p. 88)	*Exponential Random Graph Modeling:* - Relational Firm Data for knowledge-intensive firms - Positional Data of firms - Economic and spatial data at the FUA level (OSM, official employment data, ATKIS, BBSR, …)
RQ2	*1. Across all FUAs, "there is no causal relationship between our sample of knowledge-intensive employment and total employment growth."* (p. 120) *2. In any FUA, "there is no causal relationship between employment growth in our sample of knowledge-intensive firms and employment growth at the individual FUA level."* (p. 120)	*Granger Causality tests:* - Overall Employment Data as temporal data - Knowledge-intensive Employment as temporal data

Research Question	Hypotheses	Methods & Data
RQ3	*“Knowledge workers tend to relocate to the nearest, more populous functional urban areas. The relocation distance increases when knowledge workers relocate between two more populous functional urban areas. Here, workers tend to relocate from smaller, less populous functional urban areas to larger, more populous functional urban areas.”* (p. 151)	*Origin-Destination Analysis:* - Positional Data for employment at the FUA level at three points in time (2012, 2016, 2019) - Relational Data for knowledge-intensive employment with origin and destination for relocations at between two time points (2012 – 2016, 2016 – 2019)

3.6 List of publications

This section provides an overview of the three publications that form the basis for this dissertation and contains a brief summary of the key data of each publication, such as the co-authors involved, the contribution of the lead author, or the location of the publication. The complete versions of these publications can be found in Chapters 4 to 6.

Table 6 Summary & key data of Chapter 4. Own illustration.

Chapter 4	**Where do knowledge-intensive firms locate in Germany? – An Explanatory Framework using Exponential Random Graph Modeling**
Authors:	Heidinger, Mathias, Fabian Wenner, Sebastian Sager, Paul Sussmann, and Alain Thierstein
Contribution of the lead author:	Conceptualization, Methodology, Data Collection, Data Curation, Formal Analysis, Writing – Original Draft
Published in:	Review of Regional Research (online: 28 February 2023)
Accepted:	8 February 2023
DOI:	https://doi.org/10.1007/s10037-023-00183-8
The first publication examines the influence of both spatial attributes and interregional relationships on the location decisions of knowledge-based firms in 186 German regions. Different attribute data (including traffic, university presence and population) are combined with relational data (such as travel times and train connection frequencies). Exponential random graph modeling is applied on the interlocking network model, which categorizes firms according to their type of presence in the firm network. These firm networks are grouped in four distinct knowledge bases. FUAs are categorized according to their type of urbanization (BBSR). The study reveals how different spatial characteristics and connectivity factors influence firms' location choices. The results indicate that certain characteristics such as population of the FUA and the presence of universities are generally favorable firm location conditions, while the importance of transport connectivity varies greatly depending on the knowledge base.	

Table 7 Summary & key data of Chapter 5. Own illustration.

Chapter 5	**The contribution of knowledge-intensive firms to employment growth: a Granger causality approach for German regions**
Authors:	Heidinger, Mathias, Michaela Fuchs, and Alain Thierstein
Contribution of the lead author:	Conceptualization, Methodology, Data Curation, Formal Analysis, Writing – Original Draft
Published in:	Regional Studies, Regional Science 11, Nr. 1 (online: 14 February 2024)
Accepted:	22 January 2024
DOI:	https://doi.org/10.1080/21681376.2024.2312186

The second publication examines the two-way relationship between ‘overall’ employment growth and knowledge-intensive employment growth in Germany. It considers both directions of Granger causality: (1) in which ‘overall’ employment growth attracts knowledge-intensive employment and (2) knowledge-intensive employment growth may stimulate ‘overall’ employment growth. Employment data from 480 knowledge-based firms is compared to ‘overall’ employment. The analysis is aggregate to the level of FUAs for the years 1999 to 2019, using both aggregate and individual Granger causality tests. Knowledge-intensive employment is classified to APS and high-tech sectors. The results show that in a few economically strong FUAs, growth in knowledge-intensive employment precedes overall employment growth, while in many FUAs growth in ‘overall’ employment appears to Granger-cause growth employment in knowledge-intensive sectors. The results of the individual Granger causality tests are spatialized using GIS.

Table 8 Summary & key data of Chapter 6. Own illustration.

Chapter 6	**Where do knowledge workers locate in Germany? A case study using employment relocation data in the German knowledge economy from 2012 to 2021**
Authors:	Heidinger, Mathias, Michaela Fuchs, and Alain Thierstein
Contribution of the lead author:	Conceptualization, Methodology, Data Curation, Formal Analysis, Writing – Original Draft
Published in:	Raumforschung und Raumordnung | Spatial Research and Planning (online: 29 May 2025)
Accepted:	28 April 2025
DOI:	https://doi.org/10.14512/rur.3084

The third publication examines where knowledge workers relocate and how relocation patterns differ across spatial distances in Germany. It uses an innovative origin-destination analysis to track job-related employment relocations in 186 FUAs between 2012 and 2021, using official employment data for 480 multinational knowledge-intensive firms. These firms and thus their workers are categorized into three knowledge bases, analytical, synthetic and symbolic, to capture different types of knowledge creation and use in the innovation process. The results show a differentiated, multi-scalar perspective on the German knowledge economy: Overall, knowledge-intensive employment has primarily relocated to the largest FUAs such as Munich and Frankfurt. However, the relocation patterns differ depending on the knowledge base: workers in the synthetic knowledge base predominantly relocate on a large scale to and between the largest and between more decentralized FUAs, suggesting that spatial proximity plays a subordinate role in job-related relocations. Workers in an analytical or a symbolic knowledge base, however, show more localized relocations, mainly between neighboring or spatially proximate FUAs.

4 Where do knowledge-intensive firms locate in Germany? – An Explanatory Framework using Exponential Random Graph Modeling

Published as: Heidinger, M., Wenner, F., Sager, S., Sussmann, P., & Thierstein, A. (2023). Where do knowledge-intensive firms locate in Germany?—An explanatory framework using exponential random graph modeling. *Review of Regional Research*. https://doi.org/10.1007/s10037-023-00183-8.

Abstract: This paper analyzes how positional and relational data in 186 regions of Germany influence the location choices of knowledge-based firms. Where firms locate depends on specific local and interconnected resources, which are unevenly distributed in space. This paper presents an innovative way to study such firm location decisions through network analysis that relates exponential random graph modeling (ERGM) to the interlocking network model (INM). By combining attribute and relational data into a comprehensive dataset, we capture both the spatial point characteristics and the relationships between locations. Our approach departs from the general description of individual location decisions in cities and puts extensive networks of knowledge-intensive firms at the center of inquiry. This method can therefore be used to investigate the individual importance of accessibility and supra-local connectivity in firm networks. We use attributional data for transport (rail, air), universities, and population, each on a functional regional level; we use relational data for travel time (rail, road, air) and frequency of relations (rail, air) between two regions. The 186 functional regions are assigned to a three-level grade of urbanization, while knowledge-intensive economic activities are grouped into four knowledge bases. This research is vital to understand further the network structure under which firms choose locations. The results indicate that spatial features, such as the population of or universities in a region, seem to be favorable but also reveal distinct differences, i.e., the proximity to transport infrastructure and different valuations for accessibility for each knowledge base.

4.1 Introduction

Knowledge-based firms have been recognized as important drivers of urban development that increasingly shape and concentrate economic activity in only a few places (e.g., Friedmann 1986; Sassen 2001; Hall and Pain 2006; Taylor and Derudder 2016; Waiengnier et al. 2020). Transnational corporations depend on these knowledge-based firms, which function as central actors in knowledge creation and diffusion (Bathelt et al., 2004). This process has led to the formation of multilocational, often multinational, firm networks of knowledge-intensive firms offering their services globally (Derudder & Parnreiter, 2014, p. 375). Here, firms access heavily localized knowledge and make it available globally (Bathelt & Glückler, 2011). Therefore, cities increasingly act as nodes in global flows of knowledge, capital, and goods in such networks of firm locations (Castells, 1996; Sassen, 2001; Smętkowski et al., 2021). Still, how well a city or region is positioned in the global economy depends on both physical and non-physical networks (Castells, 1996).

Staying competitive in the global economy means fostering innovation and adapting new knowledge sources (Bathelt & Glückler, 2011, p. 196). Agglomeration economies enable and improve these processes through shared labor markets or spontaneous knowledge spillovers due to spatial proximity between firms (Combes & Gobillon, 2015, p. 2). At the same time, firms are increasingly embedded in functional networks fomed by cities and firms. In these networks, so-called “urban network externalities” (Capello, 2000, p. 1927) arise. Here, cities are able to “borrow” (Camagni et al., 2016, p. 140), exploit, or partially replace local agglomeration functions from other places, even ones that are not in physical proximity to each other (Burger & Meijers, 2016; Capello, 2000). This interplay of local externalities, through agglomeration economies, and connectivity, through network economies, plays a crucial role in the knowledge creation process and economic growth of a region (Bathelt et al., 2004, p. 19; van Meeteren et al., 2016). Although various location factors such as universities, a high local GDP, international airports, or corporate taxes have been identified as beneficial for attracting firms, they are not equally important to all industries (e.g., Zandiatashbar and Hamidi 2018; Adler and Florida 2020; Sigler et al. 2020; Chong and Pan 2020; Wu et al. 2022).

The main goal of this paper is to explore how multi-branch, multi-location firms of advanced producer service (APS) firms and High-Tech industries shape and use space in Germany. Our assumption is that firms specifically choose their locations to not only increase their competitive edge but also add highly localized knowledge to their knowledge creation process. Furthermore, we expect that characteristics in space, such as the mode of transport and travel time between two places, have a significant influence on how and where firms operate their firm locations. Therefore, we assume that locations in multi-location multi-branch firm networks are not independent of each other but interconnected by specific location requirements, proximities, and accessibilities. This relational approach to observing firm networks requires the use of network analysis since the standard assumption of non-independence is violated, making statistical regression analysis infeasible.

In the literature, different network analysis approaches have been used to model location choices, including exponential random graph models (ERGMs) or stochastic actor-oriented models (SAOMs) (Block et al., 2019; Broekel et al., 2014; Chong & Pan, 2020; Liu, Derudder, Liu, et al., 2013). We opt for the ERGM approach for several reasons. First, SAOMs require specific actor-based assumptions, such as specific intra-firm considerations of locations that we do not have (Block et al., 2019). Additionally, SAOMs are not unproblematic when used in a spatial context (Broekel & Bednarz, 2018). Second, we intend to understand why certain patterns of firm networks can be observed. The goal, thus, is to understand how these individual location decisions collectively shape the space we observe. Boschma and Frenken (2003) argue that, in addition to spatial concentrations, attention should be paid to the mechanisms by which knowledge is passed on, imitated, or adopted in firm networks. ERGMs provide us with the opportunity to examine these firm location patterns in Germany in more detail and go beyond the general description of location choices. Linking firm locations to the spatial characteristics of regions that are linked by transport infrastructure highlights the importance of accessibility and supra-local connectivity in firm networks. In this paper, we take the interlocking network model (INM) approach to conceptualize firm networks and relate it to local infrastructures and location factors. Taylor (2004) introduced the INM to approximate the underlying knowledge and information flows through a relationality between two places (Lüthi et al., 2018).

We base our analysis on a comprehensive dataset of firm locations, with locations of the 30 largest firms in 14 subsectors aggregated to knowledge bases in Germany and combine it with different modes of accessibility (rail, road, air). We chose Germany because it has a highly diversified economic structure, and the territory features an interesting urban system of cities and surrounding urbanized areas organized in a decentralized federalist structure. We show that the location choice of firms in a knowledge base, on the one hand, is strongly dependent on the type of sector firms are assigned to and, on the other hand, to some extent, a path-dependent development. However, distinct differences between the four bases are evident.

This paper is structured as follows. Section 4.2 briefly summarizes the theoretical background of knowledge networks and how knowledge gets created in space. Section 4.3 introduces the empirical approach, namely the exponential random graph model, as a way to model firm networks against infrastructural properties such as railway networks and introduces our datasets. Section 4.5 discusses the results of the employed models and their implications. Finally, Section 4.6 gives an outlook and concludes this study.

4.2 Conceptual background and hypotheses

At the beginning of the 20th century, Alfred Weber and Marshall (1920) opened the theoretical discussion on the location choices of firms, agglomerations, and the advantages that arise with concentrations of firms, such as labor market pooling or economies of scale. Ever since these seminal works, an abundance of research has been put into the question of where and why firms locate, co-locate, or cluster. Moreover, the growing interest in the economic activities of multinational firms (e.g., Friedmann 1986; Castells 1996; Sassen 2001; Taylor 2004), more specifically in the context of the knowledge economy, altered the hitherto prevailing state of research on agglomeration economies (Bathelt & Glückler, 2011). Here, local markets and transnational networks of firm locations are equally important to access even the most localized knowledge. However, separating the locality and globality of agglomerations in firm networks is not straightforward, as multinational firms usually use both in their internal operational processes.

For this reason, van Meeteren et al. (2016, p. 12) propose an interpretation as a complementary continuum in which agglomeration processes operate primarily at the local level, but network effects predominate with increasing distance. We argue specifically that localization economies decrease with distance. These are then complemented by network economies, where distance is negligible.

Evolutionary economic geography started to unpack these firm spatial concentration processes quite differently by studying where and why firms (re-)locate or exit certain regions (Boschma & Frenken, 2018). For example, do regions grow through spinoffs of parent firms, as Boschma and Frenken (2003; 2007) showed when they analyzed internal firm routines? Or do they grow because of regional specialization economies, as Hidalgo et al. (2007) present in their work on "product space"? We argue that both are equally true in a multi-branch, multi-location knowledge economy.

Firms in well-developed economies seek qualified personnel – which is also the case in the knowledge economy (Bathelt & Glückler, 2011; Storper & Scott, 2009). However, specifically in these advanced economies, these talent pools are unevenly concentrated in space, so firms actively (re-)locate in such regions (Adler & Florida, 2020). Bathelt and Cohendet (2014, p. 3) summarize that at the core of the knowledge creation process, firms are embedded in local ecosystems to interact with other (in-)formal organizations but are integrated into global production networks. Especially large multinational organizations profit from network economies as they have the resources to access local tacit knowledge globally (Bathelt & Glückler, 2011, p. 196; Howells, 2002; Simmie, 2003).

This leads to an increasing concentration of economic activity, which can also be observed in Germany, where only a few cities and urban regions are gaining in importance (Brunow et al., 2020; Krätke, 2007). Knowledge-intensive firms, and here especially APS firms, are widely regarded as important drivers of this formation process as they seek and incorporate new sources of knowledge to remain competitive in the market (Brunow et al., 2020; Castells, 1996; Sassen, 2001). Additionally, research on the knowledge economy system points to the fact that firms in High-Tech industries also create worldwide office networks. Some authors highlight their even more globalized firm network structure compared to APS firms (Lüthi et al., 2018).

Numerous works of literature around the Globalization and World City (GaWC) Research Network track the emergence of such knowledge-based firms or industries in many parts of the world, studying firm locations and economic developments alike. The GaWC uses multinational and multi-branch firms of the APS sector to statistically determine the relations between regions in a globalized world (Taylor, 2004). Bettencourt (2019) follows a different path by presenting a framework of how city networks in total are formed – through social, economic, and infrastructure networks. The author argues that city networks are a complex construct of historical and evolutionary elements that should be primarily studied through socioeconomic connectivity since this interaction is how historically cities developed. While focusing on the location patterns of such firms, several studies found different location choices among APS sectors at the local city scale. (e.g., Vandermotten and Roelandts 2006; Bassens et al. 2020; Chong and Pan 2020; Waiengnier et al. 2020). Waiengnier et al.'s (2020) study on Brussels, for example, shows that the location preference, and therefore the concentration of firms, depends on the size of the firm and the service they provide. In addition, the authors found that knowledge-intensive firms value centrality but, at the same time, various aspects within such agglomerations, such as market accessibility or path dependency. Chong and Pan (2020) confirm these findings on location choices by employing an ERG model to study how APS firms form a city network between different cities in China. The authors further emphasize the importance of an efficient rapid transportation network to foster network effects.

Still, several shortcomings emerge regarding these studies: they focus primarily on the agglomeration effects between APS firms or specifically study one city or region and therefore are of limited comparability. We interpret space differently by combining positional data, thus the features of regions, with the relational characteristics of both firm networks and how regions are actually connected through roads, air routes, and rail networks.

With a focus on High-Tech-oriented firms, Boschma and Wenting (2007) and Harris et al. (2019) found that competition and related activities are more important for the manufacturing industry in Britain than densely populated regions or being located in a major city. However, as of now, and given that we focus on the relationship between positional and network data, not many comparisons of APS and High-Tech firms have been carried out. In this paper, we focus not only on APS firms but on the full spectrum of knowledge-intensive firms and follow Lüthi et al. (2011) to define the knowledge economy as "that part of the economy in which highly specialized knowledge and skills are strategically combined from different parts of the value chain in order to create innovations and to sustain competitive advantage."

However, since the knowledge economy is not a homogeneous construct, it is crucial to differentiate between the various sectors to identify its dynamics more precisely (Kronenberg & Volgmann, 2014, p. 40). In order to quantify this complex spectrum of the knowledge economy, we make use of the knowledge base typology by Asheim and Gertler (2006). The authors propose a classification into three knowledge bases. Synthetic and symbolic knowledge incorporates a strong tacit body, while in analytical knowledge, codifiability is the dominant form (Asheim & Hansen, 2009). Furthermore, these three knowledge bases have different sensitivities to geographic distance (Asheim et al., 2011).

Firms with an analytical base focus on activities with a strong scientific component, such as biotechnology or information technology (Asheim & Gertler, 2006). Due to the aforementioned codifiability of analytical knowledge, it is less sensitive to distance, and the transfer can be utilized more easily across space (Storper & Venables, 2004; Tranos, 2020). Firms with a strong focus on symbolic knowledge, such as design, media, or advertising firms, depend on physical proximity; social interaction and networking are key elements in promoting the necessary knowledge transfer (Asheim & Gertler, 2006). Therefore, we often find industrial clustering of firms with a symbolic knowledge base (Tranos, 2020). Lastly, firms with a synthetic knowledge base focus on combining and applying existing knowledge. Such firms rely more on tacit knowledge and, therefore, geographic distance due to the nature of the application of knowledge and interaction, or learning by doing (Asheim & Hansen, 2009). Zhao et al. (2017) applied the knowledge base typology to analyze the location choices of knowledge workers. The authors identified four economic groups: symbolic APS, synthetic APS, synthetic High-Tech, and analytical High-Tech. The authors show that different location preference patterns are evident depending on the knowledge base. The authors further find that workers with a symbolic knowledge base show the greatest preference for urban locations, followed by APS workers with a synthetic knowledge base.

On the other hand, workers in High-Tech firms generally show less preference for urban locations. These results are in line with the literature above. However, contrary to that, the authors also identify the possible preference of synthetic APS workers for peripheral areas. Therefore, we expect different location choices for analytical and synthetic High-Tech firms, which consist of manufacturing and research-oriented firms. Furthermore, Van Oort (2004) and Raspe and van Oort (2011) found that firms profit less from their proximity to universities than from being centrally located. Building on this fundament of literature, we hypothesize that analytical and synthetic High-Tech firms have a lower propensity for urban locations than synthetic and symbolic APS firms (H1).

Knowledge-based firms rely on local infrastructural amenities. The literature agrees that universities and co-operating or industry-specific R&D institutes are key factors for firms to locate in a specific place (e.g., Audretsch and Stephan 1996; Simmie 2003; Florida et al. 2015). For example, Arant et al. (2019) show that collaborations between firms and universities can be fruitful for the innovation process, as it gives them access to new knowledge. In addition, Roesler and Broekel (2017) identify universities as nodes in a network that knowledge-intensive firms can access. Besides these beneficial collaborations between universities and firms, the literature shows that the societal, cultural, and creative image, but also the presence of recreational amenities, attracts highly skilled workers and thus knowledge-based firms (e.g., Trip 2007; Carlino and Saiz 2019; Wu et al. 2022).

Zandiatashbar and Hamidi (2018) found that the walkability and transit service quality of a place have a positive impact on attracting knowledge-based firms, thus positively influencing innovation. Earlier, Karlsson and Andersson (2004) identified a close link between accessibility and the performance of a region. The authors argue that travel time is a more appropriate measure of accessibility than physical distance. In contrast, de Bok and van Oort (2011) found no significant results for firms in the manufacturing sector and suspect a trade-off between accessibility and the cost of rent since these firms require more space to do business. Coscia et al. (2020) found that business trips decline with travel-time distance, hence why APS firms heavily depend on transportation infrastructures to facilitate face-to-face business activities. For these firms, airports are seen as nodes in a global network of firm locations. Neal (2012) and Liu et al. (2013) highlight airports as infrastructures that stimulate business activities and air passenger networks. Further, Conventz and Thierstein (2014) identify airports as hubs for events and conferences, making them also useful for short business trips.

Particularly in the Asian and European context, (high-speed) rail infrastructure complements this relationality. Wenner and Thierstein (2021b, 2021a) show the role of high-speed rail for regional accessibility, replacing air traffic on an increasing number of (inter-)national routes as the fastest mode, and the role of certain high-speed rail stations for urban development, including locational decisions of firms. Zhao et al. (2017, p. 206) found that both symbolic and synthetic APS knowledge workers tend to utilize public transport or active modes to commute more than workers in High-Tech firms.

Regarding the transport infrastructure, Krenz (2019) identified that road accessibility and short travel times are important factors for German High-Tech firms. However, Zhao et al. (2017, p. 206) highlight that synthetic High-Tech workers show a higher preference for commuting by car – and therefore road accessibility – than analytical High-Tech workers. Therefore, we assume that there is a measurable difference in how firms value different modes of accessibility – road, air, and train – to best leverage their individual networks for the exchange of information and, eventually, the creation of knowledge. This leads to the second hypothesis: We hypothesize that APS firms, in general, demonstrate a stronger preference for rail and air accessibility, while among all High-Tech firms, those with a synthetic knowledge base show a stronger preference for road connectivity (H2).

Before we present our methodology below, we present our approach to the underlying firm location decision process that is ultimately reflected in this study's dataset. We think this is an important step in understanding how space is constructed and shaped. As stated before, much research (e.g., Smętkowski et al. 2021) focuses on location factors within a city or a region. Therefore, in these studies, the focus lies on a small set of firms that choose locations based on given location factors or amenities, e.g., qualified personnel and favorable infrastructure, to exploit local knowledge sources or competitive markets. However, when focusing on firm networks rather than individual firm locations, a different approach is needed. Firms, especially knowledge-based firms, constantly re-evaluate whether the given location in their firm network still meets their internal requirements and react accordingly by relocating or adapting their network. Infrastructure, for example, must be maintained or built so the regions themselves, through public and private investment, become players competing globally to attract and retain firms in a region (Bettencourt, 2019; Boschma & Frenken, 2018). Moreover, a firm's location choice is influenced by the workers' requirements, e.g., whether proximity to a train station is important or not (e.g., Zhao et al. 2017) – hence, firms may move individual locations based on changing employee demands. Therefore, when focusing on particular firm locations, we argue that such locations can be compared to nodes in the firm-location network shaped by local specifications and workers' location preferences.

In this study, however, we go a step further by aggregating individual firm networks to a much broader firm-location network. Here, locations – their specific amenities and infrastructures – emerge as central not just to one firm but to many of them, making them key actors in the network. Thus, by overlaying dozens of firm networks, we are able to not only draw conclusions about the general behavior of knowledge-intensive firms in space but also demonstrate a hierarchy of areas where they locate.

4.3 Methodology and data

4.3.1 EXPONENTIAL RANDOM GRAPH MODEL

In this section, we discuss the setup and function of the exponential random graph model (ERGM), which we use to detect a distinct spatial pattern in our firm dataset. In short, ERGMs are statistical tools to describe the likelihood of given network structures by modeling an infinite number of possible networks and comparing these to the global structure of a network (Hunter et al., 2008, p. 2). However, ERGMs are computationally intensive; hence we opted for Krivitsky et al.'s (2021) estimation approach that relies on a central Markov chain Monte Carlo (MCMC) algorithm for estimation and simulation along with a maximum pseudo-likelihood estimator for the results. In this study, we aim to explain the given network structures of each subsector in the knowledge economy by modeling a random network model using the ERGM and additional node-level data.

ERGMs are similar to regression models, except that ERGMs do not imply that all parameters are statistically independent (Van Der Pol, 2017, p. 2). The underlying network used in our ERGM is the interlocking network model (INM), as presented later in this section. However, the conventional ERGM to be estimated is limited to binary data, meaning that it can only estimate the probability of a tie between two regions on a binary level (Krivitsky, 2012). As this methodology is discussed in detail by Hunter et al. (2008), Krivitsky (2012), and Krivitsky et al. (2021), we will present a parsimonious summary. We use functional urban areas (FUAs) as our spatial scale, which we briefly introduce in 4.4.3.

Transforming network data into binary results in a loss of information, specifically in the categorization of firm locations, according to Taylor (2004). We, therefore, use Neal et al.'s (2021a) backbone approach to dichotomize our valued INM dataset into binary space. We extracted the backbone of our dataset using the fixed degree sequence model (FDSM) with a two-tailed α of 0.05. We used this alpha for three of the four knowledge bases as we found this to be the best compromise between a good fit and preserving network details of less "meaningful" (Neal et al., 2021a, p. 7) connections. For the knowledge base synthetic APS, we chose a stricter α of 0.01 to improve the fit. For the statistical and mathematical background of this approach, we refer to the relevant literature by the authors (Neal et al., 2021a, p. 7, 2021b, p. 4). Lastly, we follow Duxbury's (2021) approach to check for multicollinearity in ERGMs and did not detect any. The authors will provide the results upon request.

In general, an ERGM models the probability distribution over all possible networks ($\forall x \in$ X). It takes the form of equation (5):

$$\Pr(X = x|\theta) = \frac{\exp(\theta^T s(x))}{k(\theta)} \quad \forall x \in \mathrm{X} \tag{1}$$

Where x is the given (observed) INM network structure, X is the random (modeled) network modeled by the ERGM, θ is a vector of weights, model parameters $s(x)$ is a vector of the network parameters or exogenous variables, and $k(\theta)$ is a normalizing constant. In our study, we used two different types of exogenous variables: Co-variables that describe each FUA on the nodal level in more detail, i.e., inhabitants or whether an FUA features an institution of higher education. On the other side, we used co-variables that describe the relationship between two FUAs, in the form of physical distances, travel times, railways, or connecting flights. We will present the results of the ERG model in more detail in the next section.

4.4 Data and model specification

4.4.1 FIRM DATA

Our dataset is formed by firms in the German knowledge economy and their respective branch locations in Germany. In identifying knowledge-intensive firms, we follow the classification by Legler and Frietsch (2006) and its updated version, Gehrke et al. (2013), based on the German Classification of Economic Activities (Wirtschaftszweige 2008). Even though this taxonomy has its shortcomings, such as the possibility that, over time, firms may have shifted operations to different economic activities, we still think this classification is robust enough since it focuses on research-intensive industries, i.e., firms that use, reuse, or create new knowledge. We further aggregated knowledge-intensive classes of economic activities into groups with a similar activity-related context. Here, we followed Zhao et al. (2017) and formed four groups, analytical High-Tech (AnH), synthetic High-Tech (SyntH), synthetic APS (SyntA), and symbolic APS (SymbA). The following subsectors were formed: In synthetic APS (SyntA), we included the sectors accounting, banking and finance, insurance, law, management and IT consulting, information and communication services, and third- and fourth-party logistics. In symbolic APS (SymbA), we grouped the advertising, media, design, architecture, and engineering sectors. In the knowledge base of synthetic High-Tech industries (SyntH), we defined the following subsectors: mechanical engineering, computer hardware, electronics, telecommunications, and vehicle construction. The last group analytical High-Tech (AnH), includes the chemical & pharmaceutical and medical & optical instruments sub-sectors. These industries were chosen because of their investment in research and development activities and a high share of highly-skilled labor (Legler & Frietsch, 2006). We created the firm database using manual and semi-automatic web-scraping methods of the online self-presentations of the 30 largest firms by employees in Germany in each group. We opted for the cut off at 30 since we aimed to cover firms that are located all over Germany and argue that this number is sufficient to make well-founded statements about the German knowledge economy. We extracted and geo-referenced 17,786 unique firm locations.

4.4.2 INTERLOCK CONNECTIVITY

The underlying two-mode network uses the interlocking network model (INM) methodology. Taylor (2004) conceptualized this methodology to measure firm and city networks globally. The INM has been used to rank cities according to their position as global centers of command and control in various contexts, both economically and politically (e.g., Derudder and Taylor 2016). In this paper, we take this approach to conceptualize firm networks and relate them to local infrastructures and spatial amenities. For each firm, all office locations were assigned a *service value* between 5 and 0 according to the presence of the firm within the FUA. Although this valuation is not required in the ERG model, it serves as a guide to understanding where firms are located or headquartered.

An important parameter in the analysis of the firm network is the sum of all firms' service values (j) per FUA (a, b), i.e., the number of firms per FUA weighted by the importance of their regional presence (v). The INM approach then infers the strength of the relation (for example, the quantity of information exchanged) between two firm sites by multiplying their (firm-internal) service values, which we call the *elemental interlock* (r_{abj}). A generalized score for an FUA-to-FUA relationship is then derived by summarising the strengths of all firm relations between the FUAs, called the *FUA interlock*. By again summarising the strength of all FUA interlocks to and from an FUA, a nodal value representing the embeddedness of an FUA in national firm networks can be obtained, which we will call *interlock connectivity*.

$$\sum_{j} r_{abj} := v_{aj} v_{bj} \tag{2}$$

The resulting network is a one-mode network as we study the relation of a subset of firms with locations in specific FUAs and not of individual firms on the node level directly. We, therefore, calculate the one-mode network separately for all four knowledge bases. These networks are then transformed in binary space using Neal et al.'s (2021a, 2021b) backbone model to get them to the appropriate form for the ERGM; see above.

In the following two sub-sections, we separately introduce all node and dyad level variables we used.

4.4.3 NODE-LEVEL DATA

In both sections, to keep matters short, we introduce abbreviations in paratheses. We mapped and binary coded all public institutions of higher education (universities and universities of applied sciences) (INST) and airports (AIRPORT) in Germany.

This spatial base unit of our analysis is based on the urban centers identified in the ESPON 111 project for Germany and nearby regions (ESPON, 2004). The project has defined urban centers and their hinterlands (so-called PUSH areas – potential urban strategic horizon) using a set of functional-spatial criteria such as in-commuting patterns. This results in a list of 186 FUAs for Germany. Importantly, the PUSH areas were defined regardless of national boundaries, which means that some FUAs extend into neighboring countries, while other border areas of Germany are not covered by an FUA.

Since we assume different locational preferences depending on the economic output or broader sector we classified each firm in, we made use of the spatial classification published by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). Each municipality is categorized according to its population density into one of the three following categories: urban areas (1; URBAN), semi-urban areas (2; SEMI-URBAN), and rural areas (3; RURAL) (BBSR 2019).

Additionally, we follow the BBSRs categorization of cities according to their population size. A *Großstadt* (> 100k) features at least 100,000 inhabitants, a *Mittelstadt* (< 100k) between 20,000 and 100,000 inhabitants (source: BBSR). Since there is at least one *Kleinstadt* (less than 20,000 inhabitants) in each FUA, we opted for > 100k and > 100k only. Similar to the threefold BBSR classification, we counted and transformed the classification to fit our FUA dataset.

Table 9 Classification of functional urban areas in Germany, applying BBSR categorization (source: BBSR)

	Count	Average population over all cities	Average employment over all cities	Average size
Großstädte (> 100k)	68	757,235	413,170	1,228 ha
Mittelstädte (< 100k)	118	266,081	132,378	1,954 ha

Lastly, we added the German metropolitan regions (METROP) as a dummy variable to our dataset. In Germany, 11 metropolitan regions are identified, usually consisting of at least one *Großstadt* and several smaller regions or districts. Metropolitan regions in Germany are thought to be drivers of economic, social, and cultural development (Zimmermann et al., 2020).

Since each FUA is computed using NUTS regions on the smallest statistical entity, the spatial unit used in Germany is the municipality. Each FUA may consist of one or more statistical entities, forming the aggregated FUA. As mentioned above, FUAs bordering neighboring countries cover municipalities outside Germany. In these cases, we used data provided by Eurostat on the level of local administrative units (LAU).

A similar approach was chosen to gather employment data. Our dataset for the German Districts comprises data from the Statistical Office of Germany for the neighboring European countries from Eurostat. As data is not collected for the countries Liechtenstein and Switzerland, we opted for official data provided by the Statistical Offices of both countries.

4.4.4 DYAD-LEVEL DATA

We calculated several proximity factors towards all other FUAs to measure transport-based accessibilities. First, we extracted and counted all direct connections by train between two FUAs (AMNT TRAIN) using the current online railway timetable of the German railway operator, Deutsche Bahn (DB 2020). Then, we calculated the *efficiency* of a train connection between two FUAs (PROX TRAIN). For this, we gathered the travel time by obtaining the time schedule of Deutsche Bahn for each central railway station in each FUA. Then, we used these travel times between two FUAs (tt_{train}) and related them to the geodesic distance between two FUAs a and b ($dist_{ab}$). This ratio represents the *efficiency* of a connection:

$$efficiency_{rail} = \frac{dist_{ab}}{tt_{rail}} \tag{3}$$

We also calculated the road distance for each FUA-to-FUA (PROX ROAD). Further, we also conducted a road-versus-rail network analysis by comparing the efficiency of the travel time in a train network against the road network (PROX RR). Again we calculated for each connection using the following term:

$$road\ versus\ rail\ (RR) = \frac{tt_{rail}}{tt_{road}} - 1 \tag{4}$$

Here, tt is the travel time using either the road or rail network. Firms may choose a location to minimize time between two places and thus prefere different modes of transport. With this term, we study which network is the better option: The term is positive if the connection is faster using the road network and becomes negative if it is the rail network. Lastly, we collected the number of direct flights between each of the airports in Germany. Since not all FUAs in our dataset host an airport, the network of air flights is rather tight, forming the third type of proximity for our analysis (AMNT AIR).

PROX TRAIN suggests that with 2,685 direct train connections (out of 35,156 possible connections), only a handful of FUAs are connected to all other FUAs in the network by rail. PROX AIR suggests an even smaller network of 23 direct connections between FUAs. PROX RR, the ratio of travel times between two FUAs, is slightly negative, suggesting a faster connection using the train network over the road network for only 16.4% of the road network represents a significant advantage. The estimation method defaults to the Monte Carlo maximum likelihood estimation (MCMLE) (Krivitsky et al., 2021). The findings are presented and discussed below.

4.5 Findings and discussion

4.5.1 MODEL VALIDATION AND FIT

The network used in our analyses in the ERGM takes the form of a two-mode dataset and describes the relation between two cities through a sum of links for each individual firm in each subsector. We use R packages to implement the ERGM developed by Hunter et al. (2008), Krivitsky (2012), and Krivitsky et al. (2021).

It is important to stress some methodological issues that we had to overcome. First, we must acknowledge that we have only taken the 30 most important firms of each subsector of the German knowledge economy under consideration. Therefore, our firm sample is not a statistically independent and identically distributed random sample of firms. It was never the intention to do so, and we, therefore, do not draw any conclusion on the population of the German knowledge economy as a whole.

We followed Statnet (2021) and tested the goodness-of-fit for each model and assessed the degree distribution. Since each subsector is one model, the results are in the appendix. One should recall that we used Neal et al.'s (2021a, 2021b) FSDM approach to extract the backbone of each network. We, therefore, compare the backbone of a network with its modeled counterpart. We discuss the empirical results of the ERG models below.

4.5.2 RESULTS AND DISCUSSION OF THE ERG MODELS

We begin by presenting the general effects of our data on the model. The results of each model for all sectors are presented and compared to validate our hypotheses later. Our base for each variable is a peripheral region (RURAL) that has no institution of higher education (INST = 0) and is not part of a German metropolitan region (METROP = 0). We separate the results by hypothesis and present both APS and High-Tech subsectors. The full results for all subsectors are presented in the appendix. Each column represents a separate individual model. The rows indicate the effect of each parameter in the form of coefficients.

4.5.2.1 Principle effects

Across most subsectors, the presence of institutions of higher education (INST) in an FUA has a significant positive influence in forming a link between two FUAs. This comes as no surprise since economic activity happens in more densely populated areas, and higher education institutions in Germany are usually located in core city areas. This is mostly true at the <0.05

significance level for subsectors in either APS or High-Tech. Interestingly, being located in a metropolitan region (METROP) has a negative impact on several branches of both High-Tech and APS. We suspect this is due to the fact that our base model suggests a location that is classified as peripheral but at the same time is not in a metropolitan region. A peripheral region in a metropolitan region could be subject to drainage of economic activity from the region's core. Similarly, the number of direct connections by train between two FUAs (AMNT TRAIN) has a significant positive influence. These assumptions are only to be considered with all other variables held constant. In the following sections, we will discuss the results for each hypothesis.

4.5.2.2 Hypothesis (1): Analytical and synthetic High-Tech firms are less centrally located

The results of the models partly yield evidence that High-Tech firms are located in less central locations. We do generally assume that a firm is more centrally located if the estimates for an FUA, the number of *Grossstädte* or location in an urban area, yield significantly positive results. For this hypothesis, we look at the parameters URBAN (urban area), SEMI-URBAN (semi-urban area), METROP (the FUA is part of a metropolitan region), > 100k, and < 100k (whether the FUA hosts a *Grossstadt* or *Mittelstadt*). Starting with the parameter METROP, we identify an interesting pattern, as it is negatively significant for both High-Tech knowledge bases. However, we must keep in mind that our base model is a rural FUA without an institution of higher education and not being part of a metropolitan region. Here, we argue that an FUA in a metropolitan region is not enough to attract firms operating in the High-Tech knowledge bases. Regarding the estimates for > 100k and < 100k, we can summarize the following observations: Firms in synthetic High-Tech seem to prefer *Mittelstädte* and not *Grossstädte*, both estimates are positive yet not significant. Further, analytical-based firms are significantly positive on FUAs with cities < 100K inhabitants and therefore seem to prefer higher populated urban areas (URBAN). This contradicts our hypothesis at first. However, with regards to the literature we discussed earlier (e.g., Asheim and Gertler 2006), we suspect that firms locate in such areas, and span firm networks between big cities. This showcases an interesting finding as we clearly identify different location patterns for High-Tech firms. Recall that in our dataset, synthetic-based (SyntH) firms are, for example, automotive manufacturers and suppliers, electronics or mechanical engineering firms, while analytical High-Tech (AnH) firms are associated, for example, with the chemical & pharmaceutical industry. Similar to Krenz (2019), we conclude that German manufacturing firms seem to prefer locations in agglomeration areas, possibly in smaller *Grossstädte* (< 100K) or near *Mittelstädte*, but with good infrastructure and accessibility for workers.

When focusing on APS knowledge bases, both analytical and symbolic knowledge-based firms return mixed results. Synthetic APS (SyntA) returns significantly positive results in semi-urban parts of Germany and significantly negative results for German *Grossstädte* (> 100K). We argue that this is due to the well-developed networks of banking & finance and insurance firms, which need to be close to customers and therefore have a strong presence in all parts of Germany. Both synthetic (SyntH; SyntA) and symbolic (SymbA) knowledge bases return significantly positive results for the variable INST – highlighting that an institution of higher education in a city is a major factor in the location decision.

Regarding our first hypothesis, we summarize that High-Tech firms in our dataset show evidence of expected location patterns. Firms with an analytical knowledge base (AnH) are significant in parameters that we associate with being central. Synthetic High-Tech (SyntH) firms seem to favor less central FUAs to set up firm networks, with an urban structure (URBAN) being significantly positive. Contrary to our assumption, we do not witness synthetic APS (SyntA) firms as the most centrally concentrated, with no significant outcomes in the variables under consideration. We suspect this is due to the well-developed network of firm locations in the banking & finance and insurance subsectors which mirrors the population distribution, thus making the spatial patterns appear random. In total, we can only partly confirm our first hypothesis by a combination of > 100K, < 100K, and URBAN.

4.5.2.3 Hypothesis (2): APS firms depend more on railway and airport accessibility while synthetic-based High-Tech firms prefer road accessibility

Starting with the dyad estimates, the parameter PROX TRAIN measures the travel time by train between two FUAs. It is significantly negative for synthetic APS (SyntA) firms. The coefficient focusing on the number of train connections between two FUAs, AMNT TRAIN, identifies another pattern as both synthetic knowledge bases (SyntA; SynthH) and symbolic APS (SymbA) are significantly positive here. We suspect that short travel times by train may be an indication of industrial clustering, as showcased by Broekel and Bednarz (2018). We further deduce that the distance by train between two FUAs may have an influence on the formation of a tie: As the distance between two places increases, the probability of a connection decreases.

The parameter AIRPORT is significantly positive in synthetic High-Tech (SyntH). Again, we interpret this with the smaller-sized, less extensive firm networks in all knowledge bases but synthetic APS (SyntA) (Tether, 2002). For firms with a symbolic (SymbA) or synthetic (SyntH) knowledge base, the results show evidence, in line with previous results (e.g., Thierstein and Conventz 2014), that these firms interact less on a regional and more on a national and global level as firms in both knowledge bases seem to make use of airport connections as both are also significantly positive for AMNT AIR – the number of direct flights between two FUAs.

Regarding the preference for road accessibility, we study the estimated parameters PROX RR and PROX ROAD. Recall that the interpretation of PROX RR is the ratio of travel times for road and railway connections, meaning that a positive outcome in PROX RR signals a more important, and thus faster, road network connection. Both synthetic-oriented knowledge bases feature a negative but statistically not significant estimate. The parameter PROX ROAD is positive for analytical firms, negative for synthetic-based High-Tech firms, and significantly negative for synthetic APS (SyntA) firms. Even though the parameter is not significant for High-Tech firms, it may be a possible indication of the preference for road accessibility to transport goods, as shown by Krenz (2019).

In any case, we cannot confirm this hypothesis as there is no clear distinction for airport accessibility, as only firms in synthetic High-Tech (SyntH) yield positive results here. We suspect that one major influence is the network structure itself of the firms in our dataset. For example, in synthetic APS, banking firms host dense networks with many subsidiaries, while in synthetic High-Tech, the value creation is concentrated at only a small number of locations in Germany. Lastly, even though the direction of road accessibility confirms our initial hypothesis, the estimates are not statistically significant, hence why we cannot confirm the hypothesis and conclude that further research is needed.

4.6 Conclusion and research outlook

With this study, we expand the theoretical debate on the locational behavior of firms in the knowledge economy. We do this by examining the influence of physical accessibility on firm locations using exponential random graph models (ERGM). ERGMs are used in social network analysis. However, since ERGMs allow us to study parameters affecting the formation of ties in a network, it offers a valuable research path to study firm networks. Since we utilize the renowned interlocking network model (INM) to map firm networks, first introduced by Taylor (2004), using an ERGM seems feasible.

Our data is based on FUAs and our results confirm previous findings on firm locations and accessibility to transport infrastructures, even though those other studies were conducted on individual city spaces (e.g., De Bok & Van Oort, 2011; Smętkowski et al., 2021; Wu et al., 2022). In this study, we departed from dividing the knowledge economy into the two main segments of APS and High-Tech. Instead, we followed Zhao et al. (2017, p. 206) by assigning the firms with their respective characters of economic activities to one of the three different knowledge bases defined by Asheim and Gertler (2006) and Asheim and Hansen (2009). Thus, we use a typology with four types of economic activities: symbolic APS (SymbA), synthetic High-Tech (SyntH), and analytical High-Tech (AnH).

The results of the ERGM confirm the descriptions of knowledge bases: Firms with an analytical knowledge base have a significant location preference in FUAs with a dense population and German *Grossstädte*, highlighting their less geography-sensitive firm networks (Asheim & Gertler, 2006). On the other hand, firms with a symbolic knowledge base depend on face-to-face social interaction also favor German *Grossstädte*. We assume any type of *Grossstadt* is sufficient (both >100K and <100K). For synthetic APS (SyntA), our results indicate that firms are distributed across German FUAs in patterns that we would also expect to find at random. In the synthetic knowledge base, which also includes fourth-party logistics firms, our results indicate a preference for the road network and airports over the rail network while being located in semi-rural regions – a possible indication of a faster or more convenient connection. Contrary to our expectations, symbolic APS (SymbA), not synthetic APS (SyntA), firms favor locations with short airport accessibility. Again, we suspect this result from the dense network of firm locations in the banking and insurance sector here.

We argue that current developments are following a common theme, as the once clear-cut dichotomy of High-Tech firms as the sole producers of goods and APS firms as suppliers of services is diluting more and more. Whether in the automotive industry, the biochemical industry, or consulting branches, more and more firms are integrating in-house consulting services or data analytics facilities to leverage new technologies, such as artificial intelligence, to support standardized processes. Such adaptions require similar knowledge resources that can only be found in certain regions or cities (Isaksen et al., 2020). This is leading to an increasing blurring of sectoral categorizations of firms in industries, as, for example, we used in this study.

Based on these findings, we state that grouping firms of the knowledge economy into only two broad groups that distinguish manufacturing from services – that is, APS and High-Tech – does not suffice anymore to identify distinct spatial location patterns comprehensively. These are strongly determined by the population of an urban area, functions, local features such as universities, accessibility, and preferred mode of transport. Therefore, we propose to discriminate the knowledge-intensive economic activities into four knowledge bases: analytical High-Tech, synthetic High-Tech, synthetic APS, and symbolic APS (Zhao et al., 2017, p. 206). Because we chose to study only dyadic independence models for each network of knowledge base, there remains significant research prospect. We argue that dependent models will provide further insights into location choices – though cross-sectional dependencies are another promising area of research. Nonetheless, our approach offers an entry point into a methodology of using ERG models that goes beyond (independent) descriptive point data: large-scale network data from firm networks can be used to simultaneously examine where multi-branch firms locate, what type of location is preferred and how proximity to transport infrastructure is valued differently across sectors.

Policymakers seeking to emulate successful knowledge-based economic environments, such as Silicon Valley, should therefore carefully reassess their regional and local settings. We summarize that our results indicate the extent a region can attract firms of certain knowledge bases but also what infrastructure is actually required - or needs ot be in place in a region - in order to attract the *'right'* firms.

There are some shortcomings to our approach. First, some networks in our dataset are too dense in form to be directly used. We, therefore, applied Neal et al.'s (2021a, 2021b) backbone model to transform the INM into binary space. The backbone model uses significance levels below which less important connections are omitted and modifies the network depending on the selected alpha. Second, the use of FUAs as a spatial unit of analysis, composed of an urban center with its surrounding area, could also be broken down to finer levels of analysis; however, the use of such levels also increases the computational complexity. Lastly, a longitudinal analysis is needed in order to explore the changing locational patterns of current firm locations. It also needs to be stressed that in this paper, we focus on the applicability of ERGMs on a dataset of firm networks and location features in an explorative way; hence why we did not do any reverse-causality test of transport infrastructures, spatial amenities, and economic activity in space. Beyond these methodological limitations, one should not forget that we focused on location choices in Germany. These findings may be transferable for other central European countries with similar settlement and infrastructure patterns that originate in a more decentralized-federal organisation of the state. However, further reseach is certainly needed for other highly industrialised or emerging economies. We believe that further exploration of other aspects that may influence the location choice, such as the price per square meter of commercial space, could provide even more precise findings.

Looking ahead, an open question for future research comes to the fore: If knowledge-intensive firms increasingly seek specific occupational skills such as computational and digital high-level literacy, where in space – in which locations and on which spatial scale – do they source it from? Eventually, such research would contribute to the resurfacing of the long-standing challenge of understanding spatial structural change: At what point in time and where in space do firms follow knowledge workers, or at what point in time and where in space is it the other way around?

4.7 References

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4.8 Appendix

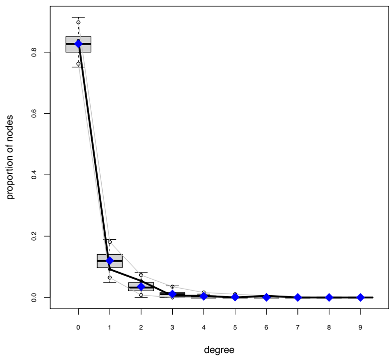
Table 10 Results of the ERGM of all models

Variables	Analytical High-Tech	Synthetic High-Tech	Synthetic APS	Symbolic APS
Node Level Data				
base (RURAL, METROP = 0, INST = 0)	-7.657403 *** (2.075337)	-6.1359503 *** (1.0213286)	-4.5706791 *** (0.3570418)	-7.3835881 *** (1.4934690)
GWESP	2.516367 *** (0.327809)	1.5299296 *** (0.1527263)	2.2670165 *** (0.1285344)	1.7843039 *** (0.2089514)
INST	0.427989 (0.301600)	0.4886928 ** (0.1490778)	0.2129041 *** (0.0396019)	0.8960853 *** (0.2342771)
METROP	-0.715169 * (0.308217)	-0.2569601 (0.1331800)	0.0449865 (0.0366146)	-0.2541782 (0.1869199)
AIRPORT	0.006425 (0.359578)	0.4204711 ** (0.1513986)	-0.0001216 (0.0663166)	0.2211411 (0.2275915)
< 100K	0.285304 * (0.132709)	0.0260576 (0.0812587)	0.0327642 (0.0257093)	0.1084815 (0.1025858)
> 100K	0.728396 (0.538650)	0.2733456 (0.2293358)	-0.6088574 *** (0.1344232)	0.4138008 (0.3295138)
MITTEL	0.052254 (0.044606)	0.0203635 (0.0145306)	0.0125618 (0.0073100)	-0.0226790 (0.0235400)
SEMI-URBAN	0.023386 (0.422577)	0.2638678 (0.2412140)	0.1362346 ** (0.0513599)	-0.0212625 (0.3004678)
URBAN	-0.091518 (0.044606)	0.4142811 (0.0145306)	-0.0179168 (0.0073100)	0.1543739 (0.0235400)
Dyad Level Data				
AMNT TRAIN	0.006588 (0.005572)	0.0054730 (0.2412140)	0.0155278 *** (0.0513599)	0.0077997 * (0.3004678)
PROX RR	0.001214 (0.105548)	-0.0445525 (0.2207886)	-0.0311974 (0.0498700)	-0.0088865 (0.2710306)
PROX TRAIN	-1.129091 (0.711540)	0.0663890 (0.0039750)	-0.5831535 *** (0.0022247)	-0.5887913 (0.0036643)
PROX ROAD	1.490212 (2.164089)	-0.9644960 (0.3462289)	-1.0019936 ** (0.0294892)	0.7360066 (0.1543991)
AMNT AIR	-0.006120 (0.022769)	0.0003264 ** (0.0001029)	0.0006995 *** (0.0001007)	0.0005532 *** (0.0001409)
AIC	333,4	1229	4580	725,9
BIC	449,5	1345	4697	842,2

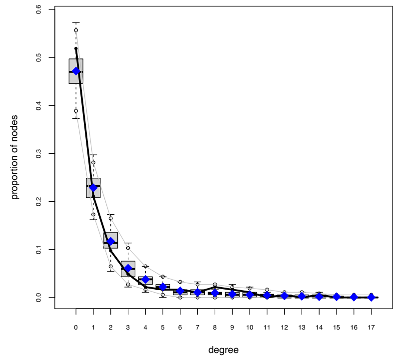
All continuous predictors are mean-centered and scaled by 1 standard deviation.
*** p < 0.001; ** p < 0,01; * p < 0,05; . p < 0,1.

Figure 6 Degree distribution of all models

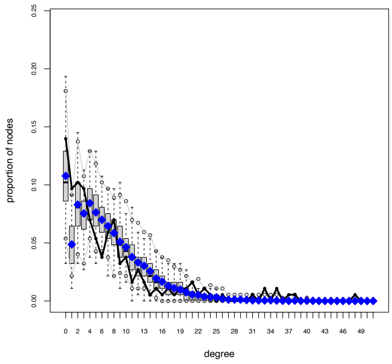
Analytical High-Tech



Synthetic High-Tech



Synthetic APS



Symbolic APS

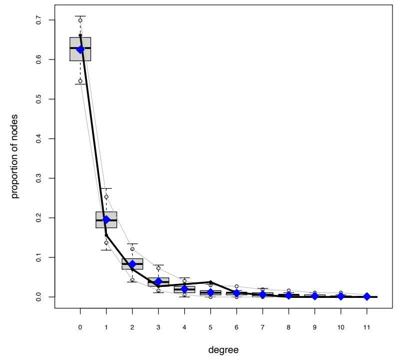


Table 11 Descriptive Statistics

Regions classified according to BBSR	count	Distribution of airports	Distribution of institutions of higher education	Distribution of Metropolitan Regions
1; Urban	106	19	63	65
2; Semi-Urban	40	4	22	19
3; Rural	66	5	11	19

5 The contribution of knowledge-intensive firms to employment growth: a Granger causality approach for German regions

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Abstract: Academic discussions have frequently examined the interrelation between regional employment growth and firm locations. Two growth patterns emerge: employment growth induced through new firm locations or vice versa, where firms locate in areas experiencing employment supply growth. The specific causal relationship responsible for regional employment growth in Germany remains uncertain. In the German context, however, more research is needed to identify contributors to employment growth, as most existing studies rely on highly aggregated data or focus on specific case studies. This paper aims to approach this subject by using a uniquely matched dataset of firm locations and the individual employment of 480 multi-locational firms in the knowledge economy and comparing it to total employment in Germany. We assume that a change in knowledge-intensive firms' employment may affect regional employment growth. The study uses longitudinal historical employment data at the functional urban area (FUA) level from 1999 to 2019, aggregated to knowledge-intensive high-tech and advanced producer services (APS) sectors. The analysis employs aggregated and individual Granger causality tests, evaluating the relationship between employment in knowledge-intensive sectors and overall employment change. Results are spatialized using GIS to provide evidence of where the Granger causalities occur at the FUA level in Germany. Findings indicate that, in general, knowledge-intensive employment growth Granger causes total employment growth in a few economically more active FUAs. In contrast, for a greater number of FUAs, total employment Granger causes knowledge-intensive employment.

5.1 Introduction

In Germany, we are witnessing unabated growth in employment in regions such as Munich, Berlin, Frankfurt, and Hamburg. The question of why such growth occurs in these urban areas has yet to be answered. Understanding regional growth patterns has long been embedded in a scientific debate across various disciplines. It was long assumed that industrialization processes and, thus, the creation of manufacturing jobs led to the economic development of a few regions with natural resources or strategic locations on waypoints (Storper & Scott, 2009). However, the question arises as to whether this is still relevant in post-industrial economies. The economic shift from manufacturing to advanced service-oriented economies, which has led to the increasing globalization of value chains, has also transformed local labor markets by externalizing and outsourcing production processes to regions with lower labor costs. This new global division of labor has resulted in the emergence of knowledge-intensive work (Tippel et al., 2017).

In these advanced economies, where the emphasis is increasingly on knowledge, qualifications, and information, an alternative path – creating new jobs in locations where the share of employment is high – has become much more prevalent in recent decades. As a result, knowledge-intensive firms selectively identify locations to operate where they can attract the best-fitting pool of talented labor (Bathelt & Glückler, 2011). For firms in such knowledge-based industries, the human capital with the specific knowledge required is even less ubiquitous than for less knowledge-intensive firms, so the choice of location for firms becomes a focus of attention (Rozenblat, 2021; Smętkowski et al., 2021). In essence, this means that regions with a higher proportion of highly qualified workers become attractive for knowledge-intensive firms and thus promote population growth by creating new jobs. This creation of jobs, in turn, attracts new labor, hence why Tervo (2016) argues that growth in regions with strong knowledge-intensive sectors is mainly driven by in-migration.

However, since human capital is not a static local resource, studying the migration of people is not straightforward, as different causes besides job opportunities may underlie it. People relocate for various reasons, such as quality of life, better education, or a more diverse job market (e.g., Carlino & Saiz, 2019; Florida, 2003; Trip, 2007). Some authors even assume that highly skilled workers place quality of life over job availability in their relocation decisions (e.g., Partridge, 2010). Thus, the question of the influence of knowledge-based firms on regional employment growth, which has been addressed in academic discussions (e.g., Østbye et al., 2018; Tervo, 2016), is yet to be answered.

With this paper, we want to contribute to this discussion by focusing on how knowledge-intensive firms' locations and employment growth in urban areas are interrelated. For firms in the knowledge economy, it is essential to continuously adapt their location strategies so that they can always access and, in turn, create new knowledge. This constant process of restructuring value chains to maintain competitiveness in the market may affect regional employment growth. We approximate this by using longitudinal employment data for Germany's top 30 knowledge-intensive firms and comparing it to total employment growth in each urban area.

The dataset includes locations of 480 multi-branch, multi-location firms in German functional urban areas (FUAs). It is linked to individual employment surveyed in each firm for every year from 1999 to 2019. The firms are grouped into advanced producer service firms and high-tech firms. We argue that this number is sufficient to describe how knowledge-intensive firms in Germany reorganize their value chain to stay competitive and attract the best talent.

We follow previous research (e.g., Tervo, 2016) using a panel Granger causality model to analyze the temporal interrelatedness between the change in knowledge-intensive employment and total employment for each FUA. Thus, when we observe that changes in knowledge-intensive employment follow changes in total employment, we can say that knowledge-intensive employment Granger causes growth in total employment. This would imply that the change of employment in knowledge-intensive jobs within a FUA can indicate how knowledge-intensive firms can contribute to local employment growth – but also vice versa. Additionally, it sheds light on whether firms are drawn to growing labor markets or induce, through their presence in a FUA, changes in total employment themselves.

This paper is structured as follows. The second section briefly summarizes the theoretical background, the peculiarities of the knowledge economy, and how knowledge is being created in space. The third section introduces the Granger causality model as our empirical approach. Here, we also present the data used. The fourth section presents the results of the models, and we discuss our findings using a geographical map as an interpretation support tool. The fifth section gives an outlook and concludes this study.

5.2 Conceptual background and hypotheses

The question of the causation of regional growth has received considerable attention in academia over the decades since Weber (1899). In this section, we will examine both sides of the debate: supply and demand. To understand how and where the knowledge economy grew over the last two decades and how it relates to regional employment growth in Germany, we link the conceptual basis of knowledge-intensive activities with the current academic debate on knowledge workers and agglomeration economies.

In recent years, a large body of work has focused on the importance and impact of the knowledge economy on the global economy. The question of where knowledge-based economic activities are located, and also how to define and differentiate the knowledge economy, has been the subject of various studies (e.g., Asheim & Gertler, 2006; Cooke et al., 2007, p. 200; Rozenblat, 2021; Taylor, 2004; Taylor et al., 2013; Zillmer, 2009).

Florida's (2003) work on the "creative class" postulates that regions experience growth when the three aspects, talent, technology, and tolerance, overlap. He argues that workers in creative industries would prefer to work in such an environment and thus entail economic growth. Although his arguments received criticism for being too broad and not applicable to the European context (e.g., Krätke, 2010; Tippel et al., 2017), the core idea of studying the location choices of highly skilled workers is essential for an understanding of current urban development.

Highly skilled or so-called knowledge workers are an integral part of a knowledge-based economy as they function as knowledge resources, key transmitters, and creators of new knowledge. However, classifying *the* knowledge worker is not straightforward, as various aspects ranging from occupation, qualification, and skills can have an influence.

Nevertheless, the knowledge-intensive tasks that a knowledge worker has to perform can guide a better understanding of the location behavior of knowledge workers. The conceptual framework of knowledge bases aims to add insights here as it provides a more granular view of how knowledge is being created and shared (Asheim & Gertler, 2006). It further helps us understand how and why knowledge spillovers appear differently depending on the knowledge-intensive sector (Reades & Crookston, 2021). We distinguish three knowledge bases: analytical, synthetic, and symbolic knowledge (Asheim, 2007). Analytical knowledge refers to tasks where the scientific component is vital, such as in biotechnology or information technology. Symbolic knowledge, on the other, can be found in activities that focus on design, aesthetics, and creativity (Asheim & Gertler, 2006). Lastly, a synthetic knowledge base refers to combining and applying existing knowledge. In practice, firms can hardly be assigned to a single knowledge base since they employ various combinations of knowledge bases (Grillitsch et al., 2017). Still, this intrinsic preference for a location where knowledge workers are concentrated shapes firms' location, especially if a firm solely depends on labor.

The competition between knowledge-intensive firms for talent that offers needed skills leads to higher wages (Neffke & Henning, 2013). Higher salaries in certain regions further induce in-migration of the specific highly skilled workers (Storper & Scott, 2009) but at the same time attract other firms in the same sector, as, in general, the higher cost of being located in such congested regions is compensated for or exceeded by higher productivity through labor pool sharing (Duranton & Puga, 2004). Kronenberg (2013) for example, found in the Netherlands that relocating firms are more likely to be attracted to densely populated regions with high wage levels and a diverse market if the firm operates in an advanced producer services sector. Otherwise, the firm is likely to relocate to regions where it is sectorally specialized if it is low-technology manufacturing. This underscores the need for knowledge-intensive firms to continually adjust and re-evaluate their location decisions to optimize the knowledge resources they need at each step of their knowledge-creation process to remain competitive – and they find these knowledge workers in densely populated urban areas with high wage levels.

However, knowledge workers are unevenly distributed. Some of these knowledge resources are highly localized (Bathelt & Glückler, 2011; Storper & Scott, 2009) and are not immobile resources that firms can access but rather mobile ones (Tippel et al., 2017). In general, job-related migration can happen for two reasons: soft and hard location factors (Florida, 2003; Musterd & Gritsai, 2013; Storper & Scott, 2009). Soft location factors attracting workers are social or cultural connections to a place, such as the social milieu and the image or recreational amenities (e.g., Carlino & Saiz, 2019; Florida, 2003; Tippel et al., 2017). This is also in line with Kronenberg and Volgmann's (2014) findings that regional employment dynamics in the knowledge economy and the soft factors of a region are closely tied.

Regarding hard location factors in the European context, studies highlight that knowledge workers tend to move jobs if the regional labor market does not offer the opportunities to stay or, on the other side of the scale, if the local labor market is competitive enough to allow intraregional job-hopping (Fallick et al., 2006; Krabel & Flöther, 2014). For example, Engel and Heneric (2013) found that knowledge-based entrepreneurs in the biotech industry tend to relocate to regions with a similar scientific orientation, while non-knowledge-based entrepreneurs are not so selective or do not move at all. A competitive labor market opens up opportunities for workers in the knowledge economy to find a better work environment or wages. For firms, it opens up possibilities of knowledge spillover and easy access to localized knowledge (Parr, 2004). In this context, Serafinelli (2019) found that intraregional job-hopping fosters knowledge spillovers and productivity in highly productive firms, even requiring higher wages. Tambe and Hitt (2014) argue that regional differences are generated by knowledge transfer and the mobility of highly skilled workers to more competitive environments. However, the literature does not answer how much a knowledge worker might value a place's social or cultural aspects over a competitive labor market.

Research on agglomeration economies argues that such concentrations of firms and knowledge workers – and thus competition – benefit the firms' productivity (van Meeteren et al., 2016). Here, we focus on urbanization economies, as we are interested in the location strategies of different firms. The literature agrees that an urban environment can be fertile ground for knowledge exchanges (Rammer et al., 2020). Storper and Venables (2004) highlight that agglomerations comprise sectors that share common inputs and clients. Being located near other firms thus allows for knowledge spillovers and fosters innovation (Boschma, 2005). Geographical proximity increases the probability of encounters and informal communication (Vissers & Dankbaar, 2013). However, Bathelt et al. (2004) found that agglomerations of firms do not necessarily create a meaningful local buzz (or knowledge transfer). The authors argue that integrating extra-local knowledge networks is just as important (Bathelt et al., 2004). Local buzz usually means a transfer of tacit knowledge, while extra-local knowledge flows are codified knowledge (Growe, 2019). The terms tacit and codified knowledge go back to Polanyi (1958), who introduced a dichotomic approach to classifying knowledge. Tacit or explicit knowledge is gained through experience and depends on the physical accessibility of other knowledge sources. Codified knowledge can be easily shared, exchanged, and replicated (Simmie, 2003). It is evident that this classification also applies to knowledge workers in specific industries such as research and development or public-private interaction – which are mainly based on tacit knowledge (Simmie, 2003).

Volgmann and Münter (2022) studied how urbanization externalities affect metropolitan growth in German polycentric urban regions (PURs). The authors find that PURs with major urban functions such as a diversified labor market, good transportation infrastructure, or governmental institutions – may generate metropolitan growth more successfully than smaller PURs or monocentric urban regions in Germany. This shows the importance of metropolitan functions in promoting agglomeration economies at the regional scale, highlighting the significance of urban size, density, and diversity as highly influential in the emergence of urbanization externalities. Additionally, the authors emphasize the role of PURs' dispersed spatial structure. These enable large PURs with "endowment advantages" (Volgmann & Münter, 2022, p. 108) to leverage urbanization externalities better, which, in turn, contributes to their growth. Lastly, the authors emphasize the need to promote economic, cultural, political, social, and institutional integration within PURs to maximize agglomeration benefits and ensure sustainable regional growth. This is in line with Meijers and Burger's (2017) study on 'borrowed size,' which the authors describe as the process when smaller regions located close to larger regions exhibit urban functions usually expected in the neighboring (larger) region. This concept is thus the opposite effect of 'agglomeration shadows,' in which a region has fewer urban functions than expected (Meijers & Burger, 2017).

In summary, where specific growth patterns happen precisely remains to be seen or stays ambiguous. Why do we see different growth patterns of the knowledge economy across different cities and regions? Do locations of multi-branch knowledge-based firms have an effect on the general workforce of a region? Does the workforce follow the knowledge worker population, or vice versa? Do these knowledge workers – and thus knowledge-based firms – increase the general workforce? The literature does not give us a unanimous answer – especially when focusing on our case study on German functional regions. However, we can approach these questions using our linked firm location–employment dataset. We, therefore, formulate the following research question:

To what extent do multi-locational knowledge-intensive firms contribute to employment growth in German functional urban areas?

This research question focuses on two aspects: first, the spatially visible multi-locational work organization of multi-branch knowledge-intensive firms and their approach to optimizing firm locations to enhance efficiency, increase productivity, and access the most relevant knowledge-related resources. Consequently, this dynamic may increase the number of other firms attracted to the same knowledge resources and knowledge workers seeking better job opportunities, all driven by spatial proximity. Thus, second, whether such location choices affect knowledge-based employment and the rest of the local workforce. This opens the question of causation, whether such firms induce employment growth or whether they locate to areas with a growing employment market. However, to our knowledge, studying this (Granger) causation has never been done in the German context, especially using a dataset of firm locations and their respective employment for each location.

In contrast to Tervo (2016) or Volgmann and Münter (2022), who use city regions or polycentric urban regions respectively, we base our spatial scale of analysis on the urban centers identified in the ESPON 111 project (ESPON, 2004). This spatial scale includes urban centers and their hinterlands, thus incorporating commuting patterns. This results in a list of 186 FUAs for Germany. Thus, we test the following null hypothesis:

1. *Across all functional urban areas (FUAs), there is no causal relationship between our sample of knowledge-intensive employment and total employment growth.*

Given that the relationship between growth in employment and knowledge-intensive employment is underexplored in the German context, we follow Tervo's (2016) approach and apply the Granger causality method for a selected timeframe from 1999 to 2019. Thus, we control for the number of firms in our dataset. For our null hypothesis, we assume that across all FUAs, we cannot identify a Granger causal relationship in any direction. Additionally, since we are not only interested in this overall relationship but also in how the growth is composed on the level of FUA, we assess the following hypothesis:

2. *In any functional urban area (FUA), there is no causal relationship between employment growth in our sample of knowledge-intensive firms and employment growth at the individual FUA level.*

For this step, we spatialize the results using GIS by mapping the Granger causality results for each FUA. This facilitates the comparison of individual results for each FUA and allows us to identify additional spatial-regional relationships that go beyond a single urban region and form regional clusters, and also possibly identify 'borrowed size' effects and thus add new knowledge of regional growth in Germany – meaning that smaller urban areas perform better by accessing urban functions or amenities from larger neighboring urban areas (Meijers & Burger, 2017). We introduce our methodology hereafter.

5.3 Methodology and Data

5.3.1 GRANGER CAUSALITY

In this section, we introduce the methodology to test our hypotheses. Granger causality, named after Granger (1969), was originally designed to test the hypothesis that one time series variable does not Granger-cause another. Alternatively, simply, whether one time series (Granger-)causes another time series. With the increasing availability (and use) of panel datasets, various extensions on Granger causality tests accommodating panel data have been proposed. Dumitrescu and Hurlin (2012) provided seminal work with the Granger non-causality test for heterogeneous panel data. This approach has been the most popular extension for panel analysis, being implemented in statistical software such as STATA or R.

In this paper, we present a two-step Granger analysis framework. First, we employ the latest panel data analysis adaptation proposed by Juodis et al. (2021). One of the key advantages of their test over the Dumitrescu and Hurlins (2012) Granger test is the better handling of datasets with $T << N$, which applies to our dataset since it is based on the Half-panel jackknife (HPJ) method – a resampling technique to estimate the variance that is more suitable for small T and large N as we have 20 years (T) and 186 FUAs (N).

The applied framework is shown in **Figure 7** and is based on Tranos and Mack (2016). The results of this test will give us an indication of significant causalities in our panel. Hence, we follow the linear dynamic panel model proposed by Juodis et al. (2021):

$$y_{i,t} = \phi_{0,i} + \sum_{p=1}^{P} \phi_{p,i} y_{i,t-p} + \sum_{p=1}^{P} \beta_{p,i} x_{i,t-p} + \varepsilon_{i,t} \tag{5}$$

Where $i = 1, \dots, N$ (in our case FUAs), $t = 1, \dots, T$, and $x_{i,t}$ is assumed to be scalar. The authors denote the parameters $\phi_{0,i}$ for the individual effects, $\phi_{p,i}$, on the other hand for heterogeneous autoregressive coefficients, and $\varepsilon_{i,t}$ as the error term. Here, $p = 1, \dots, P$ signifies the lag order, capturing the impact of the previous P time periods. $\beta_{p,i}$ are the heterogeneous feedback coefficients. In our case, y denotes the dependent variable, and x denotes the independent variable.

This method tests for two potential causal scenarios: A) The null hypothesis: there is no Granger causality in any panels (for all i and p the null hypothesis is H_0: $\beta_{q,i} = 0$). This leads to the alternative scenario and hypothesis B): Granger causality does happen for at least one panel in our dataset (for some i and q: H_1: $\beta_{q,i} \neq 0$). For a detailed discussion of the approach, we refer to the literature of the corresponding authors, Juodis et al. (2021).

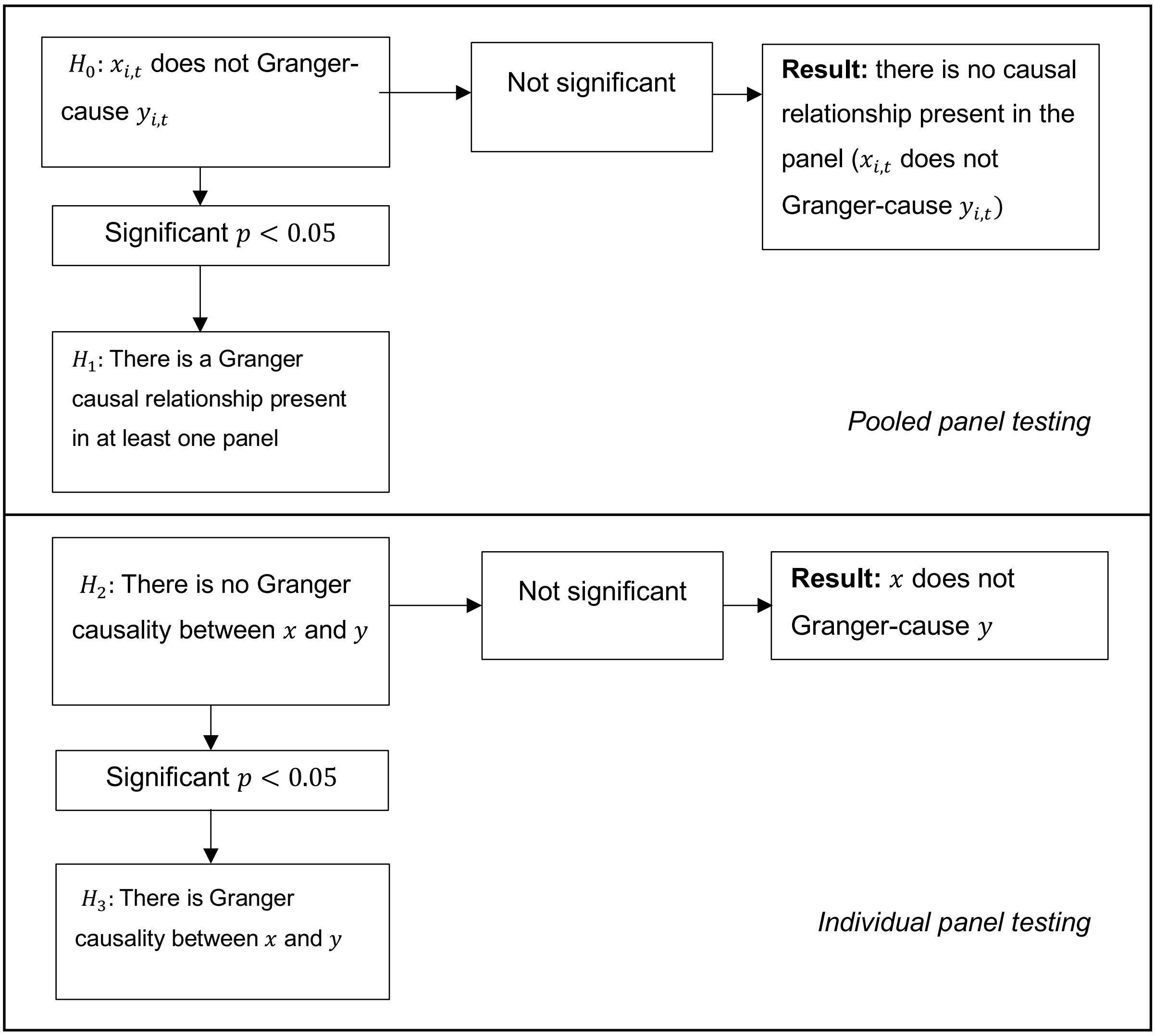

Figure 7 Two-step Granger causality framework

After identifying potential directional causalities between two variables, we move to the second step in our research framework: We employ a pairwise Granger causality test at the level of FUAs. This is because we are interested in possible causalities between x and y and where these causalities emerge in space. Here, we follow the standard Granger causality equation in the form of a bivariate regression (Becketti, 2013):

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-1} + \beta_1 x_{t-1} + \cdots + \beta_l x_{-l} + \varepsilon_t \tag{6}$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-1} + \beta_1 y_{t-1} + \cdots + \beta_l y_{-l} + u_t \tag{7}$$

This regression is run for all possible pairs (x, y) of variables in our dataset. In essence, it checks for each FUA if changes in knowledge-intensive employment "Granger-cause" changes in total employment. This causation would mean that our matched firm employment dataset can be used to explain changes in total employment. In other words, knowledge-intensive employment has a causal influence on total employment. This test is again done in both directions. Since Juodis et al.'s (2021) equation is based on this simpler bivariate regression, the null hypothesis (here H_2) is the same with $\beta_1 = \beta_2 = \cdots = \beta_l = 0$. In this model, we choose the lag length (l) as proposed by the first test above. We use the software Stata 16 and apply the extension *xtgranger* (Xiao et al., 2021) and the base command *vargranger* (Becketti, 2013).

5.3.2 DATA

5.3.2.1 Firm Data

Our dataset consists of firms in the German knowledge economy and their respective branch locations in Germany. In identifying knowledge-intensive firms, we follow the classification by Legler and Frietsch (2006) and Gehrke, Frietsch, and Neuhäusler (2013), based on the German Classification of Economic Activities (Wirtschaftszweige (WZ) 2008). We categorized knowledge-intensive economic activities into classes based on similar activity-related context[2] and further grouped them into advanced producer services (APS) and high-tech. These industries were chosen because of their investment in research and development activities and a high proportion of highly skilled labor (Legler & Frietsch, 2006). The firm database was created using semi-automatic web-scraping methods on online information published by the 30 largest firms by employees in each group, 480 firms, and their respective firm locations in Germany. The decision to cut off 30 firms is based on our objective to a) include firms throughout Germany and b) assume that this number sufficiently reproduces the division of labor in Germany in the knowledge economy.

[2] These can be found in the appendix

We specifically chose multi-location and multi-branch firms for several reasons: Unlike single-location firms, whose decision-making is often limited to local considerations, the choices of multi-location and multi-branch firms to open or relocate locations within their network go beyond strategic growth and access to new employment resources. These decisions also illustrate how these firms more effectively distribute work across space – and their individual value chain. Each change in their firm network enables them to generate and disseminate knowledge more efficiently while continuously adapting to the dynamic changes in the economic landscape. By focusing on the 30 largest firms in each subsector, we aim to provide a snapshot of firms that operate internationally and leverage local knowledge resources. We matched the individual employment data for each firm location, as described in the following chapter.

5.3.2.2 Employment Data

The employment data for 1999-2019 was gathered using the Establishment History Panel (BHP) of the Institute for Employment Research (IAB) in Nuremberg. It contains detailed information about all establishments in Germany with at least one employee liable to social security or with at least one marginal part-time employee. This dataset represents about 75% of the German workforce. Our dataset of the 30 largest firms matched with IAB employment data captures an average of 19% of the German knowledge economy. The firm data and the BHP were merged with this via a record linkage using firm identifiers (e.g., address), and we extracted all employees in every establishment. Matching both datasets lets us study how employment in each FUA (through sums of employment per firm and location) developed from 1999 to 2019. Our comparative dataset, called total employment, only uses employment data subject to social security contributions.

We grouped all employees according to their economic activities using 3-digit WZ coding into APS and high-tech industries. **Figure 8** illustrates the yearly development of both sectors and the total employment in Germany over the entire period under review of 20 years. Even though the high-tech sector was higher in absolute terms in 2019 with 801,245 employees (a growth of 21.8% since 1999), we can see that the relative growth of employment in APS sectors is higher as the employment grew from 546,633 to 732,055 (33.9%). In comparison, total employment in Germany grew by 16.9% to 29,338,404 employees.

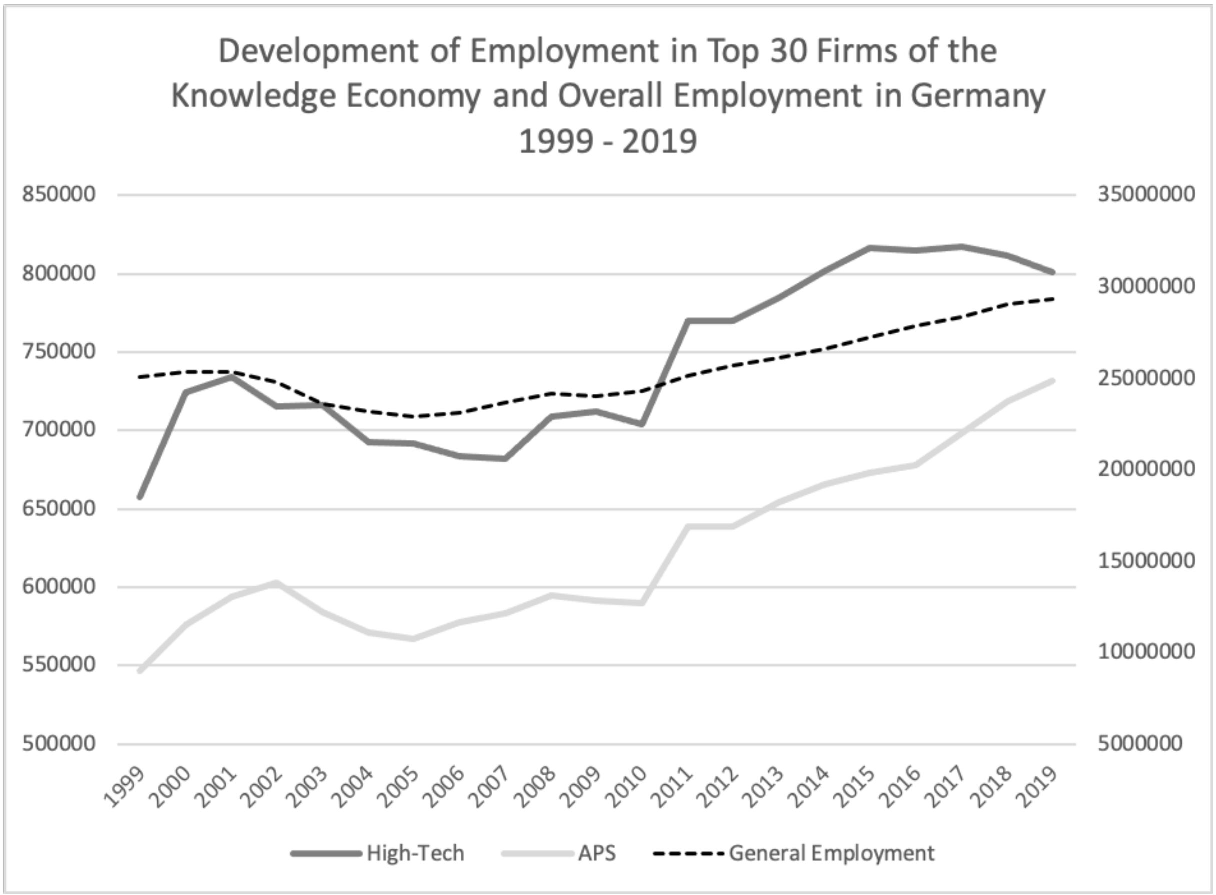

Figure 8 Employment in Germany, 1999-2019. Scale for Overall Employment on the right. Source: Firm panel linked to the Establishment History Panel (BHP) of the Institute for Employment Research (IAB); authors' own calculations.

The average annual growth rate in total employment of the top ten FUAs in Germany from 1999 to 2019 peaked at 1.19% compared to all German FUAs, with an average growth rate of 0.80%. In general, 50% of all employment is located in 12 urban areas, which is constant over time. The highest average growth rates can be observed in Wolfsburg, with 2.69%. Outside urban centers, the highest growth rates can be observed in the FUA of Ingolstadt, with 2.08%.

We subtracted the sum of APS and $HighTech$ from the total employment to prevent autocorrelation when studying the growth of sectors. Therefore, in this paper, Emp stands for this substracted variable. We transformed all data into natural logs. This is common practice if a dataset, such as ours, has skewness (Schulze, 2004). In total, we generate three different variables of employment: $lnAPS$, $lnHighTech$, and $lnEmp$. Thus, we analyze and compare the growth rates of the two sectors and total employment (Tervo, 2009).

5.4 Findings

In this section, we will present the results of the Granger causality analysis. It is necessary when doing pretests to check for potential unit roots and achieve time stationarity before doing time-series analyses such as Granger causality tests (Baltagi, 2013; Becketti, 2013). A unit root test is a statistical method used to determine if a time series variable is non-stationary, indicating a lack of long-term trend or mean reversion. The widely used augmented Dickey-Fuller (ADF) tests are known to be weak hypothesis tests for stationarity in panel data (Baltagi 2013). We, therefore, follow Akkemik and Göksal (2012) and use the Levin-Lin-Chu (LLC) test as well as the Im, Pesaran, and Shin (IPS) test to check for unit roots. We achieve stationarity for our data at the first difference – thus, no unit root. The Granger non-causality test proposed by Juodis et al. (2021) automatically selects the optimal lag length, choosing to balance short- and long-term trends while avoiding over- or under-fitting the data. The test utilizes the vector autoregressive (VAR) lag length criterion, Bayesian information criterion (BIC), with a maximum of 4 lags (Xiao et al., 2021).

Since we are interested in a potential direction of Granger causality, the hypothesis is tested for each variable, $lnAPS$, $lnHighTech$, and $lnEmp$, as both a dependent and independent variable. This leads to four tests in two groups: We test employment growth in high-tech sectors (and APS) against the growth of total employment (and vice versa). It is important to stress that we also test $lnAPS$ against $lnHighTech$, but the Granger non-causality test did not return significant results, and we, therefore, leave this aspect open for further research.

The results of the Granger non-causality test are shown in **Table 12**. The tests are based on the HPJ-based Wald test statistics, as discussed earlier (Juodis et al., 2021). In all cases, the optimal number of lags $\hat{P} = 1$ according to the automatic lag length selection using the BIC criterion. Note that the number of FUAs with significant Granger causality tests is 146. The results show that two of the four tests are statistically significant at the 1%. However, since we are interested in both directions of causality, we opted for the 5% level, where all four tests are significant. The results indicate that total employment Granger-causes growth in APS and high-tech sectors at the 1% level for some FUAs (at least one panel). In the opposite direction, the results are significant at the 5% level, indicating that APS and high-tech sectors also Granger-cause total employment growth for some FUAs.

Table 12 Granger non-causality test results following Juodis et al. (2021)

Null hypothesis	Wald statistic	p $value$	N	T	Optimal lag $\hat{P}$
APS					
Employment -> APS Employment	72.83	0.000	146	19	1
APS Employment -> Employment	4.46	0.035	146	19	1
High-Tech					
Employment -> High-tech Employment	12.61	0.000	146	19	1
High-tech Employment -> Employment	4.68	0.030	146	19	1

As mentioned above, Juodis et al.'s (2021) test does not determine where in space such a relationship exists; it only indicates that at least one FUA for each test in our dataset is significant. Hence why we will proceed with our second causality test. To do so, we employ individual pairwise Granger causality tests for each FUA under consideration[3].

We identified 49 significant relationships between APS employment and total employment growth and 43 for high-tech employment and total employment growth – therefore, 75 out of 186 FUAs show significant causalities. In the next step, we proceed to analyze the second hypothesis. For this, we spatialize the results using GIS. **Figure 9** and **Figure 10** present the results of the four Granger causality tests for each high-tech and APS sector. Each category represents a Granger test: (1) FUAs where the growth in employment causes a change in high-tech employment, (2) FUAs where the growth in employment causes a change in APS employment, (3) FUAs where the growth in high-tech employment causes a change in employment, and (4) FUAs where the growth in APS employment causes a change in employment. Additionally, the general growth in employment since 1999 is visualized as a base

[3] We do not report the code and results to save space. They are available from the authors upon request.

layer. The change in total employment ranges from a loss of over 20% in an FUA to a growth of over 30% since 1999.

In the following, we define three types of relationships: *APS/ high-tech employment causes employment growth* – meaning that firms in either group Granger cause a growth of the overall employment in that FUA; *employment causes APS/ high-tech employment growth* – meaning that the overall growth of employment Granger cause growth in employment in our firm sample—lastly, a bi-directional relationship, where both Granger cause each other simultaneously. The complete list of coefficients for each test can be provided as supplementary data upon request.

5.4.1 GRANGER CAUSALITIES IN ADVANCED PRODUCER SERVICES EMPLOYMENT

First, we focus on the 49 FUAs with relationships between APS employment and total employment growth. The results indicate that 14 FUAs follow the relationship "*APS employment causes employment growth*," 32 FUAs follow the relationship "*employment causes growth in APS employment,*" and three FUAs follow bi-directional causation. First, we consider the former relationship, where the results do not suggest whether this causality is mainly present in denser and economically stronger urban areas. Even though Stuttgart, Cologne, and Mönchengladbach show significant growth caused by APS employment, we identify smaller FUAs such as Kempten, Bayreuth, Erfurt, and Erlangen that show employment growth caused by APS employment. One reason could be that each FUA is a university location, confirming common literature on knowledge-intensive firms preferring locations near institutions of higher education (e.g., Raspe & van Oort, 2011).

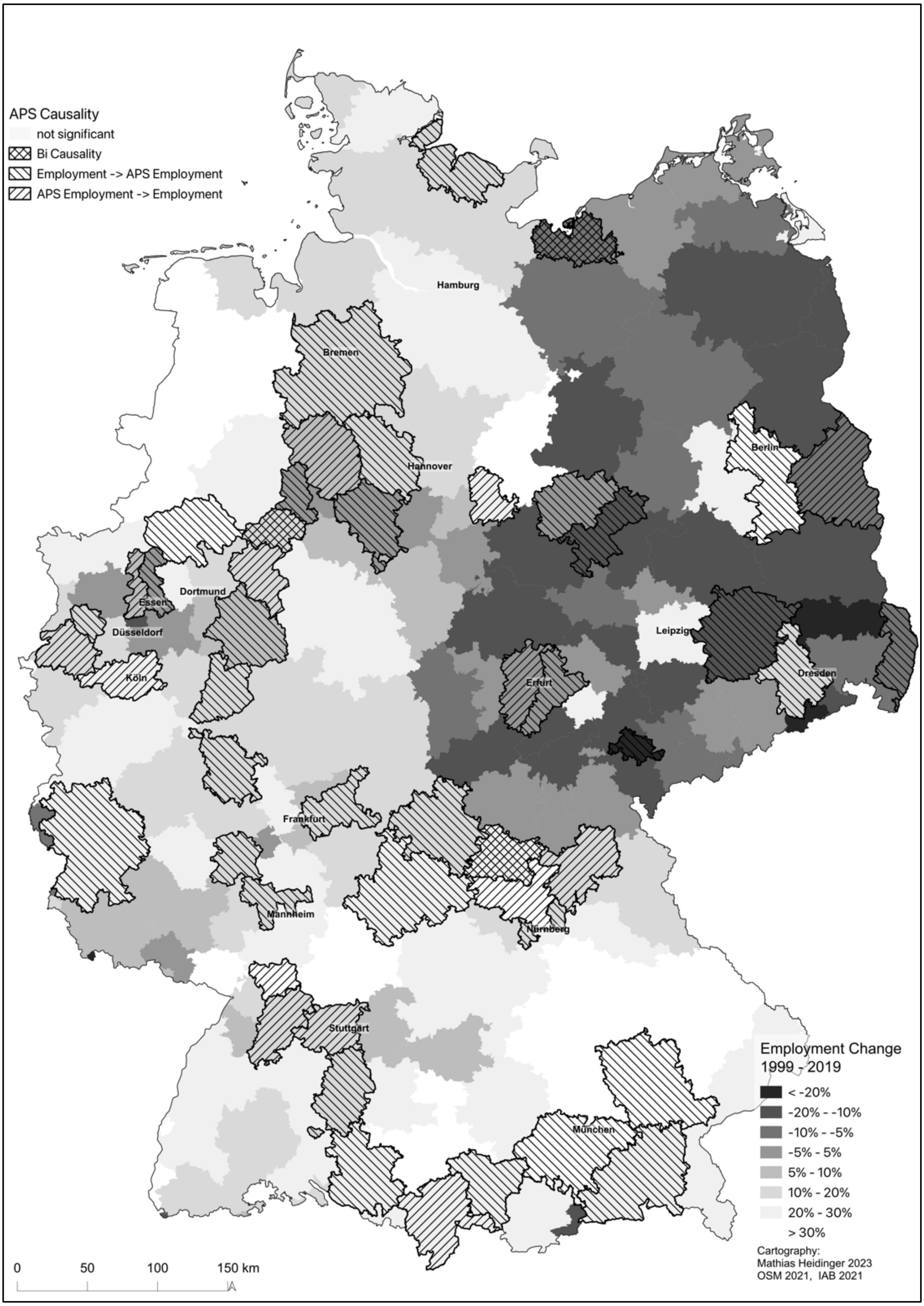

Figure 9 Granger causality results in APS sectors. Source: Firm panel linked to the Establishment History Panel (BHP) of the Institute for Employment Research (IAB); authors' own calculations.

The causality in the other direction, total employment causes APS employment growth, is confirmed in 32 FUA. Here, we identify mostly economically more powerful urban areas, such as Berlin, Munich, Nuremberg, Dresden, and Hanover. While Granger causality does not provide direct verification of spillover effects for geographically close FUAs – since each FUA is studied independently – the existing literature, specifically Meijers and Burgers (2017) or, in the German context, Volgmann and Münter (2022), helps us to propose a theoretical explanation as smaller FUAs located nearby metropolitan urban areas (e.g., Munich, Berlin or Hamburg) benefit from agglomeration benefits – as we identify in our study for Mainz, Ravensburg, Hanau, Landshut, and Rosenheim. Lastly, the Granger test identifies three FUAs with bi-directionality (Bamberg, Wismar, Bielefeld). Bi-directionality indicates that both APS and total employment growth are causing each other, or more simply, there is no single direction of causality. One possible explanation could be the location between two differently developing FUAs (regions with opposite causalities), which benefits a general growth in employment of knowledge-intensive activities and simultaneously of total employment, which is valid for both Bamberg and Bielefeld.

5.4.2 GRANGER CAUSALITIES IN HIGH-TECH EMPLOYMENT

For FUAs with high-tech-related growth, the results indicate that 23 FUAs follow the "*employment causes high-tech growth*" relationship, 15 the "*high-tech employment causes employment growth*" relationship, and five have a bi-directional relationship. Again, starting with the causality induced by high-tech employment, we identify a cluster in the Nuremberg urban area, consisting of Nuremberg, Weiden in der Oberpfalz, and Bayreuth. Further, we identify significant relationships in more densely urban areas such as Hanover and Dresden, where high-tech employment seems to attract total employment. The 23 FUAs with significant growth in the inverse direction highlight similar urban areas as in the APS counterpart, such as Rosenheim, Hanau, and Reutlingen. Further, the growing high-tech cluster in the Leipzig area is visible, consisting of the regions of Leipzig and Halle. Here, the employment growth caused a growth in knowledge-intensive employment, as, for example, newly founded firms depend on suppliers along the value chain. Bi-directional causalities again seem to appear where two FUAs with opposing Granger causality results are spatially close. One example is Gera, which lies between Jena and Zwickau.

In addition, we may provide evidence on larger regional configurations in Germany consisting of several FUAs at once. FUA, which we consider economically powerful, seem to influence growth patterns in close regions by indicating significant spatial-functional relations. For example, the FUA of Munich spans to the west up to the urban area of Ravensburg, influencing growth developments in smaller FUAs such as Augsburg and Kaufbeuren. This pattern also appears between Leipzig and Dresden, the Frankfurt Rhine-Main area with its bordering city regions Mainz, Offenbach, and Hanau, and lastly, the urban areas of Hanover-Wolfsburg and Bremen.

To summarize these findings, we identified 55 FUA where total employment Granger causes growth in the knowledge economy (APS or high-tech). Conversely, in 29 FUAs, employment in the knowledge economy Granger causes total employment growth. Therefore, similar to previous studies from other European countries (e.g., Østbye et al., 2018; Tervo, 2009, 2016), we conclude that in general, our hypothesis that growth in the knowledge economy follows employment growth can also be accepted for the studied FUAs and time series in Germany.

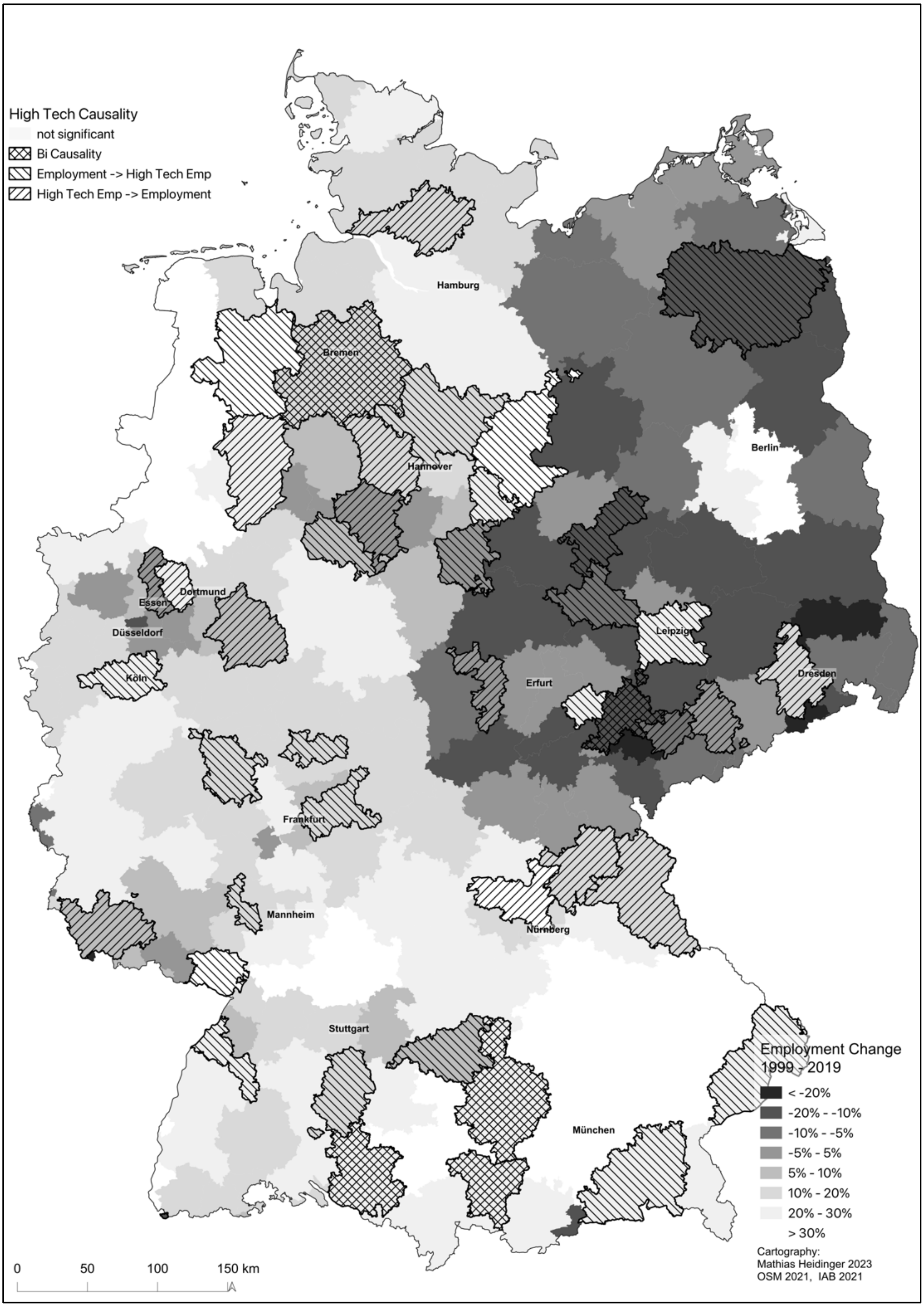

Figure 10 Granger causality in high-tech sectors. Source: Firm panel linked to the Establishment History Panel (BHP) of the Institute for Employment Research (IAB); authors' own calculations.

5.5 Discussion

Over the past two decades the global economy, and therefore the German economy, has experienced several periods of turbulence and restructuring, such as the dot-com bubble, the 2008/2009 financial crisis, and the uprise of the tech industry in the 2010s. These shocks impacted the structural shift towards a knowledge-based economy in Germany in 2019, as seen in **Figure 8**. This prior knowledge is needed to understand the Granger causation patterns we identified in the previous section in **Figure 9** and **Figure 10**.

In general, we can identify increasing knowledge-based activities in only a small number of FUAs, Stuttgart, Frankfurt, Berlin, Munich, and Hamburg. These host an average of 30% of the German knowledge economy. This is unsurprising, as the share of total employment in these five FUAs increased from 14.7% to 18.1%.

The employed two-step framework clearly shows a differentiated image of the employment sector in Germany. In its first step, the adapted Granger causality test by Juodis et al. (2021) tests whether there is Granger causality taking place between the knowledge economy and total employment for the whole of Germany. We reject the underlying null hypothesis that the knowledge economy does not Granger-cause total employment growth at the 5% level of significance (and vice versa). In other words, there is a Granger causal relationship between knowledge economy growth and total employment growth in at least one FUA in Germany. In at least one FUA, this null hypothesis can be rejected.

The Granger causality test we tested for our second hypothesis yielded mixed results. We departed from the knowledge based on the existing body of literature, specifically Tervo (2016), who found that employment follows highly educated workers and hypothesized that this is the same for FUAs in Germany. We reject this hypothesis since we do not find enough evidence in our data. One possible explanation could be the population size within each FUA, as larger ones, such as Munich, Berlin, or Hamburg, return mixed or non-significant results. Here, we argue that changes in employment cannot be successfully identified with a Granger causality test. The same applies to the inverted test, whether regional employment induces growth in the knowledge economy – hence, we cannot generalize our results and leave this open for future research.

The novelty of our approach, compared to just conducting single univariate tests for each of the 186 FUAs, is the Granger non-causality test, as proposed by Juodis et al. (2021), for large panels that return significant results fast. We use this test to identify possible relationships between variables. Then, we build on this and do individual tests for each FUA. This opens up a new perspective on employment growth in Germany. Thus, on the one hand, we confirm the widely held, but so far not systematically verified, assumption that employment causes knowledge-based employment. However, we provide evidence that reality should not be generalized into binary dependencies and that many factors, such as the choice of location or the firm's activity, influence this relation.

5.6 Conclusions

This paper contributes to the debate on whether knowledge-intensive firms can induce regional employment growth through their presence in a functional urban area (FUA) or if they are instead drawn to FUAs already experiencing growth. Germany is an interesting case study, as it is a country with a high share of knowledge-based firms and has a history of internal migration effects caused by reunification processes from former East German regions. However, to our knowledge, a similar study has yet to be conducted on our research question. Using Granger causality tests, we aim to add new knowledge to fill this gap. We use a comprehensive employment dataset for the 480 largest firms in the knowledge economy in Germany grouped in APS and high-tech, along with total employment data, and link these datasets with German urban areas. We use FUAs as our spatial unit of analysis as they overcome the fixed spatial boundaries of cities and place the interdependent regional space at the center of inquiry. Our findings highlight the relationship between total employment growth and knowledge-intensive employment growth.

Our data suggest that, in general, knowledge-intensive employment follows total employment growth. However, this relationship varies depending on whether APS or high-tech is considered. From a statistical point of view, in APS sectors, more knowledge workers work in only a handful of FUAs, regardless of the subsector itself. These FUAs are mostly metropolitan regions with diverse and thick markets, such as Munich, Frankfurt, or Berlin. By visualizing the results of the Granger causality tests, we further identified that smaller, neighboring FUAs benefit from employment growth Granger-causing knowledge-based employment growth in such metropolitan areas. We witness a different development in the high-tech sector. There has been more movement in the employment market over the last two decades. One reason for these movements could be the number of large production facilities in automotive manufacturing or biochemistry in Germany: Through the automatization of production processes, many firms laid off employees at their main locations or relocated entire production facilities. Using Granger causality tests, we may see these relocation strategies from manufacturing plants in the output as we identify FUAs in the east of Germany benefit from a growing employment base. This growth potentially Granger-causes high-tech employment growth in several FUAs.

This study of relationships in regional employment growth has some limitations. First, we acknowledge that we only took the 30 most important firms of each subsector of the German knowledge economy under consideration. Additionally, our firm selection approach was limited to multilocational firms that either offer their services or sell products in locations that are strategically important for the respective firm (Heidinger et al., 2023). Even though this means that we took a sample with the largest employers in each sector, we lose out on important information on small or sole proprietor firms that may choose locations quite differently.

As Granger causality tests are broadly accepted in longitudinal economic studies and sometimes used in growth studies on population data, this methodology should be embedded in an extended, two-step framework, as suggested in this paper. We used Juodis et al.'s (2021) Granger non-causality test, which is more sensitive to panel data with small T, to find significant relationships than Dumitrescu and Hurlin's (2012) popular panel test. Second, we used the full panel of 186 FUAs to identify regional differences and ran individual panel Granger tests. Like Tranos and Mack (2016), we used maps to spatialize our results. We are convinced that this step is necessary to make local dependencies between knowledge-intensive and total employment visible and analyze them in relation to neighboring FUAs, thus facilitating the interpretation of the analysis results.

More research is needed on three key aspects. First, we could not show any relationships between growth in APS and high-tech sectors, as the Granger causality test did not return significant results. In this regard, we must emphasize that due to the nature of the longitudinal data and the lack of control variables for each year for each FUA. This leaves a blank spot in our analysis, was outside the scope of our research, and would have affected generalizability. In addition, we suspect that controlling for past values of a control variable may lead to multicollinearity problems for longitudinal data, complicating interpretation additionally.

Second, one could link time-series analysis to specialization tests for a FUA. We assume that the firms in our dataset continuously adapt their supra-local networks by resizing and relocating offices, thus enabling them to tap localized knowledge pools globally. Also, we argue that other infrastructural amenities in an FUA, such as a hub airport or high-speed rail station for fast intra-regional commuting, may further positively influence such growth as identified by, for example, Wenner and Thierstein (2021) or Heidinger et al. (2023). However, we leave it open for future research to incorporate this in Granger causality tests. In this context, alternative approaches, such as a random coefficient model, may also yield interesting results.

Third, Granger causality tests cannot model the strength of the effect of one variable on the other variable. Although this was not the object of this study, future research may employ Granger causality tests to, for example, identify relationships and, in a subsequent step, delve deeper by using additional modeling techniques to identify shocks that may have contributed to a prevalence of growth or decline.

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5.8 Appendix

Table 13 Classification of knowledge-based subsectors

Classification of subsectors	
Advanced Producer Services (APS)	**High-tech**
Accounting	Automotive
Advertising and media	Chemical & pharmaceutical
Banking and finance	Computer hardware
Design, architecture, and engineering	Electronics
Information and communication services	Mechanical engineering
Insurance	Medical & optical instruments
Law	Telecommunications
Management and IT consulting	
3rd and 4th party logistics	

6 Where do knowledge workers locate in Germany? A case study using employment relocation data in the German knowledge economy from 2012 to 2021

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Abstract: In Germany, employment is becoming increasingly concentrated in urban areas, largely driven by knowledge-intensive firms competing to attract the most qualified and appropriate labour. Therefore, this paper addresses where knowledge workers relocate to and how relocation patterns vary across spatial distances. Using an innovative origin-destination analysis, we examine job-related employment relocations across 186 functional urban areas in Germany from 2012 to 2021, using official employment data for 480 multi-locational firms, classified into one of three knowledge bases: analytical, synthetic and symbolic. This classification helps explain how firms create and use knowledge in their innovation process and allows us to differentiate workers' relocation patterns. Our findings reveal a nuanced, multi-scalar perspective on the German knowledge economy. Between 2012 and 2021, knowledge-intensive employment has primarily relocated towards the largest functional urban areas, such as Munich or Frankfurt. However, relocation patterns diverge by knowledge base, and we can reveal the underlying dynamics driving this concentration. Workers in synthetic knowledge bases predominantly relocate on a large scale to and between these largest functional areas and between more decentralised functional areas, suggesting that spatial proximity plays a subordinate role in job-related relocations. In contrast, workers in analytical and symbolic knowledge bases exhibit less frequent relocations to other functional urban areas, instead relocating on a regional scale, mostly between neighbouring or spatially closer functional urban areas.

6.1 Introduction

In this paper, we examine the location and movements of knowledge workers in Germany from 2012 to 2021 by studying job-related relocations. While relocations are primarily driven by job availability, they are also influenced by a range of individual factors, such as employer strategies, city or regional attractions, and personal motivations, which makes it difficult to assess where workers will relocate (Dorfman et al., 2011; Niedomysl & Hansen, 2010; Tippel et al., 2017). On the other hand, knowledge-intensive firms locate where they find a pool of appropriate labour, thus ensuring proximity to other firms (e.g., Diodato et al., 2018). Therefore, a causal relationship exists between firm locations and the number of employees (e.g., Heidinger et al., 2024). Following previous research in this area, we argue that the need for workers to relocate is strongly influenced by the type of knowledge base to which a firm, and thus its workers, is assigned (Heidinger et al., 2024; Zhao et al., 2017). For example, firms in industries classified as having a symbolic or synthetic knowledge base, such as consultancy or advertising, rely on face-to-face interaction for effective knowledge creation and hence tend to be located in regions with a high concentration of workers who possess the necessary knowledge (Bathelt et al., 2004; Wood, 2002). These concentrations, in turn, attract more workers with the necessary knowledge from other regions. In contrast to previous research on employment mobility, which often focuses on cities, regions, or areas as statistical entities, we link both origin and destination to visualise the underlying spatial interdependencies that arise through worker relocations, tracking relocations over two points in time.

To do so, this study uses employment relocation data based on a dataset of multi-branch, multi-location firms in the knowledge economy. Knowledge-intensive firms typically organise their value chains across multiple locations, implementing strategies to optimise value and knowledge creation over time. Unlike single-location firms that concentrate resources in one place, multi-location firms distribute processes across various firm locations. Although the approach chosen here excludes smaller firms, it allows comparability of employment among similarly sized firms with multiple locations across Germany. We argue that studying employment relocation patterns offers new insights into possible regional dependencies, as workers who relocate bring new knowledge to regions and encourage interactions between workers that drive knowledge exchange. Their presence also attracts additional firms seeking to benefit from such knowledge spillovers and helps avoid regions becoming “locked-in” (Boschma, 2005, p. 72).

Thus, employment serves as a proxy for the knowledge creation process within firms, as an appropriate workforce is the modern 'resource' for knowledge-intensive firms, reflecting their efforts to foster innovation and maintain competitiveness (Cooke et al., 2007, p. 26). To assess these issues, we rely on data provided by the Institut für Arbeitsmarkt- und Berufsforschung (IAB), enabling us to link firms' location data to their respective employment data. As introduced above, we classify our data into four knowledge bases: analytical high-tech, synthetic high-tech, synthetic Advanced Producer Services, and symbolic Advanced Producer Services. By spatialising the results of the origin-destination analysis, we can thus visualise the relocations of knowledge workers over time, showing where they previously worked and where they moved for a new job. For example, we can show which functional urban areas are important destinations for knowledge workers across the knowledge bases, as well as how these functional urban areas are linked to other functional urban areas through worker relocations. Our data is aggregated to 186 German functional urban areas from 2012 to 2021. This period covers about ten years and is sufficient to gain insight into a constantly evolving and changing knowledge-based economy in which workers stay in one job for ever shorter periods.[4] Thus, this paper comprehensively studies a key aspect of how the knowledge economy shapes space by focusing on job-related relocations.

In short, this paper defines workplace or job-related relocations exclusively as relocations that are associated with a change of work location, i.e. to another functional urban area. When we refer to relocation, we specifically mean the movement of a knowledge worker to a new workplace in a different functional urban area. Therefore, we analyse all workers in our firm dataset across all functional urban areas, examining their origins and destinations, and endeavour to answer the following research question:

> *"What are identifiable spatial patterns of the relocation of workers within the knowledge economy in functional urban areas in Germany between 2012 and 2021?"*

The paper is organised as follows. First, in Section 6.2, we introduce the conceptual background of the study by defining knowledge-intensive employment and discussing the

[4] cf. https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Qualitaet-Arbeit/Dimension-4/dauer-beschaeftigung-aktuell-Arbeitgeber.html (24.04.2025).

importance of knowledge to firms, as well as its localisation mechanisms. In this section, we also present our hypothesis. The third section outlines our data and methodology. In the fourth section, we present the results of our analysis. Finally, the study concludes with a discussion of the findings, limitations, and an outlook for future research.

6.2 Conceptual background and literature review

To understand the spatial distribution and relocations of knowledge workers in Germany, it is essential to consider workers' location preferences and the backdrop of firm location strategies in the knowledge economy. Thus, we first provide a comprehensive overview of the current state of academic research on delineating the knowledge economy from the rest of the economy, on knowledge-intensive firms and their differentiation, and then focus on knowledge-intensive employment and its localisation in Germany.

6.2.1 KNOWLEDGE-INTENSIVE FIRMS

Research continuously explores where firms (co-)locate or cluster (Asheim & Gertler, 2006; Barlet et al., 2013; Duvivier et al., 2021; Rozenblat, 2021; Smętkowski et al., 2021; Storper, 2011). Over the last decades, driven by processes of deregulation and liberalisation, multinational firms have emerged as key drivers of globalisation (Bathelt & Glückler, 2011; Cooke et al., 2007). Knowledge-based firms profited significantly from these processes due to the nature of their reliance on and implementation of new knowledge to stay competitive in the global market. For these firms, innovation arises from integrating local knowledge sources into their internal global networks with other specialised firm locations (Bathelt & Glückler, 2011; Broekel et al., 2014; van Meeteren, Neal, et al., 2016). Firms in the knowledge economy thus use knowledge sources to improve a product or service, effectively offering knowledge as a product (Cooke et al., 2007). Following Polanyi's (1958) fundamental work, firms depend on two sources of knowledge to foster their innovation processes: codified and tacit knowledge. While codified knowledge can be easily shared and exchanged, tacit knowledge depends on physical accessibility to other knowledge sources (Simmie, 2003). Asheim and Gertler (2006) later added that rather than a simple dichotomy, the innovation process in firms consists of an intricate firm-internal and firm-external process that combines tacit and codified knowledge. Even though codified knowledge is ubiquitous due to digitalisation, the specialised tacit knowledge needed is still highly localised (Gertler, 2003; Simmie, 2003). Thus, firms must actively (re-)locate and access these localised or "sticky" (Balland & Rigby, 2017, p. 2) knowledge resources. Over time, this has led to a growing concentration of knowledge-intensive activities in a few urban areas, particularly near hubs of innovation such as research and development centres or universities, and in proximity to firms requiring specialised services. This trend is evident in Germany as well (Alcacer & Zhao, 2010; Brunow et al., 2020). Research on industry-university collaborations has shown that proximity positively affects the innovation process, and universities themselves can be seen as a network of nodes for knowledge transfer (Arant et al., 2019; Roesler & Broekel, 2017). Additionally, firms depend on various location factors, such as accessibility to regional and global networks through a well-developed train system or airports (Heidinger et al., 2023; Karlsson & Andersson, 2004). In short, a diverse and competitive local market is beneficial, as it not only improves the likelihood of knowledge spillovers between firms but also provides access to much-needed tacit knowledge (Boschma, 2005; Parr, 2004; Storper & Venables, 2004).

6.2.2 KNOWLEDGE BASES AND THEIR SPATIAL DISTRIBUTION

As described above, different factors influence the spatial distribution of knowledge-based activities, as the knowledge economy is diverse, encompassing various economic sectors. How can we make generally applicable statements about the location choices of their workers? Our study is informed by Asheim and Gertler's (2006) classification of knowledge to study the location choices of knowledge workers. The framework allows us to explore workers' spatial behaviours by focusing on the occupational skills of employees and comparing different approaches to knowledge creation. It categorises knowledge into three bases: analytical, synthetic, and symbolic. In the analytical knowledge base, codified knowledge is frequently used. Here, scientific knowledge – developed in-house or in collaboration with research organisations – is essential. Such occupations include scientists and analysts who work on producing outputs like patents and publications (Asheim & Gertler, 2006; Asheim & Hansen, 2009). Due to the codifiability of this knowledge, the choice of location is little dependent on physical proximity, and other location factors such as available building space or rent come into play (Asheim et al., 2011; De Bok & Van Oort, 2011; Harris et al., 2019). At the other end of the knowledge spectrum, the symbolic knowledge base relies primarily on tacit knowledge. It is highly adaptive to needs, as seen in the media, advertising, or design industries (Asheim et al., 2011). These occupations tend to be more creative, with designers, media producers, or advertising experts working closely with clients (Asheim & Hansen, 2009). Hence, face-to-face interaction and geographical proximity are pivotal in this knowledge base (Asheim & Coenen, 2005). Due to the dynamic nature of this knowledge base, customers and collaborators are predominantly based in densely populated urban areas. The synthetic knowledge base lies between these two extremes, blending elements of codified knowledge and the tacit body. Here, occupations such as consultants, project managers, or engineers play a key role in applying and combining existing knowledge to solve problems (Asheim & Hansen, 2009). Thus, new knowledge is synthesised through social interaction with clients but applied to the needs of the industry (Asheim & Gertler, 2006). Although not free of empirical criticism, particularly for its broad classification of sectors in knowledge bases and the lack of a temporal component (e.g., Wagner & Growe, 2023), this approach nonetheless provides valuable insights into firm location strategies and the workplace choices of knowledge workers.

We adopt the classification by Zhao et al. (2017), which expands this framework into four distinct groups: analytical high-tech, synthetic high-tech, synthetic Advanced Producer Services, and symbolic Advanced Producer Services. The authors identify different location choices regarding work and residence for each knowledge base for the metropolitan region of Munich. For example, knowledge workers in a symbolic knowledge base prefer central, urban locations that offer proximity between work and residence, consistent with existing literature. In contrast, workers with a high-tech knowledge base show less of a preference for proximity to work and often choose suburban locations. Those assigned to a synthetic Advanced Producer Services knowledge base show a mixed preference, balancing between urban and suburban locations. We see this fourfold classification as a valid approach to add nuance to the knowledge economy without exclusively focusing on specific sectors, such as Advanced Producer Services, manufacturing, or tech.

6.2.3 KNOWLEDGE-INTENSIVE WORKERS AND REGIONAL EMPLOYMENT GROWTH

Research on regional employment in knowledge-intensive industries, particularly with a temporal or longitudinal component, has shown that not only are firms unevenly clustered in space, this also applies to employment (Boschma & Fritsch, 2009; Heider & Siedentop, 2020; Mossig, 2011; Wagner & Growe, 2023). As a result, firms must either relocate to regions with appropriate workers or open subsidiaries there (Balland & Rigby, 2017; Storper & Scott, 2009). Krätke (2007, p. 25), who used knowledge-intensive employment as a proxy for economic activities, defined this process of increasingly uneven concentrations as “metropolisation”, since certain metropolitan regions function as the "motors" of economic development. This competition for labour also leads to greater specialisation of knowledge, as highly skilled workers adapt to the firm's recruitment needs (Hidalgo et al., 2007; Serafinelli, 2019; Storper, 2010; Stoyanov & Zubanov, 2012). Higher specialisation comes with a price. Due to competition for the most appropriate workers, salaries have increased (Neffke & Henning, 2013; Serafinelli, 2019). However, paying a wage premium does not necessarily have to be a disadvantage since the literature assumes a higher probability of innovation from these workers (Berry & Glaeser, 2005). Besides innovation, knowledge workers usually perform non-routine, non-codifiable tasks such as analysis or management, which are also assigned higher wages (Harrigan et al., 2021). Tambe and Hitt (2014), for example, found that within-region job changes in IT sectors impact productivity and knowledge spillovers. The pressure for higher wage levels is conducive to in-migration, as every job change opens up the possibility of new knowledge workers moving in from within the region or outside it (Deng et al., 2022). Workers look for the best economic setting and tend to factor in soft location factors, such as the region's social, natural, or cultural environment (Carlino & Saiz, 2019; Tippel et al., 2017). However, to our knowledge, no research has been conducted to determine whether knowledge workers favour soft location factors over a competitive, well-paying environment. It can be summarised that local concentrations of workers and firms that constantly compete for the best match benefit productivity, even if we see a steady concentration in space (Balland et al., 2020; Berry & Glaeser, 2005; van Meeteren, Neal, et al., 2016).

In the context of employment growth in knowledge-intensive industries, Mossig (2011) and Boschma and Fritsch (2009) studied contributing factors, particularly within creative industries. Boschma and Fritsch (2009), for example, applied spatial regression analysis to examine how factors such as tolerance and labour mobility influence spatial distribution. The authors found that while urbanisation and cultural environment play a role, growth in employment is linked to the presence of highly educated workers and the extent of relatedness among creative occupations, which aligns with the findings above.

Heider and Siedentop (2020), on the other hand, compared knowledge-intensive and total employment growth between German and US city regions using a longitudinal GINI and concentration analysis. The authors found that in Germany, the distribution of employment remained stable on average, with knowledge-intensive employment being more centralised and a moderate deconcentration of employment in manufacturing. However, the authors also found evidence that city size does play a role, with larger cities showing a higher tendency for reconcentration than medium-sized core cities (Heider & Siedentop, 2020, p. 13). Lastly, Wagner and Growe (2023) analysed knowledge-intensive employment growth in knowledge bases across large city regions in Germany. They found a general concentration of knowledge-intensive work in large cities, with spatial distributions varying by knowledge base. Analytical knowledge work, which relies on proximity to infrastructure such as laboratories, was relatively evenly distributed, while employment in synthetic knowledge, which is increasingly facilitated by remote working, showed a tendency towards regionalisation. In contrast, workers in symbolic knowledge remained predominantly in core cities due to their dependence on cultural and urban infrastructures.

A major limitation of most of these studies is their tendency to analyse regions as isolated statistical entities. However, viewing cities, regions, or functional urban areas solely in this way alone fails to fully capture the complexity of spatial interconnectedness. Goods and people flow, commute, or relocate across various spatial scales, continuously shaping and redefining these spaces, contributing to growth or decline.

6.2.4 THE SPATIAL AND FUNCTIONAL RELATIONALITY OF THE KNOWLEDGE ECONOMY

In the context of this study, it is thus important to understand how spatial relationality crucially influences the space we observe, resulting from a complex interplay between morphological and functional structures (Kloosterman & Lambregts, 2001; Meijers, 2005). While the former focuses on measuring or quantifying entities such as cities or people, the latter examines the relationships and interactions between entities within a given space (Growe, 2012). These interactions can occur either in a reciprocal exchange or in a more hierarchical form favouring one entity (Taylor, 2004). Typically, functional dependency is oriented towards one entity, such as a ‘core’ city, in a monocentric agglomeration, where most economic activities are concentrated. Reciprocal exchange, on the other hand, refers to the more even distribution of economic activities among spatially proximate agglomerations. Two or more ‘core’ cities dominate in such a polycentric structure. This study uses the spatial scale of functional urban areas, which encompass the geographical extent of a city, including a 45-minute commute area from its core, and are considered cohesive, functional entities rather than just administrative regions (ESPON, 2004). Our focus is thus on worker relocation patterns between two functional urban areas. We take a functional perspective and apply an origin-destination (OD) analysis using employment data. This approach allows us to understand how relocations in the knowledge economy have shaped the space we see and visualise spatial-temporal relationality. Therefore, we formulate the following hypothesis, which we test for each knowledge base:

> *"Knowledge workers tend to relocate to the nearest, more populous functional urban areas. The relocation distance increases when knowledge workers relocate between two more populous functional urban areas. Here, workers tend to relocate from smaller, less populous functional urban areas to larger, more populous functional urban areas."*

To the best of our knowledge, the relocation patterns of knowledge workers or employment in regional economies have not been widely studied using origin-destination analysis, likely because the specific, personalised data required for scientific investigation are not publicly or readily available and must first be modelled. Origin-destination analysis has been used for various types of research in regional studies, such as commuting patterns or transportation flows (LeSage, 2014). For example, Pitoski, Lampoltshammer, and Parycek (2021) combined origin-destination analysis with network analysis and found that while the number of migrations increased over time, the network remained constant, with more people moving between two regions than within a region.

6.3 Data and methodology

6.3.1 FIRM AND EMPLOYMENT DATA

To study the employment and relocation of knowledge workers, we must first establish a clear delineation of knowledge-intensive firms from which to extract data. As an initial step, we employed the categorisation established by Legler and Frietsch (2006), as well as Gehrke, Frietsch, Neuhäusler et al. (2013), to define which firms can be classified as knowledge-intensive based on the German Classification of Economic Activities (Wirtschaftszweige 2008). Here, we grouped knowledge-intensive classes of economic activities with similar activity-related contexts. We followed the logic of Legler and Frietsch (2006) and chose subsectors focused on investing in research and development activities and with a high concentration of skilled labour. Each subsector was then assigned to its relevant knowledge base following the classification of Zhao et al. (2017). The complete list of subsectors and their corresponding knowledge bases are available upon request. We then used Dun & Bradstreet data[5] to identify the top 30 firms by employees in each subsector in 2019. Based on this grouping process, we built a dataset of 480 firms, including the top 30 firms in each subsector, which we selected based on the condition that each firm must be multi-branch and multi-locational − and thus must have at least two locations in Germany. We argue that analysing the top 30 firms allows us to make well-founded statements about the German knowledge economy while focusing on the interpretability of large, multi-branch, multi-locational firms. In contrast, firms with only a few locations do not face the same complexity in location optimisation and can relocate and adapt more flexibly to changing market conditions. By excluding them, we focus on firms whose location decisions are more strategic and stable, providing deeper insights into the spatial dynamics of the German knowledge economy.

We used the Establishment History Panel (BHP) provided by the Institut für Arbeitsmarkt- und Berufsforschung (IAB) to identify and extract all firm locations in Germany for all available years and assign them to the appropriate knowledge base. The Establishment History Panel contains all firm locations with at least one employee who is subject to social security

[5] Dun & Bradstreet is a business analytics database that provides various commercial information on firm locations such as size, age, and revenue.

contributions. It also includes other information, such as the economic sector or location. The data is very reliable due to legal sanctions for false reports.

By using this firm location dataset, we were able to identify and extract the relevant employment information from the Employment History Panel (BeH) of the IAB, as firms in both datasets are linked by a common ID. The Employment History Panel provides information on all employees subject to social security contributions in Germany, who are recorded according to various characteristics. To identify workers who relocated for jobs, we further filtered the data to include only those who changed their place of work between two dates. If a worker's entry shows such a change in work location, it is categorised as a job-related relocation in our framework. To visualise the evolution of relocation patterns over time and to account for changes in labour market participation, we introduced an intermediate step in our analysis, 2016. Due to a reclassification of jobs in 2011, we opted to start tracking jobs − and thus firms − from 2012, as considering any earlier data would lead to classification errors. Consequently, we limited our analysis to the years 2012 to 2021 and divided the period into two distinct time spans, 2012 to 2016 and 2016 to 2021, each in the form of an OD matrix. Since our study is based on knowledge bases, each worker in our dataset is assigned to their employer's corresponding knowledge base.

Lastly, employment and firm data provided by the IAB are highly sensitive, so we aggregated the data to the functional urban area level to avoid overly compromising interpretability. We argue that it does not matter where a firm is located within the range of one functional urban area, because spatial proximity is sufficient at this supraregional level. This shifts the focus from changes in local commuting patterns caused by job changes within a functional urban area to large-scale relocation behaviour between functional urban areas. In Germany, 186 functional urban areas can be identified. Since migration data can be difficult to interpret, we developed a systematic scheme to overcome this by grouping workers' relocations into meaningful categories. We briefly introduce our approach in the next section.

6.3.2 ORIGIN-DESTINATION EMPLOYMENT NETWORKS

This section introduces our methodology for analysing origin-destination employment flows between two functional urban areas. The visualising and interpreting of origin-destination flows often face the problem of visual cluttering with increasing flows of movements, hence various graph bundling approaches have been developed to simplify this (Holten & Van Wijk, 2009; Hurter et al., 2012). To analyse the dynamics of worker relocations, we use two complementary visualisation approaches. First, chord diagrams provide an overview of the intensity of relocations. Second, maps spatialise these flows, allowing us to uncover potential regional patterns, i.e., whether relocations occur over short or long distances. The maps further reduce complexity by focusing on the dependencies between two functional urban areas and presenting only the ‘destination’. Both visualisation approaches were developed in R; for the chord diagrams, we relied on the R package ‘circlize’, developed by Gu, Gu, Eils et al. (2014).

For the maps, we first defined the magnitude or strength of relocations between two functional urban areas by aggregating the flow between them in both directions. We then normalised the employment flows across all four knowledge bases to achieve visual comparability. We defined five groups of relocations based on their relative strength in 0.2 steps, ranging from 1.0 to 0.1, and one additional group for less than 0.1 relocations. However, to avoid losing the directional information when two opposing directions were combined, we added a comparison of the ratio between the two functional urban areas. We assigned the direction to the more substantial flow. We use a colour classification to study whether the more substantial relocation flow goes to the less or more populated functional urban area, where a green line indicates that more workers were relocated to the more populous functional urban area, a purple line indicates the opposite, and a yellow line shows a more balanced distribution of relocations between the two functional urban areas. Thus, a straight line between two functional urban areas symbolises the strength of relocation and the directionality. We only display the name of the functional urban area that has attracted more workers than it has lost in the pair. Thus, we colour-coded the labelled functional urban areas as follows. If a label appears in both time spans, it is displayed in black. If the destination only appears in the 2012–2016 period and not in 2016–2021, it is coloured in light green. If it only appears in 2016–2021, it is displayed in light blue. We made use of the 2022 urban and rural concept developed by the German Bundesinstitut für Bau-, Stadt- und Raumforschung (BBSR)[6] for both the maps’ backgrounds and the classification of functional urban areas. To capture nuanced spatial distinctions while maintaining visual interpretability, but also to assess whether more workers relocate to urban areas rather than the contrary, we opted for a threefold classification: urban,

[6] https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/Raumabgrenzungen/deutschland/regionen/siedlungsstrukturelle-regionstypen/regionstypen.html (24.04.2025).

urban-rural, and rural. Since functional urban areas are functional but not administrative demarcations, we assigned each functional urban area its BBSR category using spatial statistics.[7] Additionally, we aim to check the concept of metropolitan regions by examining the underlying assumption that agglomeration effects are gradually concentrating economic activity in urban areas. Therefore, we included the delineation of metropolitan regions on the maps using dashed lines to provide a backdrop for comparing the regional extent of relocations with a normatively defined metropolitan region (van Meeteren, Poorthuis, et al., 2016). For the chord diagrams, we clustered the functional urban areas into their respective BBSR category, as discussed above. For each functional urban area, all relocations are shown with the help of incoming and outgoing arrows. The scale on the ring reflects the absolute magnitude of relocations for each functional urban area. **Table 14** shows the summary statistics for each knowledge base and time span. The relocations of workers between two functional urban areas range from 1 to 1284. Notably, our data is right-skewed in all knowledge bases, as the mean ranges from 3.7 to 14 workers relocating between two functional urban areas. The total is the summed relocations of all workers in one knowledge base to another functional urban area, ranging from 1657 to 48,948, with the fewest relocations in symbolic Advanced Producer Services and the most relocations in synthetic Advanced Producer Services. In total, the relocations increased from 2016 to 2021. We normalised the relocations between two functional urban areas using the maximum of 1284 relocations as the baseline (1.0).

[7] The only functional urban area that we assigned manually was the functional urban area Berlin, as it is monocentric.

Table 14 Summary statistics of job-related relocations

		Min	Mean	Standard Deviation	Max	Total	25%	Median	75%
2012–2016	***Analytical high-tech***	1	3.9	8.4	75	2364	1	1	3
	Synthetic high-tech	1	7	22.8	410	13,084	1	2	5
	Synthetic APS	1	14	50.5	977	48,948	1	3	8
	Symbolic APS	1	2.9	7.4	96	1657	1	1	3
2016–2021	***Analytical high-tech***	1	4.3	9.6	81	3340	1	1	3
	Synthetic high-tech	1	7.5	31.7	554	14,205	1	2	4
	Synthetic APS	1	13.8	58.8	1284	48,939	1	3	8
	Symbolic APS	1	3.7	9.7	112	2191	1	1	3

6.4 Findings

6.4.1 HIGH-TECH KNOWLEDGE BASES

Leveraging the insights gained from the literature review, we can now present our findings on job-related relocations of knowledge workers, categorised by their specific knowledge bases. Hence, only workers who found a new job in another functional urban area are shown. As mentioned above, our relocation dataset is right-skewed, with many cases containing only a single or few relocations in total. To improve interpretability and better emphasise the underlying relocation patterns, our synthetic high-tech and synthetic Advanced Producer Services knowledge base analysis focuses on relocations that account for at least 10% of all relocations in the maps and the chord diagrams. All of the following figures illustrate the relocation of high-tech and Advanced Producer Services employment in two different time periods. The left-hand side shows the relocations from 2012 to 2016, while the right-hand side shows the relocations from 2016 to 2021. For clarity and consistency, all figures are presented in the same format.

We begin our interpretation of the results for high-tech knowledge bases, which are shown in **Figure 11** and **Figure 12**. In analytical high-tech, as shown in **Figure 11**, we only find low numbers of relocations. Although there are a few long-distance relocations, such as to and from the functional urban area of Berlin, most occurred between neighbouring functional urban areas or functional urban areas in the same BBSR category. Two persistent, interconnected groups of functional urban areas, i.e., where a number of workers relocate between more than two functional urban areas, can be identified: Krefeld-Duesseldorf-Cologne and Friedrichsdorf-Mainz-Darmstadt-Ludwigshafen. Focusing on relocation destinations that appear only once across the two time spans reveals that most are situated near the aforementioned functional urban areas, suggesting that relocations within this knowledge base tend to be oriented towards nearby functional urban areas.

Compared to its analytical counterpart, synthetic high-tech exhibits more relocations, as shown in **Figure 12**, especially larger numbers of moves towards more populous functional urban areas. Given the size of the automotive sector in this knowledge base, we can identify two cases for neighbouring functional urban areas where more relocations appear: Wolfsburg-Hannover-Braunschweig and Stuttgart-Heilbronn. The maps show that a similar relationship also appears between the German part of the functional urban areas of Bregenz and Ravensburg, underscoring the prominence of the high-tech sector in the region spanning Austria, Germany, and Switzerland. More workers relocated to the smaller functional urban area of Bregenz in the first time span. However, this trend reversed in the subsequent period, with a greater influx of workers into the more populous functional urban area of Ravensburg. Furthermore, many workers relocated from the functional urban area of Coburg, north of Bamberg, to the more populous functional urban area of Bamberg. Compared to analytical high-tech, we observe more relocations overall towards larger functional urban areas, predominantly classified as urban-rural. Particularly in the second time span, from 2016 to 2021, it can be seen that less populous, neighbouring functional urban areas like Heilbronn and Salzgitter experienced an influx of relocations from the more populous functional urban areas such as Stuttgart and Wolfsburg.

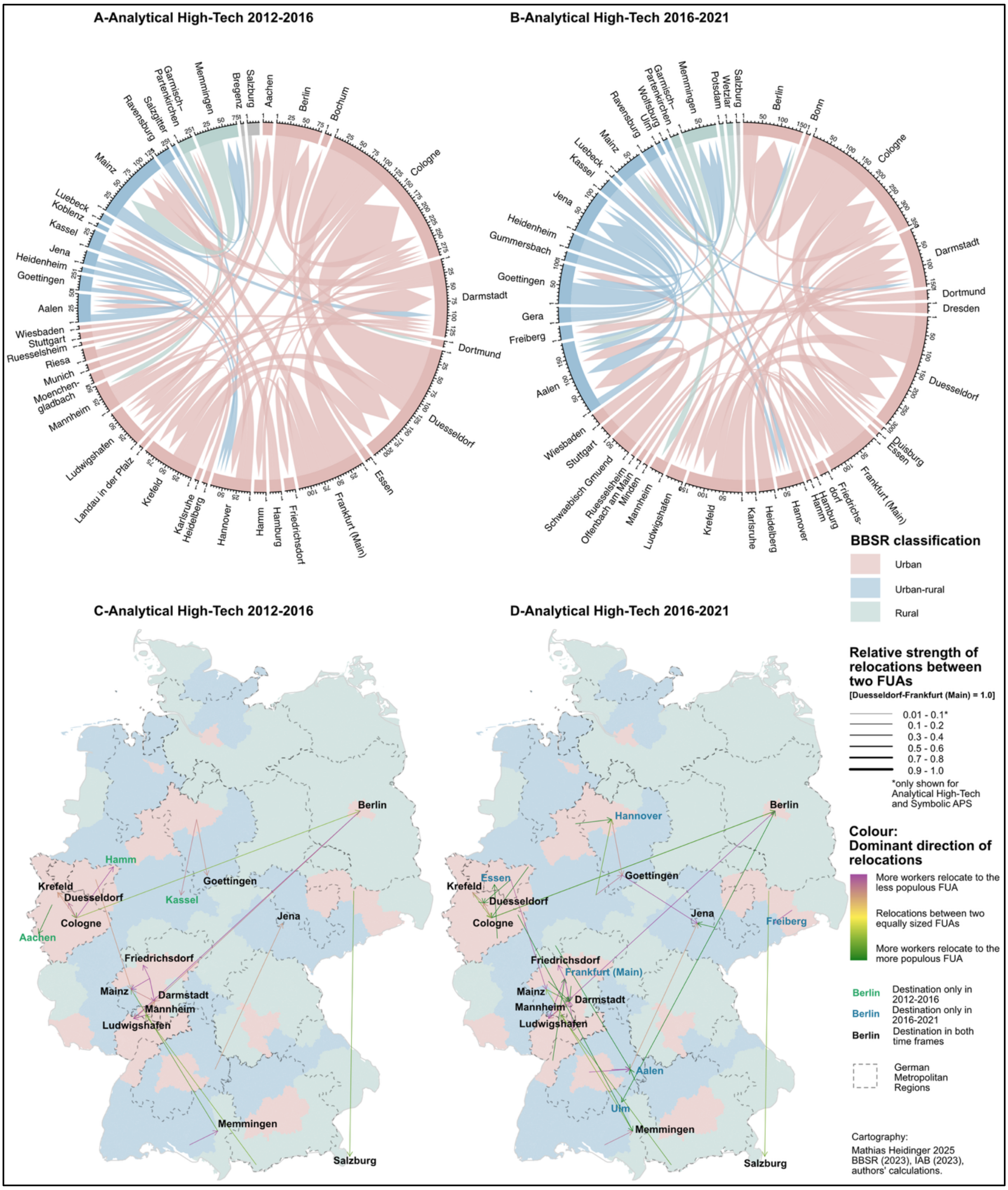

Figure 11 Chord diagrams and maps illustrating job-related relocations for analytical high-tech across both time spans

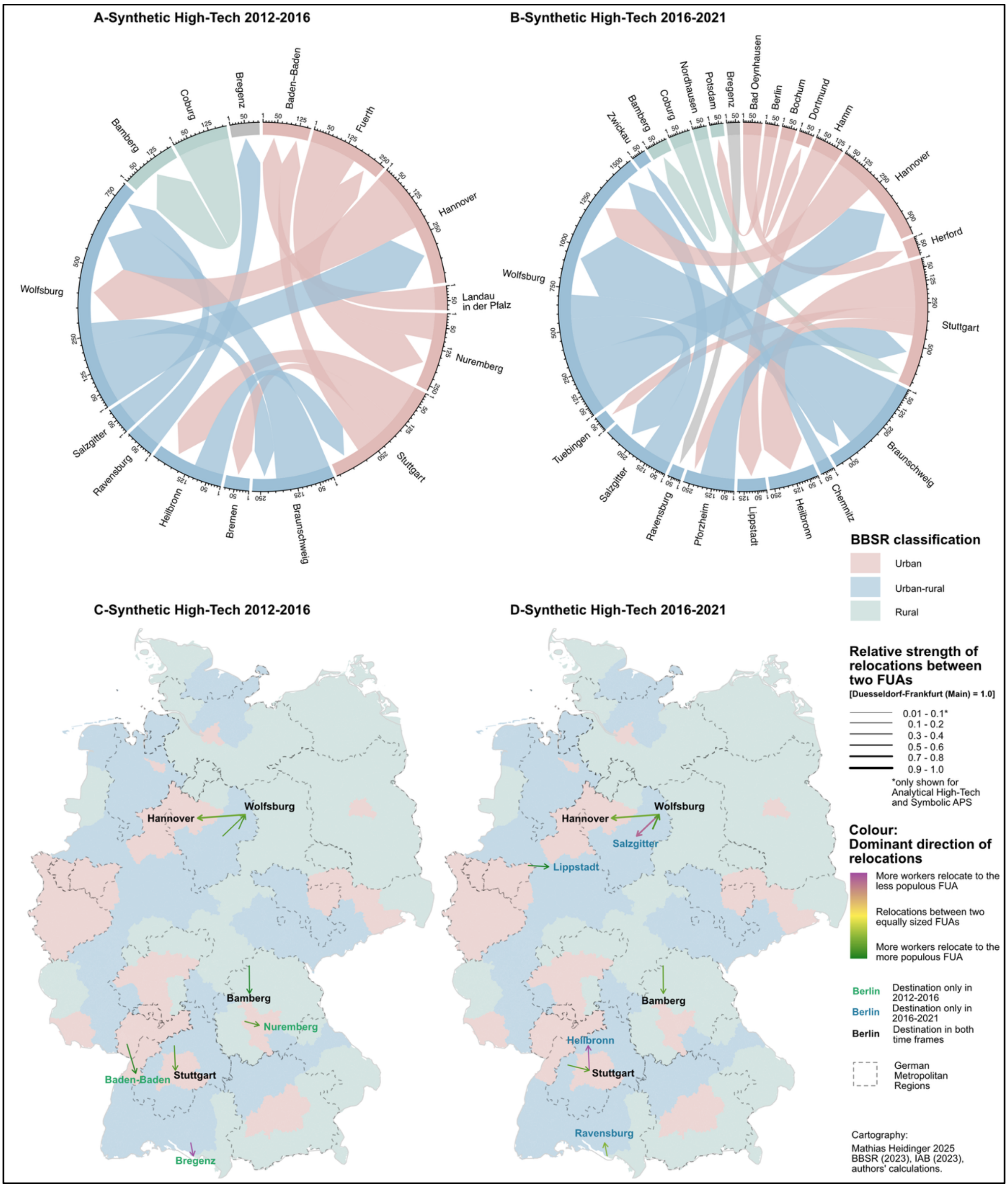

Figure 12 Chord diagrams and maps illustrating job-related relocations for synthetic high-tech across both time spans

6.4.2 ADVANCED PRODUCER SERVICES KNOWLEDGE BASES

Synthetic Advanced Producer Services are displayed in **Figure 13** and clearly had the most relocations in both time spans. The relocations demonstrate the importance of firms adapting and innovating based on new knowledge gained through new employees, thus attracting new workers constantly (Fallick et al., 2006; Krabel & Flöther, 2014; Serafinelli, 2019). From 2012 to 2016, many workers relocated to less populous functional urban areas, but this declined from 2016 to 2021, with most workers then moving to more populous functional urban areas. Three distinct changes of direction can be identified. During the first time span, more workers relocated from the functional urban area of Frankfurt to the functional urban area of Duesseldorf, which also had the highest number of relocations in our data. We find similar cases for the functional urban areas of Freising and Potsdam, where workers relocate to the larger functional urban areas of Munich and Berlin in the second time span. Using the chord diagrams, we also identify many relocations originating in the functional urban area of Aschaffenburg, possibly due to a firm location closure during the first time span. The maps for the second time span generally show a concentration towards fewer, yet populous, functional urban areas, such as Frankfurt, Munich, Hamburg, and Berlin. Like its high-tech counterpart in **Figure 12**, the functional urban area of Stuttgart appears to have experienced an outflow of workers in 2021, relocating to smaller neighbouring functional urban areas such as Heilbronn and Ulm. The largest number of workers in this knowledge base relocate to and between more populous functional urban areas, i.e., the functional urban areas of Munich and Berlin or Frankfurt and Berlin, likely due to the concentration of workers and knowledge-intensive firms there. These results largely support our hypothesis that workers tend to relocate to larger functional urban areas.

Similarly to analytical high-tech, we identify only a few workers relocating in the symbolic Advanced Producer Services, as shown in **Figure 14**. Furthermore, only a few large functional urban areas, such as Berlin, Hamburg, and Stuttgart, serve as persistent destinations. Unexpectedly, while we identified many relocations in spatial proximity to the origin functional urban area during the first time span, longer distance relocations become increasingly prevalent in the second time span, such as between the functional urban areas of Kiel and Hildesheim or Fulda and Wiesbaden. This aspect requires further study.

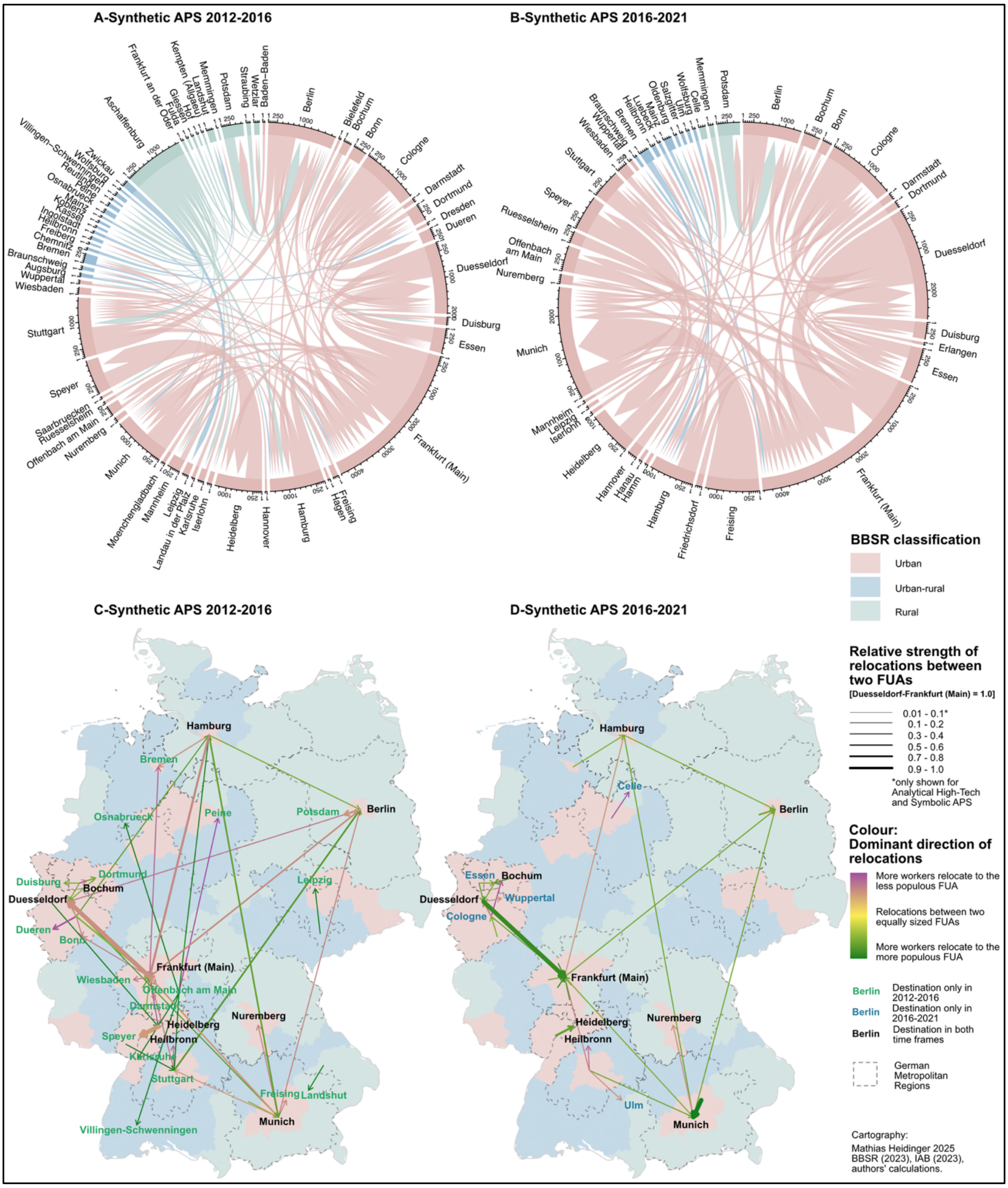

Figure 13 Chord diagrams and maps illustrating job-related relocations for synthetic Advanced Producer Services across both time spans

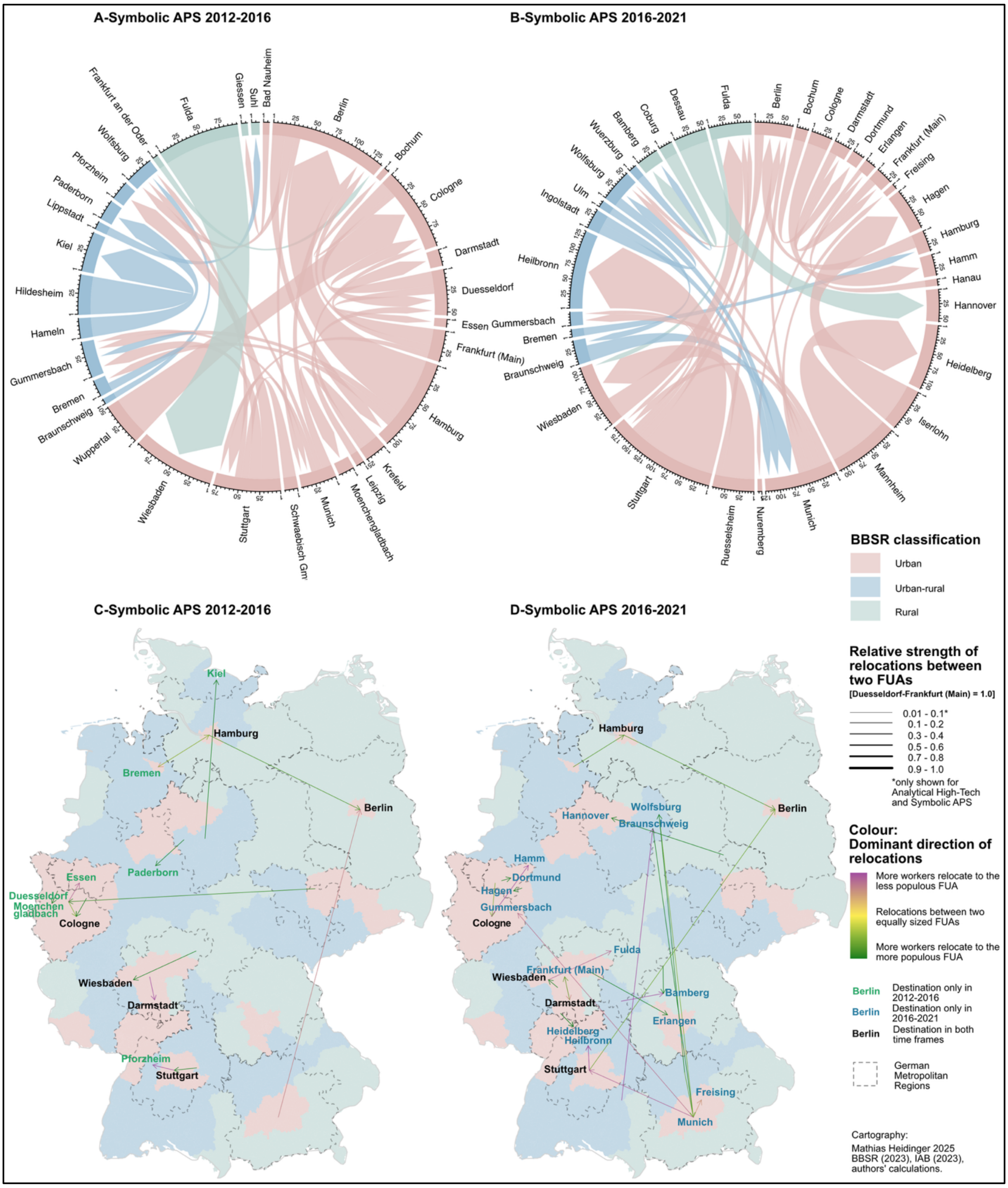

Figure 14 Chord diagrams and maps illustrating job-related relocations for symbolic Advanced Producer Services across both time spans

6.5 Discussion

Our analysis provides a nuanced picture that emphasises the need to reconsider the role of knowledge in firms' innovation processes, as this influences both their choice of location and who they attract. Firms within the analytical knowledge base rely heavily on scientific knowledge and employ workers who produce outputs like patents or technological advancements (Asheim et al., 2011). In contrast, firms within the symbolic knowledge base depend on worker creativity and are thus typically located in urban environments. As a bridge between these, the synthetic knowledge base firms focus on solving practical problems by synthesising new knowledge, often collaborating across different industries to provide solutions (Asheim et al., 2011). This is reflected in the relocation patterns we observed.

We found that employees in an analytical or symbolic knowledge base tend not to relocate in large numbers. Following the literature, we assume several reasons for this. For one, workers in analytical high-tech are trained in-house or hired directly from universities due to extensive collaborations with research institutes and universities on research and development projects. This can reduce reliance on external knowledge resources by leveraging internal knowledge and close ties with academic institutions (Roesler & Broekel, 2017). Also, research on PhD graduates suggests this strategy is more likely to be true in science, technology, engineering and mathematics (STEM) fields (Ghosh & Grassi, 2020). Thus, workers in analytical high-tech are less dependent on physical exchanges with clients, and fewer relocations may be needed. Similarly, firms using a predominantly symbolic knowledge base may also attract more workers from within their functional urban areas, as only a few knowledge workers relocate for a new job to another functional urban area in the symbolic knowledge base. Asheim and Hansen (2009) argue that workers in this knowledge base rely most on tacit knowledge, so face-to-face interaction and specific local knowledge are essential. However, due to the low magnitude of relocations for both knowledge bases, we have not drawn any conclusions and leave this open for future research. Therefore, in the following, we spotlight two knowledge bases only, synthetic high-tech and synthetic Advanced Producer Services, examining the interconnectedness of functional urban areas driven and visualised by worker relocations.

In the synthetic high-tech knowledge base, we identified two patterns of relocations. First, we identify relocation patterns between small numbers of neighbouring functional urban areas. One example can be found between the functional urban areas of Hannover, Salzgitter, and Wolfsburg, with a focus on the largest and most populous functional urban area, Hannover. In particular, the functional urban area of Wolfsburg is known for its automotive and mechanical engineering firms, which may influence the whole region. Second, we identify functional urban areas that are not the most populous of a metropolitan region yet showcase strong relocation connectedness with neighbouring functional urban areas, such as Bamberg-Coburg, Ravensburg-Bregenz, or Stuttgart-Heilbronn. This may indicate decentralised concentration at the level of metropolitan regions. Another explanation derived from previous research could be that these functional urban areas may have found suitable partners to share a labour pool (van Meeteren, Poorthuis, et al., 2016) or complement each other's capabilities (Balland & Boschma, 2021).

For the synthetic Advanced Producer Services knowledge base, we observe the most relocations. The diverse yet changing relocation patterns highlight the need for synthetic Advanced Producer Services firms to attract the best knowledge resources – which they seem to find in the most populous functional urban areas. Again, our analysis shows a pattern of relocations between regionally close functional urban areas, e.g., around the functional urban areas of Duesseldorf and Frankfurt. Additionally, workers mostly relocate between Germany's largest functional urban areas, such as Berlin, Munich, and Frankfurt, with a tendency towards the more populous functional urban areas in the second time period. In addition to the greater number of workers and firms in absolute terms, this also suggests that workers in this knowledge base are more likely to relocate in larger numbers. The literature argues that this is due to an increasing up-skilling of workers in and between these areas (Hidalgo et al., 2007; Neffke & Henning, 2013). Balland, Jara-Figueroa, Petralia et al. (2020) explain that the increasing concentration of workers in large urban areas is due to the rising complexity of activities within firms, particularly in Advanced Producer Services firms. While functional urban areas within metropolitan regions attract many relocations, we also observe substantial relocations between metropolitan regions and functional urban areas outside these demarcations. This suggests that the normatively defined delineations of metropolitan regions do not fully capture the complex nature of worker relocation. Similarly, the BBSR classification clearly distinguishes between urban, urban-rural, and rural areas, concealing the underlying relationality of economic activities. For instance, the largest functional urban areas, which are thus classified as urban, are not always the main destinations for workers, as they are for synthetic Advanced Producer Services. Instead, urban-rural or even rural linkages often dominate at the regional level, particularly in the high-tech knowledge bases.

We can only partly accept our hypothesis: workers relocate to a nearby larger functional urban area in Germany. While most workers relocate towards larger functional urban areas, results for synthetic high-tech show that smaller, neighbouring functional urban areas are also favoured destinations for knowledge workers, although in fewer numbers (see **Figure 11** and **Figure 12**). These functional urban areas are not the dominant urban 'cores' of a region, but instead may rather indicate decentralised concentration effects within metropolitan regions.

6.6 Conclusion

This paper provides an innovative way to understand the relocation patterns of knowledge workers by examining the role of the underlying knowledge base, which influences not only the spatial distribution of knowledge-intensive firms but also the relocation behaviour of workers. The concept of knowledge bases, which encompasses analytical, synthetic, and symbolic knowledge, provides a useful framework for analysing how firms use different forms of knowledge to drive innovation (Asheim & Gertler, 2006). Each of these knowledge bases has specific dependencies on tacit and codified knowledge, shaping the location preferences of firms and the underlying knowledge creation processes. Thus, we argue that these dynamics directly influence the demand for specific knowledge workers due to their specific skills. Using an origin-destination analysis and a comprehensive dataset covering all employees of 480 multi-branch, multi-location firms in Germany between 2012 and 2021, we visualised worker relocations across functional urban areas. We identified two key findings in line with the theoretical foundation. First, by studying worker relocations, we observed that relocations in synthetic Advanced Producer Services tend to be oriented towards the more populous functional urban area. Building on the literature, we assume that this continuous relocation of workers and the resulting concentration of employment is due to increasing competition for the best talent and skills. The synthetic knowledge base, which combines tacit and codified knowledge, exemplifies this trend (Asheim & Hansen, 2009). For our second time span of analysis, we identified that, specifically, workers in synthetic Advanced Producer Services, thus the largest number of workers, relocated to more distant and more populous functional urban areas, which is in line with the findings of Balland and Rigby (2017). Increased complexity of work due to competition may drive a greater number of highly skilled workers into a smaller number of larger functional urban areas (Balland et al., 2020). We did not identify many such relocation patterns in the analytical and symbolic knowledge bases. Two possible explanations in this context are that firms in the analytical knowledge base may rely on in-house employment training (e.g., Roesler & Broekel, 2017) or that the spatial scope of functional urban areas, including the city and its 45-minute commute area, may conceal job changes within individual functional urban areas. The latter suggestion cannot be investigated for data protection reasons. Second, in the synthetic high-tech knowledge base, we found that workers mostly relocated to neighbouring or spatially close functional urban areas. These functional urban areas are usually categorised as urban-rural, indicating a concentration of workers in decentralised locations within metropolitan regions, away from the most populous functional urban areas of these regions – where most workers in Advanced Producer Services firms work.

Our study has limitations that need to be considered and call for further research. Using functional urban areas as our scale of analysis presented challenges. We suspect that a more detailed spatial delineation could offer deeper insights into knowledge workers' (re-)location decisions – even if it would be difficult to reconcile such an analysis with data protection. Workers in analytical high-tech or symbolic Advanced Producer Services may have relocated just as often but predominantly within their respective functional urban areas, data that we did not focus on (Zhao et al., 2017). We also only concentrated on job-related relocations, not on household-related moves or other reasons for relocating, and thus face gaps when there is a relocation of workplace but not of the household. A methodological challenge was the definition of relocation. We chose to track workers present in the dataset between specific points in time (2012 & 2016 or 2016 & 2021), excluding those who joined the labour market at a later stage (e.g., graduates) but also those who moved in from abroad. Finally, classifying workers based on the firm's knowledge base, which is fundamentally derived from the German Classification of Economic Activities (Wirtschaftszweige 2008), does not fully capture what defines a knowledge worker. Future research could explore this further by including occupational classifications, which the Institut für Arbeitsmarkt- und Berufsforschung also provides.

Moving away from how knowledge is created and transported, digital transformation within the knowledge creation process adds another layer of complexity. Formerly, Advanced Producer Services firms provided services to predominantly manufacturing firms worldwide (Bassens et al., 2024). Digitalisation has transformed their service portfolios and contributed to the rise of big tech firms that have redefined the traditional value chain, where outputs now include physical and digital products (van Meeteren et al., 2022). These digital services, such as cloud-based collaboration platforms or machine learning services, are permeating how firms, especially Advanced Producer Services firms, operate. It puts their location choices (back) in the spotlight (Bassens et al., 2024; Trincado-Munoz et al., 2023). Bassens, Hendrikse, Lai et al. (2024) raise the question of whether this transformation and the COVID-19 pandemic further altered global location choices. While our dataset covers parts of the COVID-19 pandemic, it does not yet fully capture its influences or the post-pandemic period's impact on workers' relocation behaviour. Many workers may have adopted alternative working models during the pandemic, such as working from home or choosing not to apply for jobs in different cities, potentially altering pre-pandemic relocation patterns. This resulting complementarity between centralised, synchronous work and decentralised, asynchronous remote work, along with current geopolitical turmoil, may further shape relocation patterns at a variety of spatial scales for both firms and workers (e.g., Yeung, 2024). As a result, a growing number of knowledge workers may choose not to relocate at all. The definitive effects of these changes remain to be seen and hence cannot be assessed in this study. Lastly, it is also important to note that more and more firms require similar knowledge resources, such as statistics, computational skills, and artificial intelligence, in their innovation processes. Future research could delve into this to understand the impact of such skills on firm location choices.

Yet, our findings emphasise the importance of examining the underlying knowledge base of a worker or firm, as this plays a crucial role in understanding worker relocation patterns. It determines where workers relocate to, from, and in what numbers. Specifically, in synthetic knowledge bases, we observe a simultaneous trend of large-scale concentrations of workers in fewer functional urban areas, while other knowledge bases exhibit decentralised concentration at smaller scales.

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7 Discussion

This chapter begins with a concise summary and discussion of the results of the previous chapters and then draws on those findings to address each research question introduced in Section 2.5. It interprets the findings and brings to light the nuanced insights that have emerged over the course of the last three chapters, i.e., the peer-reviewed publications that form the core of this dissertation. These chapters collectively contribute to understanding where knowledge-intensive firms and employment (re-)locate and how workers, thus the knowledge economy, shape regional growth. The chapters also reflect the underlying research process of this dissertation. Therefore, in Chapter 4, the spotlight was put on firms and their networks to understand what spatial and relational features may influence the network generation within firms or, put more simply, where firms choose to locate. Chapters 5 and 6, on the other hand, were concerned with different interrelations of knowledge-intensive employment in space. All three chapters use the same spatial extent and definition, focusing on FUAs in Germany, as described in Chapter 3. Furthermore, the consistency makes it possible to compare and draw broader conclusions across the chapters, which are also explored and discussed in detail.

Chapter 4 investigated the location choices of knowledge-intensive firms in Germany using a network approach, specifically employing an exponential random graph model (ERGM). This analysis was built on self-collected firm locations of 480 knowledge-intensive firms and their respective firm locations, totaling 17,786 locations. The INM approach was used to build valued firm networks and identify the most important nodes in each network. Firms were classified into four distinct knowledge bases, with networks within each knowledge base aggregated into a single network. Therefore, this analysis compared four different networks of knowledge bases: firms in analytical high-tech, firms in synthetic high-tech, firms in synthetic APS, and firms in symbolic APS. Since most ‘standard’ forms of ERGMs only accept binary networks, the firm networks were transformed into a binary-like space using the backbone approach, as proposed by Neal et al. (2021a, 2021b). Generally, especially for firms that rely on knowledge, the choice of locations is made deliberately to optimize their knowledge creation processes and gain access to localized knowledge resources. The ERGM-based network approach highlights the relational and spatial conditions, such as accessibility and the location of a research institution, that are crucial for knowledge-intensive firms to effectively manage these processes. The underlying network theory examines which of these aspects or conditions contributes to forming a tie. For instance, when a firm only establishes firm locations in cities with specific amenities, the likelihood of opening a new location in a city that offers that amenity is significantly higher well. This is because the theory has its roots in the social sciences (see Subsection 3.4.1). In principle, the results can be interpreted similarly to regression analyses, where coefficients are understood in relation to a baseline model.

The findings generally confirmed previous research, e.g., the importance of operating a location in highly populated areas, as well as the proximity to universities and other institutions, as only firm networks in analytical high-tech do not return significant results here. Firms that are classified as analytical high-tech, in turn, seem to prefer more rural locations since the coefficient that tracks the affiliation of a FUA to a metropolitan region is significantly negative. The analysis further suggested that firms that are classified in a synthetic knowledge base, especially, choose locations with frequent air and train connectivity. Some results were surprising since both assumed spatial conditions, attracting knowledge-intensive firms associated with 'urban' or being in a very large city, did not yield significant results. This fact is especially reflected in the extensive firm networks of the synthetic APS knowledge base, where some coefficients, such as the efficiency of a connection between two FUAs using the train and road network, are both significantly negative. One possible explanation for this is that, within a dense network of firm locations, it is difficult to quickly reach any point in the network from any other point. This result highlight that the knowledge exchange in firms in the synthetic APS knowledge base happens in other ways an ERGM does not capture, such as through digital networks, locally via face-to-face, or between each regional headquarters and its managed smaller regional locations – here, further research is needed. Therefore, the second hypothesis could not be accepted. Overall, the results have shown that ERGMs are a flexible tool for studying complex spatial networks in relation to factors that may influence firms' location choices. Based on these findings, the chapter recommends that local policymakers closely evaluate what spatial features and relational connections (train or air) are available to attract the right knowledge-intensive firms.

The results gained in Chapter 4 also raised some important thoughts: There is consensus that knowledge-intensive firms tend to locate where they find or have access to fitting labor. While ERG modeling captures the outcome of a firm's location decision, often years in the making, the model doesn't illustrate the process leading to that choice. The establishment of a new firm location, whether a subsidiary or headquarters, in a city or region can also trigger significant, often parallel developments, attracting not just competing or complementary firms, but importantly, driving regional and employment growth. This is why Chapters 5 and 6 put the spotlight on changes in knowledge-intensive employment over time.

Chapter 5 approached the relationship between the knowledge economy and the overall economy by examining changes in employment as an indicator. In essence, this chapter tackled the question of whether employment in the knowledge economy induces employment growth or whether the causality runs in the opposite direction. In short, this analysis employed Granger causality tests to explore the causal relationship between the two types of employment.

For this purpose, the study used longitudinal employment data extracted from 480 knowledge-intensive firms in APS and high-tech sectors spanning from 1999 to 2019. The overall economy is approximated using the 'total' employment data for all other firms in Germany over the same period. Total employment was defined as the sum of all employees in a FUA, minus knowledge workers, summarized in APS and high-tech employment. All datasets were provided by the Institute for Employment Research (see Section 3.3 for a detailed description). Two nested hypotheses were tested via a two-step Granger causality framework to study the causality analysis. The first hypothesis assessed whether a causal linkage existed between the two panels of employment, in an aggregated form. Based on these results, the second hypothesis examined the direction of causality at the individual level of FUAs, across 186 FUAs in Germany. The results for the first hypothesis revealed significant relationships in all cases. It is important to note that the more detailed knowledge base approach did not yield significant results, which led to the use of the more 'aggregated' binary classification of APS & high-tech employment. Consequently, the second round of tests was restricted to those cases where significant causal relationships were identified in the initial aggregated analysis. Granger causality tests, originally developed by Granger (1969), are used to approximate 'real' causality by determining if one time series can predict changes in another time series.

First, aggregated Granger causality panel tests examined the relationship between APS and total employment, as well as high-tech and total employment. These tests drew on Juodis et al.'s (2021) non-causality approach for panel data due to their flexibility in use and returning meaningful results with few observation periods. Since Granger causality can appear in both directions, i.e., APS causing growth in 'total' employment and vice versa, four individual tests were conducted. The results for these four tests showed significant statistics, meaning that the so-called Granger causality could be identified in either direction, for both APS and high-tech, in at least one panel dataset (i.e., in one of the 186 FUAs). However, this non-causality test approach can only identify overarching panel relationships, but not which one of the panels. Thus, a second round of tests was conducted. In this second round of tests, each of the 186 FUAs was tested for Granger causality (see Subsection 5.3.1 for a more detailed methodological explanation). Since all 186 individual panel tests were conducted on FUAs, the results could be spatialized using GIS in the third step. Here, the patterns revealed that Granger causality is largely based in economically robust FUAs (such as the FUAs Munich, Frankfurt, or Berlin) for APS. However, nearby smaller FUAs, such as the FUAs of Augsburg and Kaufbeuren related to the FUA of Munich, also demonstrated that total employment growth precedes growth in APS employment. In high-tech sectors, Eastern German FUAs notably showed that total employment drives high-tech employment (e.g., in the FUA of Leipzig), likely due to past relocations of manufacturing and production facilities that attracted related high-tech supply chains. In both APS and high-tech, so-called bidirectional causalities could be observed. These mostly appeared when an FUA was located between two FUAs that had a diverging development, i.e., in one FUA, the knowledge-intensive employment Granger-caused total employment growth, while in the other, it was reversed. Overall, these results led to only partially accepted hypotheses.

Chapter 6 outlines the (re-)locations and concentrations of knowledge-intensive employment in Germany. This study utilized temporal relocation data for knowledge-intensive workers from 2012, 2016, and 2021, relying on the firm dataset detailed in Section 3.1. In summary, a dataset of all employees was extracted for each firm location using official employment records from the IAB. Only those who relocated between 2012 and 2016 or between 2016 and 2021 were considered. A worker was classified as ‘relocated’ if their workplace changed during either of these intervals. This method allows for the creation of an origin and destination dataset (see Section 3.3). The study is grounded in a temporal-relational conceptual framework, indicating that employment growth in one region may trigger structural changes in another. To understand where these changes occurred, two separate flow chart analyses were developed and applied (see Subsection 3.4.3 for a summary of the methods used).

The first analysis, a circular flow chart, examined where workers in the knowledge economy relocated from and to which FUAs in absolute numbers. FUAs were grouped according to the threefold urban-rural classification provided by the BBSR (2023), adding another layer of analysis (see Sections 3.2 and 6.3 for a more detailed introduction to this approach). The second analysis ‘spatializes’ the relocations in Germany. The advantage of this method over solely using the first type of analysis is the now visible introduction of spatial proximity – do workers relocate from neighboring FUAs or over larger distances? The relocations were categorized into five groups based on their relative intensity, with the highest number occurring between the FUAs of Frankfurt and Düsseldorf serving as a reference. Consequently, an additional category was defined for relocations in the analytical high-tech and symbolic APS knowledge bases with values below 0.1, as only a few relocations were identified here. Both analyses are displayed in **Figure 11** through **Figure 14**.

Two main observations can be made. First, most relocations of workers appeared in the synthetic knowledge base, both in high-tech and APS, as shown in **Table 14** and the figures. However, there is not only a difference in the total number of relocations but also in the destinations of the relocations of workers.

For example, **Figure 13** illustrates that employment has increasingly relocated primarily to the most populous FUAs during both 2012–2016 and 2016–2021, particularly to the FUAs of Munich and Frankfurt. Notably, most of these relocations occurred toward or between the largest FUAs in Germany. One could argue that these FUAs serve as the 'cores' of the surrounding regions, such as metropolitan areas. The latter time span, 2016–2021, revealed that more workers relocated to fewer FUAs, specifically to the FUAs of Frankfurt, Munich, and Berlin. Recent studies indicate that such concentrations are occurring in a smaller number of cities (or FUAs, in this case) due to the growing complexity of activities, thus, demand for skilled workers within firms (e.g., Balland et al., 2020). In synthetic high-tech, a decentralized concentration in urban-rural FUAs was identified, implying that workers tended to relocate in relatively large numbers to and between smaller, neighboring FUAs. Notable examples are the FUAs Bamberg and Heilbronn (see **Figure 12**). Possible explanations for this pattern are discussed in the literature, with van Meeteren, Poorthuis, et al. (2016) suggesting that these FUAs either share a common labor pool or, as Balland and Boschma (2021) argue, complement each other's capabilities. Finally, only a limited number of relocations appeared in analytical high-tech and symbolic APS. Most relocations occurred between geographically proximate FUAs in both knowledge bases, particularly around Frankfurt and Cologne. These results led to only a partially accepted hypothesis. Overall, both the circular and spatialized OD analyses offered a multi-scalar view of where relocations occurred on a broad scale and regionally, with workers in the synthetic APS knowledge base playing a significant role in relocations within the largest FUAs in Germany.

7.1 Discussion of the Research Questions

Taken together, the findings from the three chapters present a nuanced yet varied perspective on the evolution of the knowledge economy in Germany. Before this section addresses the results in relation to the research questions, it is important to briefly revisit the underlying knowledge base approach, as this offers a valuable contribution to the discussion.

Knowledge bases are not only a framework for conceptualizing and categorizing different types of knowledge; they also provide theoretical insights into how knowledge-intensive firms innovate. As such, the three knowledge bases, analytical, synthetic, and symbolic, as defined by Asheim and Gertler (2006) and further elaborated by Asheim (2007), directly influence the location choices of firms and their demand for knowledge workers, which are essential for knowledge creation and innovation. Knowledge bases can be conceptualized as a spectrum, representing the innovation process in firms as a dynamic combination of tacit and codified knowledge. The predominant form of knowledge within this spectrum is assigned to one of the three knowledge bases and, as a result, plays a crucial role in shaping the firm's knowledge output and, consequently, the innovation process (Asheim & Coenen, 2005, p. 1176). The analytical knowledge base, therefore, describes an industrial environment in which scientific knowledge, i.e., the use of codified, widely accessible knowledge, predominates (Asheim & Gertler, 2006, p. 297). Firms in the synthetic knowledge base apply and combine these codified knowledge sources, positioning them in the 'middle' of the spectrum between predominantly codified or tacit knowledge. These firms often engage in or consult on cross-industry collaborations, developing solutions to address clients' problems (Asheim et al., 2011; Asheim & Coenen, 2005). On the opposite end of the spectrum lies the third knowledge base, symbolic, which contrasts with analytical knowledge. Therefore, firms in the symbolic knowledge base primarily rely on tacit and localized knowledge in their knowledge creation process and are typically situated in a 'design-oriented' environment (Asheim, 2007; Grillitsch et al., 2017). This leads to frequent face-to-face interactions with clients and a flexible approach adapted to their needs (Grillitsch et al., 2017, p. 4).

In practical terms, the knowledge base approach offers a valuable middle ground between studying 16 distinct economic sectors (as outlined in Chapter 3, which details the selection process) and aggregating these sectors into the two primary pillars of the knowledge economy: APS and high-tech. These characteristics were evident in the firm and worker locations discussed in the preceding chapters and sections.

7.1.1 HOW DO KNOWLEDGE-INTENSIVE FIRMS ESTABLISH THEIR FIRM LOCATION NETWORKS, AND WHAT ARE THE PREFERRED LOCATIONS IN GERMANY? (RQ1)

The preceding revisit of the knowledge base approach helps to approach this research question. For firms with a symbolic or synthetic knowledge base, the following applies: they maintain their network of locations in FUAs that are home to large cities according to the German definition of large cities (see Subsection 4.4.3). This aligns with Zhao et al (2017, p. 207), especially when the focus shifts from 'where workers reside' to 'where their workplace is.' The authors' findings suggest that workers with a symbolic knowledge base are particularly inclined to live in central areas and prefer to be close to their workplace. By contrast, firms that operate within an analytical knowledge base, such as research-oriented, manufacturing firms, tend to follow a different spatial logic (see Subsection 2.2.3). From a perspective of knowledge exchange, these firms depend more on their intra-firm research divisions than on face-to-face contacts. Additionally, manufacturing firms also depend on available buildings and cheaper land to maintain their production, which was discussed by Harris et al. (2019), for example.

It should be noted that the results generated by the ERGM analysis represent only a snapshot at a specific point in time (2018-2019, when the data was collected; see Section 3.1) and are based on a specifically selected set of firms within each knowledge-intensive sector in Germany. These requirements or preferred locations may change over time.

7.1.2 *DOES EMPLOYMENT IN THE KNOWLEDGE ECONOMY INDUCE EMPLOYMENT GROWTH OR VICE VERSA*? (RQ2)

The question of causality is one of the core elements of this dissertation. Previous research, such as from Tervo (2009, 2016) and Østbye et al. (2018), has already approached this question of causality; however, either for a different geographical context, here Nordic countries, or using more aggregated, more accessible data. Chapter 5 was able to provide an answer to this research question. The findings in Chapter 5 revealed that 75 of 186 FUAs exhibit significant relationships: 49 between APS and total employment and 43 between high-tech and total employment, with no significant relationship between APS and high-tech employment. With a view to the above-mentioned research question, it can be stated that, in general, knowledge-intensive employment follows total employment growth, and not vice versa. This pattern was observed in 55 out of 84 significant relationships in this study. These results are in line with

Tervo (2009, 2016) and Østbye et al. (2018). The reverse, knowledge-intensive employment causing growth, was only determined in a few FUAs.

Similar to the discussion of RQ1 in Subsection 7.1.1, the results presented in Section 5.4 indicate, however, that although the relationship holds true in absolute terms, it becomes less clear when a spatial delineation, such as in **Figure 9**, is applied. It must also be mentioned that the Granger causality tests use a rather short time span for the time series analysis of employment.

7.1.3 *WHAT ARE IDENTIFIABLE SPATIAL PATTERNS OF RELOCATIONS OF KNOWLEDGE WORKERS IN GERMANY, AND HAS THIS CHANGED OVER TIME?* (RQ3)

There are several ways to study the spatial patterns of relocation of workers. Overall, why and where a worker relocates depends on various factors (see (Sub-)Sections 2.4.2, 5.2, 6.2.3). Most studies that deal with these types of questions are typically situated in migration studies and apply a statistical approach using, for example, regression tables (e.g., Abel & Sander, 2014; Giacalone et al., 2020; González-Leonardo & Rowe, 2022; Ioramashvili, 2023; Vossen et al., 2019). While there is nothing fundamentally wrong with conducting research in this manner, the studies lack a 'spatial pattern,' meaning the relationality of where a person relocates from. To study such relationality, typically, so-called flow maps using origin-destination data are applied (e.g., Pitoski et al., 2021; Sander et al., 2021; Stawarz et al., 2022) (see Subsection 3.4.3 for a brief overview).

Chapter 6 identified such spatial patterns of relocation of knowledge workers by distinguishing four different knowledge bases, always with the underlying assumption described above. The analysis revealed that knowledge workers do not follow a distinct spatial pattern. Instead, a more nuanced picture emerges (which has also been discussed in a different context in, e.g., Zhao et al. (2017)). While this complexity makes it challenging to provide a definitive answer to the research question, the results nonetheless offer a meaningful contribution. The findings indicate that workers in synthetic APS showed the highest number of relocations, both in total and over larger distances. In contrast, only a few relocations occurred in analytical high-tech and symbolic APS. Although this pattern has not fundamentally changed over time, one knowledge base continues to have significantly fewer relocations; it is evident that relocations are increasingly aimed at the largest FUAs in Germany, such as Berlin, Frankfurt, and Munich (see left and right in **Figure 13**).

It should be noted that relocations among the four groups of knowledge bases vary considerably, raising the question of why this is the case. The data on firms in all four knowledge locations considered the largest firms in each group, suggesting that the firms' sizes are comparable. Additionally, due to data availability, this analysis focused only on workers present at both points in time, meaning that in-migration from outside of Germany was not considered.

7.2 Synthesis of the Findings

This section synthesizes the findings from Chapters 4 to 6 to highlight key patterns across the studies.

The relocation analysis in Chapter 6 showed that workers in a synthetic knowledge base tend to relocate more than workers in analytical or symbolic knowledge bases. Thus, by focusing on worker relocations depicted in **Figure 11** to **Figure 14**, particularly within synthetic knowledge bases, deeper insights into the patterns illustrated in **Figure 9** and **Figure 10** can be gained. For instance, the FUA Freising, situated northeast of and adjacent to the FUA Munich, demonstrated a notable Granger causality, with overall employment growth serving as a Granger cause for subsequent growth in APS employment from 1999 to 2019. **Figure 13** shows many relocations of workers in the synthetic APS between the FUA Munich and the FUA Freising. These findings underscore the hypothesis that smaller FUAs can leverage agglomeration benefits through proximity to larger urban 'cores,' such as Munich, as illustrated in previous literature (e.g., Meijers & Burger, 2017).

In the context of the knowledge base of synthetic high-tech, a decentralized concentration effect could be identified at the level of metropolitan regions. Notably, the largest number of relocations occurred between neighboring FUAs, which were not necessarily the largest FUAs or 'cores' of a metropolitan region. This aligned with the findings in Chapter 4, which revealed that synthetic high-tech firms predominantly establish their firm networks in FUAs with 50,000 to 100,000 inhabitants. However, as **Figure 10** illustrates, these relocations in synthetic high-tech alone did not appear to directly lead to a Granger causal growth in total employment. For example, the FUA of Bamberg did not return significant results regarding employment growth, but it appears to be an important destination for knowledge workers (see **Figure 12**). Again, it is important to note that the underlying employment data for knowledge-intensive employment utilized in both Chapter 5 and Chapter 6 is derived from the 30 largest multi-branch, multi-locational firms in Germany. Thus, consistent with the findings in Chapter 5, which indicate that knowledge-intensive employment tends to follow total employment growth, one possible explanation for the observed results is the influence of external, unobserved variables. For instance, the observed relocations of knowledge workers may have been influenced by firms and their employment that were not included in our dataset of the 30 largest knowledge-intensive firms.

Due to the limited number of relocations of knowledge workers in both the analytical high-tech and symbolic APS, providing a comprehensive overview of the findings in Chapter 6 in relation to **Figure 9** and **Figure 10** is challenging. As outlined above, analytical high-tech and symbolic APS represent two contrasting approaches within the knowledge base framework, reflecting fundamentally different methods of how knowledge is created in firms. Firms in the analytical high-tech primarily draw on scientific knowledge, which is often developed in collaboration with, or directly sourced from, academic institutions (Asheim, 2007, p. 225). This reliance explains their tendency to hire or train in-house university graduates, as highlighted by Roesler & Broekel (2017). Therefore, workers in this knowledge base, despite incorporating skills and experience with widely accessible, codified scientific knowledge, seemed to be less inclined to relocate to more distant FUAs. When applied to analytical high-tech firms, this indicates that a significant proportion of their workers are sourced from research institutions or universities located in geographical proximity, i.e., from within the same FUA or a neighboring one, as visualized in **Figure 11** and **Figure 12**.

Lastly, workers in the symbolic knowledge base are associated with jobs in creative industries and are known to favor urban environments and cultural diversity (Asheim, 2007) (see also **Figure 14**). These are the places where the likelihood of face-to-face contact is highest (Asheim & Hansen, 2009; Storper & Venables, 2004). This aligns with findings in Chapter 4, which demonstrated that firms in the symbolic knowledge base would return positive coefficients for large cities in Germany, indicating a preference for such cities. Workers thus may be inclined to relocate in fewer numbers due to the necessity of acquiring and gaining access to the local knowledge of actors, the culture and norms, and the "*know-who*" (Cooke et al., 2007, p. 60), which may be a barrier for relocation. Nonetheless, more research is needed.

These observations, for both analytical high-tech and symbolic APS, reveal a limitation in the scope of this dissertation. Addressing these blind spots could be a fruitful avenue for future research, as concluded in the next chapter.

8 Conclusion

This dissertation has shed light on the dynamics of knowledge-intensive firms and their employment, locations, networks, and dependencies, adding new insights into where knowledge gets produced in space. In this concluding chapter, a synthesis and categorization of the findings within the framework of research questions and the current state of existing research is carried out. Finally, it addresses limitations encountered during this research, highlights challenges faced throughout this dissertation, and suggests avenues for future research.

8.1 Positioning the Dissertation Within the Conceptual Framework

Firms rely on new knowledge to drive innovation. Understanding *where* firms are located and *why* requires examining *how* they innovate, which can be approached by focusing on the firms' underlying knowledge base. Firms rooted in an analytical knowledge base, thus, those focused on creating patent-worthy innovation or formal research output, often favor different locations than firms in a synthetic knowledge base, which combine diverse knowledge resources for activities such as management, consulting, controlling, and engineering. Meanwhile, firms with a symbolic knowledge base rely on informal, creative exchanges and thus thrive in environments that are often associated with urban and culturally diverse (Asheim, 2007; Asheim & Gertler, 2006; Bathelt et al., 2004; Simmie, 2003). This results in different location factors for firms, not only depending on rent prices and available land or accessibility, but also on how much and how often personal interaction and exchange are necessary to create specific, new knowledge. Location factors for firms are additionally influenced by the predominantly tacit knowledge resources being highly localized (Bathelt & Glückler, 2011). Therefore, firms seeking to leverage such knowledge sources often face challenges in accessing them. This is especially true for multi-branch, multi-locational firms, for whom each new location in the network of firm locations represents a calculated risk of investment and a bet on the future of the firm to enhance their productivity.

This dissertation has shed new light on this topic in three chapters by examining how multi-branch, multi-locational firms establish location networks and manage employment. It also targets the identified research gaps in Section 2.5 by utilizing a self-collected, geo-coded firm dataset that was extended using official employment data for each firm location. This way, the lack of studies on the firm-employment nexus could be addressed. By adopting a longitudinal framework in two studies, this dissertation advances beyond the limitations of cross-sectional analyses in firm location research. The use of network-based approaches, such as the ERG model, extends research beyond a singular-entity perspective by analyzing networks of multi-locational firms. Furthermore, this dissertation counters the overall US-oriented bias in the literature by focusing on the German context. Finally, it addresses the underexplored topic of worker relocations within Germany by incorporating relocation data that identifies both the origins and destinations of workers.

Chapter 4 paints a more nuanced picture of the knowledge economy: firms operating in a high-tech knowledge base exhibit a lower tendency to maintain firm locations in densely populated urban locations, in contrast to firms operating in an APS knowledge base. However, unexpectedly, for the assumptions taken from the literature review, the results were not so clear. The underlying data structure and its disadvantages must be clarified to understand why this is the case. First, the dataset of firm locations is valued, which means that it is possible to distinguish a more 'important' firm location, such as a headquarters, from a 'less' important, smaller location, such as a regional office with fewer employees. Especially in big data analysis, such differentiations and valuations are common methods to avoid binary classifications and more effectively model the real world. Yet, the ERG modeling approach in its standard form only allows for binary data. Such a binary approach would result in a loss of valuable information, as described above; hence, in Chapter 4, the 'backbone model' by Neal et al. (2021a, 2021b) was applied, which reduces a network to its statistically most significant links. However, this adjustment still leads to a loss of information, making it more challenging to identify structural patterns. As a result, high-tech firms did not show the expected 'less centrally located' statistical results. Similarly, in cases of highly dense and saturated firm networks, such as synthetic APS firms, the expected significance of infrastructure effects, such as preference for rail or air accessibility, did not fully emerge. The sheer number of firm locations within the network likely overshadowed the potential impact of infrastructure. In other words, the widespread distribution of smaller firm locations in the financial and insurance sectors across Germany may have masked the preference of regional and global headquarters for air accessibility.

These findings also highlight the operational structure of such service-oriented firms: their locations prioritize proximity to customers, whether in smaller, rural parts of Germany or the largest FUAs. Only when focusing on these firms' management and executive levels can the hypothesized trends become apparent, yet both parts are essential in the organizational structure of a firm. In short, all locations are important in the knowledge creation process. Nonetheless, the ERGMs applied here produced meaningful results, supporting literature on where knowledge-based firms choose to operate firm locations through firm network analysis (e.g., De Bok & Van Oort, 2011; Smętkowski et al., 2021; Zhao et al., 2017), while proving that the underlying knowledge base of a firm does play a role, which confirms the need to differentiate knowledge-intensive firms. Lastly, the results of this study could have been further enhanced if the underlying firm data collection process had been specifically adapted to suit the method better, for example, by only sampling headquarters locations or all locations that exceed a minimum size of employment, with the disadvantages mentioned above.

Nonetheless, the underlying conceptual framework has shown that firm locations are not static. Firms continuously adapt in response to changing circumstances: they may close, open, or relocate locations to better align with their strategic goals, including attracting a more suitable workforce. It is the knowledge worker who generates and exchanges knowledge, serving as a catalyst for innovation in knowledge-intensive firms. This dynamic nature of firm location highlights the importance of knowledge workers, which was explored in Chapters 5 and 6.

Chapter 5 approached the relationship between firm locations and changes in knowledge-intensive employment, utilizing data on employment dynamics. The chapter concludes that growth in knowledge-intensive employment follows overall employment growth, which is in line with existing literature on this relationship, such as Tervo (2009, 2016). However, it must be noted that the more detailed knowledge base approach did not yield significant results, hence why the 'aggregated' binary classification of APS & high-tech was used. The results extend the literature on agglomeration economies by spatializing the relationships using GIS maps. For example, Volgmann & Münter (2022) and Meijers & Burger (2017) argue that smaller cities, or in the context of this dissertation, FUAs, can 'borrow size,' i.e., urban features from a larger 'core' FUA. However, the analysis had several limitations. First, the timeframe from 1999 to 2019 was rather short for Granger causality tests, as noted by Juodis et al. (2021), who developed the method used in this study. Second, no causal relationships were identified despite some FUAs being large and characterized by significant knowledge-intensive employment, such as Munich, Frankfurt, or Berlin. Third, FUAs are not closed systems; firms and individuals within them interact with neighboring and other FUAs by relocating or commuting. The methodology used in this study does not account for such spatial interactions. Fourth, no Granger causal relationship was found between APS and high-tech employment. Lastly, the knowledge base approach, which could have provided a more nuanced understanding of these relationships, was not feasible here due to the lack of significant results in the first Granger test, necessitating the more aggregated approach of APS and high-tech.

Chapter 6 examined spatial dependencies by analyzing worker relocations, focusing on the question of which spatial patterns of knowledge worker relocations can be identified. For this study, the knowledge base approach was utilized once more. The underlying central hypothesis focused on the tendency of knowledge workers to relocate to the nearest, more populous FUA, especially from smaller to larger FUAs, and how the distance of these relocations increases when occurring between already densely populated FUAs.

This chapter thus positions itself at the intersection between studies of migration and those examining regional concentration, particularly by examining whether employment tends to be concentrated in the largest FUAs in Germany, as suggested by key literature (e.g., Balland et al., 2020; Florida, 2003; Storper, 2010). Concentration is approximated here by a large number of in-migrations of workers to certain FUAs over two points in time. The findings of this study indicated that the main factor driving the concentration in the largest FUAs appears to be employment in synthetic APS. Furthermore, the analysis revealed that relocations in analytical high-tech and symbolic APS occurred less frequently, which can be attributed to how knowledge is created and shared within firms.

However, several limitations should be acknowledged. First, conducting an origin-destination analysis to visualize relocations requires selecting two specific points in time, a process that proved to be challenging. The definition of these timeframes significantly influences the findings and introduces potential biases, e.g., COVID-19. Second, this study did not consider two critical groups of potential workers: graduates and those moving to Germany from other locations. Research on migration patterns highlights important trends in these groups. For instance, STEM graduates are often recruited directly from academic institutions (Ghosh & Grassi, 2020) and are generally more inclined to relocate as their qualifications increase to pursue better wages (Mitze & Javakhishvili-Larsen, 2020). Similarly, workers relocating from outside Germany tend to move to cities or regions they are already familiar with, e.g., through media, further contributing to the discussed concentration effects (Graves et al., 2020; Shirvani Dastgerdi & De Luca, 2019). Lastly, this study's spatial definition of FUAs is too broad to detect relocations occurring within the same FUA. This is a significant blind spot, as knowledge-intensive firms may draw a substantial portion of their workforce locally. Despite these challenges, the approach employed in this study offers notable advantages. It allows researchers to identify relocation patterns and visualize where workers are moving from and to, thereby providing a new layer of understanding of spatial relatedness. The findings refine the assumptions of existing literature on the concentration of knowledge-intensive work in urban areas, i.e., more populous FUAs (e.g., Storper, 2010), by examining worker relocations across knowledge bases. The OD analysis contributes to the literature by revealing distinct patterns: a simultaneous concentration of workers in certain knowledge bases, while other knowledge bases demonstrate a more decentralized concentration at smaller scales.

One of the key personal objectives of this dissertation was to establish comparability and gain cumulative insights across the analyses, which was achieved. The spatial scale and knowledge base approach used in this research, however, inevitably presents challenges and limitations that affect the scope and interpretation of the study results. While FUAs, as a spatial extent, have advantages, such as implying that knowledge transfer does not end at the borders of a city by overcoming administrative borders and focusing on the commuting patterns of workers (e.g., Graf & Henning, 2009), this spatial delineation has some limitations, especially when applying a multi-scalar perspective. For one, studying intra-FUA relocations of firms or employment is impossible. While this is not a problem when comparing FUAs on a global scale, e.g., the number of firms or employment in the FUA Munich with the FUA Berlin, the local scale cannot be studied. As concluded above, this makes it challenging to identify and interpret relocations of both firms and employment. Although the firm selection process was consistent for all firms and aimed to identify similar-sized multi-branch, multi-locational firms in different knowledge-intensive sectors, some firms were excluded. Thus, the longitudinal approach focused exclusively on the 30 largest firms in each sector at the time of data collection. While this focus is less problematic when it comes to capturing the actual largest firms, it may have inadvertently overlooked smaller, emerging, or fast-growing firms that already have a large number of locations in Germany. Logically, the focus on multi-branch, multi-locational firms inherently resulted in a dataset biased toward Germany's largest and, consequently, the most significant firms.

Lastly, this dissertation has also highlighted the limitations of the knowledge base approach, particularly its reliance on three predefined categories, which do not fully capture the complex dynamics of knowledge-intensive industries and employment. For one, firms in the knowledge economy increasingly need to hire workers with similar skills. Recently, Alekseeva et al. (2021) found that AI skills are in growing demand across industries, especially in IT, engineering, and management. Additionally, firms were offering a wage premium for positions requiring skills in artificial intelligence (AI). Interestingly, Dahlke et al. (2024) found that AI adoption among firms is influenced by geographical proximity to firms that produce AI knowledge, thus co-location, and the embeddedness within AI networks. These recent studies show that knowledge-intensive work is increasingly concentrated in places with an already strong knowledge economy.

8.2 Avenues for Future Research

Building on the findings of this dissertation, this concluding section outlines potential directions for future research, addressing both the limitations discussed earlier and the open questions that emerged across the studies. Particular attention is also given to the question introduced at the beginning: *Do jobs follow people, or do people follow jobs?* This chapter proposes approaches and consolidates pathways to examine this dynamic as thoroughly and effectively as possible. Before addressing these possibilities, however, an outlook on potential improvements to the applied methods, the data, and spatial delineations must first be provided.

While the firm selection process does not present inherent drawbacks, some areas could be refined in future research. Two aspects stand out: (1) the focus on large firms and the rather pragmatic firm location and firm network approach. A major issue is the somewhat arbitrary yet pragmatic cutoff value, which limits the analysis to the top 30 multi-branch, multi-locational firms. As outlined in Chapter 3, this dissertation builds upon a previous DFG-funded research project from 2009 that focused on the locations of knowledge-intensive firms (refer to Lüthi, 2011). Thus, to ensure comparability to the research and the data used there, a similar dataset of firms was created for the DFG and SNF-funded project in which this dissertation is situated. Regardless of that, newer data collection techniques in the field of data mining and big data analysis may allow for the collection of more than the top 30 firms in each sub-sector, thus, a more complete picture of the knowledge economy. (2) It should also not be forgotten that the data collection was subject to a relational approach, meaning that each firm was collected in relation to its entire network of firm locations. This presents a unique and uncommon approach and thus dataset, as other research in this field has typically focused on either 'the number of firms in a region' or one specific set of firms in a selected number of regions. This dissertation does not challenge such research or the importance of a single network. Instead, it offers methods to study firm location choices in relation to other firm locations. Building such a dataset was time-consuming and imposed challenges and constraints on the analysis. For example, assessing and weighing the relative importance of a firm location is extremely complex, i.e., which location is considered 'more valuable' in the process of knowledge creation. Therefore, as of the time of writing, a manual assessment of weighting firm locations is still required.

Future research could be carried out with a finer spatial delineation than the FUAs to enable a deeper, more detailed analysis. While this limitation was initially imposed to facilitate cumulative findings across all studies and to enhance the efficiency of visual interpretations due to its high level of aggregation, it also represents a ‘regional view.’ Such studies should aim to loosen this constraint for a more nuanced analysis at a more local level, i.e., local administrative borders. To reiterate, the relocation behavior of knowledge workers in the analytical high-tech or symbolic APS knowledge base could also have happened within the FUA, such as at the city level. However, due to the aforementioned comparability of results and data protection issues, the level of FUA was retained.

The knowledge base approach is a method of grouping firms with a similar approach to knowledge generation (Asheim & Coenen, 2005; Asheim & Gertler, 2006). However, both the authors (Asheim & Coenen, 2005, p. 1176) and the studies in this dissertation have shown that the applied differentiation of different knowledge-intensive sectors has its limits. For example, firms increasingly search for workers with similar skills, i.e., in mathematics, statistics, or computer science. This shapes where firms locate and what workers they attract. Thus, future research could apply a bottom-up approach and study how sectoral and functional changes shape the knowledge-creation process (Bassens et al., 2024). One example is proposed by van Meeteren et al. (2022, p. 4), and later Trincado-Munoz et al. (2023, p. 4), who group firms by using industrial tags, i.e., hashtags, for each firm. For the sake of completeness, it should be mentioned that these tags were probably assigned subjectively and can become problematic over time, especially in a time series analysis.

Nevertheless, such approaches can extend the common classification of firms to knowledge-intensive subsectors. A more sophisticated classification and definition of knowledge workers would also yield interesting results in future research. Alekseeva et al. (2021), for example, studied the diffusion of skills related to AI in industries. Developing a similar approach could lead to a new, potentially evolutionary understanding of knowledge workers. This, in turn, could help answer critical questions such as: Which skills are needed in which industries and at what point in time? Such insights could then be matched with official employment data provided by the IAB to spatialize the data, i.e., visualize them on maps.

8.3 Reconsidering the Question of Causality

All these avenues for future research boil down to one question: How can the causal relationship, ‘Do jobs follow people or do people follow jobs?’ be effectively addressed? Rather than concluding with a single answer, a few consolidated pathways could provide meaningful insights. As this dissertation has shown, the relationship between jobs (i.e., firms) and people (i.e., workers) is not solely determined by firm locations attracting workers or, conversely, knowledge workers attracting firms. Rather, it emerges from the complex interplay between firms and workers, job creation, industries, collaborations between firms, demand & need for certain skills at a certain time, and a variety of local, regional, and global factors, such as the connectivity to other cities and regions, both through knowledge and transportation networks, and the economic context. These path dependencies within a region have not only influenced where firms and workers are located today but they also shape the future dynamics of the firms and people who want to locate there. Therefore, one pathway to approach this question, in line with Bathelt & Glückler (2011, 2018), is from a relational perspective, which opens up two possible avenues for further research.

The first approach is a bottom-up, evolutionary approach that prioritizes capturing this interplay between firm locations and worker relocation at a more granular, local level. This approach would move beyond administrative, spatial delineations, possibly a self-defined local scale, to limit the factors mentioned above as locally as possible. A panel dataset of selected firms and their respective firm networks would need to be built. Rosenthal and Strange (2020, p. 43), for example, argued that one should even go so far as to examine the interaction between firms within a building, as their analyses had shown that employment density in tall commercial buildings increases significantly when two or more interdependent firms are located on similar floors, suggesting localized productivity spillovers that dissipate after a vertical distance of about three floors. This opens the way for new, microlocal research approaches and enables evolutionary interpretations, especially when viewed through the lens of time series analysis. To further understand the location decisions of firms, qualitative methods, such as interviews and surveys, must be conducted (Bathelt & Glückler, 2011). As mentioned in Subsection 5.3.2.2, the IAB has highly specific employment data starting in 1999, which would serve as a good starting point for analysis, at least in the German context. Thus, research within this framework could generate first results through case studies of firms, their employment in a selected number of regions, similar to Otto et al. (2025), who analyzed 401 NUTS regions in Germany, but placed particular focus on two case regions to generate deeper insights. The second approach is a more refined, top-down evolutionary method that would also rely on panel datasets of both firms and employment from a global perspective. This approach could incorporate machine learning techniques, similar to those used by Litmeyer & Hennemann (2024), for example, to model the decision-making process of both firms and workers regarding co-location. This approach could implement a variety of variables, such as spatial, industrial, and personal factors.

In addition, the question can be approached by examining the topic in the segments or 'layers' described above. Instead of focusing on the knowledge economy as a whole, a step-by-step analysis of its basic building blocks could provide more nuanced insights. For example, by putting a spotlight on certain regions (i.e., Bentlage et al., 2021) or industries (i.e., Roesler & Broekel, 2017), but then also comparing them with other regions or sectors. Ideally, one would harmonize both the global and local perspectives to create a holistic and relational understanding. Until then, the answer to this question lies in the approach future researchers choose to pursue and the direction of research they decide to take.

Finally, a brief review of the future of globalized firm networks is in order at this point. According to recent research, events such as geopolitical turmoil, developments towards de-globalization, and the COVID-19 crisis, which have intensified the interplay between centralized, synchronous work and decentralized, asynchronous remote work, will have a significant impact on firms' locations, their strategies, and choices in the future (Bassens et al., 2024; van Meeteren et al., 2022; Yeung, 2024). In this context, research has focused on workers' location decisions triggered by COVID-19, particularly in terms of how the increase in remote working might affect residential location preferences and the potential for relocation away from urban centers (e.g., Moser et al., 2022). This shift could impact housing markets and commuting patterns, aspects not considered in this dissertation. Another important aspect in this context is how the 'styles of work,' i.e., remote or hybrid work, affect firm location strategies and how firms can address the challenges of replacing physical proximity to enable the effective exchange of tacit knowledge in an increasingly digitalized world. Initial findings on start-ups suggest that geographic proximity is important, but virtual platforms and tools increasingly enable access to tacit knowledge from diverse, non-local sources. These platforms create digital ecosystems in which knowledge can be exchanged and enable collaboration across distances, potentially eliminating the need for physical proximity (i.e., Cuvero et al., 2023). While the definitive spatial effects on firm locations, their networks, but also their employment remains to be seen, it can be argued in line with Knoblauch & Löw (2024, p. 14) that these political and economic changes should instead be interpreted through the lens of refiguration, emphasizing the simultaneity between fragmented and territorialized spatial logics, rather than a linear transition from globalization to de-globalization.

Building on the foundations of this dissertation, in which a relational approach was applied to both firm locations and employment relocations, and utilizing the proposed methods, future research could enhance the understanding of how firm locations and employment are interconnected, providing deeper insights into how new knowledge is created spatially. Moreover, research could explore the evolving causal relationship between firm locations and employment over time, moving beyond a static analysis at a single point in time to capture the dynamic nature of these processes.

Afterword

When I joined the chair in late 2019 and was first introduced to the DFG-SNF funded research project, much of the world we now know was different. The research project initially had the goal to study the effects of the 2008 financial crisis and its aftereffects on the global distribution of both labor and firm locations. However, as we all know, that changed dramatically just a couple of months later when the COVID-19 pandemic, the lockdowns, and working from home started. Personal interaction was quickly replaced with Zoom & Teams meetings, local co-working was replaced with Miro boards. Obviously, I could have just focused on comparing firm and employment data from 2008 with 2018, but would this even matter in 2020 anymore? Research moves on, and especially with such profound cuts in not only economic relationships but foremost the freedom of movement, thus social interaction, research moves on fast. A new question rose: will the pandemic change forever how we, and firms, work? For example, my colleagues Johannes Moser, Fabian Wenner, and Alain Thierstein (2022) acted fast and focused on the effects of working from home, which was a success in municipalities and for regional planners alike.

Now, a couple of years later, in 2025, not much can be seen or felt that reminds us of the pandemic. Yes, the pandemic changed how firms use (and allow) remote working, and it can be clearly seen that employers trust workers to possibly work from anywhere, as long as the work gets done. But by no means to the extent that early research in 2020 was suggesting or proposing. Some firms have even completely rolled back their remote work agendas or significantly reduced them, forcing employees to return to the office again. Firms still prefer locations in fitting urban environments, possibly more than ever before. However, the world continues to evolve, and the global turmoil instigated by some countries may once again alter the economic landscape by raising the question: Is the global value chain and the exchange of knowledge at risk?

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Appendix

Knowledge-Intensive Sector	Firm Name
3rd and 4th party logistics	Amazon Logistik GmbH
3rd and 4th party logistics	ARWE Group
3rd and 4th party logistics	Bremer Lagerhaus-Gesellschaft AG
3rd and 4th party logistics	Condor Flugdienst GmbH
3rd and 4th party logistics	DACHSER Group SE & Co. KG
3rd and 4th party logistics	DB Cargo Aktiengesellschaft
3rd and 4th party logistics	Deutsche Lufthansa AG
3rd and 4th party logistics	Deutsche Post AG
3rd and 4th party logistics	DPD Deutschland GmbH
3rd and 4th party logistics	Duvenbeck Solution and Engineering GmbH
3rd and 4th party logistics	EUROGATE GmbH & Co. KGaA, KG
3rd and 4th party logistics	Fiege Logistik Stiftung & Co. KG
3rd and 4th party logistics	Geis Gruppe
3rd and 4th party logistics	General Logistics Systems Germany GmbH & Co. KG
3rd and 4th party logistics	Hamburg Südamerikanische Dampfschifffahrts-Gesellschaft KG
3rd and 4th party logistics	Hapag-Lloyd AG
3rd and 4th party logistics	HAVI Global Logistics GmbH
3rd and 4th party logistics	Hellmann Worldwide Logistics GmbH & Co. KG
3rd and 4th party logistics	Hermes Germany GmbH
3rd and 4th party logistics	Hoyer GmbH Internationale Fachspedition
3rd and 4th party logistics	Imperial Logistics International B.V. & Co. KG
3rd and 4th party logistics	Kühne & Nagel (AG & Co.) KG
3rd and 4th party logistics	Kühne & Nagel (AG & Co.) KG
3rd and 4th party logistics	Oldendorff GmbH & Co. KG
3rd and 4th party logistics	Rhenus SE & Co. KG
3rd and 4th party logistics	Rudolph Logistik Gruppe GmbH & Co. KG
3rd and 4th party logistics	Schenker AG
3rd and 4th party logistics	Schnellecke Group AG & Co. KG
3rd and 4th party logistics	STUTE Logistics (AG & Co.) KG
3rd and 4th party logistics	TNT Express GmbH
Accounting	ADS Allgemeine Deutsche Steuerberatungsgesellschaft mbH
Accounting	Baker Tilly AG Wirtschaftsprüfungsgesellschaft
Accounting	Baker Tilly GmbH & Co. KG Wirtschaftsprüfungsgesellschaft
Accounting	BANSBACH GMBH Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	BDO AG Wirtschaftsprüfungsgesellschaft
Accounting	Connex Steuer- und Wirtschaftsberatung GmbH Steuerberatungsgesellschaft
Accounting	Consilia GmbH Wirtschaftsprüfungsgesellschaft
Accounting	CURACON GmbH Wirtschaftsprüfungsgesellschaft
Accounting	DBB DATA Beratungs- und Betreuungsgesellschaft mbH Steuerberatungsgesellschaft
Accounting	ECOVIS AG Steuerberatungsgesellschaft
Accounting	ECOVIS BLB Steuerberatungsgesellschaft mbH

Knowledge-Intensive Sector	Firm Name
Accounting	Ernst & Young GmbH Wirtschaftsprüfungsgesellschaft
Accounting	ETL AG Steuerberatungsgesellschaft
Accounting	FALK GmbH & Co KG Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	FIDES Revision KG Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	FIDES Treuhand GmbH & Co. KG Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	KPMG AG Wirtschaftsprüfungsgesellschaft
Accounting	LBH-Steuerberatungsgesellschaft mbH
Accounting	Mazars GmbH & Co. KG Wirtschaftsprüfungsgesellschaft
Accounting	MÖHRLE HAPP LUTHER Partnerschaft mbB WIRTSCHAFTSPRÜFER STEUERBERATER RECHTSANWÄLTE
Accounting	NEXIA International
Accounting	PKF Fasselt Schlage Partnerschaft mbB Wirtschaftsprüfungsgesellschaft Rechtsanwälte
Accounting	PricewaterhouseCoopers GmbH Wirtschaftsprüfungsgesellschaft
Accounting	RWT Anwaltskanzlei GmbH Rechtsanwaltsgesellschaft
Accounting	RWT Dienstleistung und Beratung GmbH Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	Schmidt & Partner GmbH Steuerberatungsgesellschaft
Accounting	SHBB Steuerberatungsgesellschaft mbH
Accounting	Solidaris Revisions-GmbH Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	Sonntag & Partner Partnerschaftsgesellschaft mbB Wirtschaftsprüfer, Steuerberater, Rechtsanwälte
Accounting	Treuhand Hannover GmbH
Accounting	TREUKONTAX-Steuerberatungsgesellschaft mbH
Accounting	TRINAVIS GmbH & Co. KG Wirtschaftsprüfungsgesellschaft Steuerberatungsgesellschaft
Accounting	Warth & Klein Grant Thornton AG Wirtschaftsprüfungsgesellschaft
Accounting	WTS Group Aktiengesellschaft Steuerberatungsgesellschaft
Advertising and media	Aachener Verlagsgesellschaft
Advertising and media	Axel Springer SE
Advertising and media	Badische Neueste Nachrichten Badendruck GmbH
Advertising and media	Bavaria Film GmbH
Advertising and media	BBDO Group Germany GmbH
Advertising and media	Bertelsmann SE & Co. KGaA
Advertising and media	C. W. Busse GmbH
Advertising and media	Deutscher Sparkassen Verlag Gesellschaft mit beschränkter Haftung
Advertising and media	Deutscher Sparkassen Verlag GmbH
Advertising and media	DuMont Mediengruppe GmbH & Co. KG
Advertising and media	Ernst Klett AG
Advertising and media	Funke Mediengruppe GmbH & Co. KGaA
Advertising and media	Heinrich Bauer Verlag KG
Advertising and media	Hubert Burda Media Holding KG
Advertising and media	Kurier Verlag Lennestadt GmbH
Advertising and media	medien holding:nord gmbh
Advertising and media	Medien Union GmbH Ludwigshafen
Advertising and media	Nordkurier Mediengruppe GmbH & Co. KG
Advertising and media	ProSiebenSat.1 Media SE

Knowledge-Intensive Sector	Firm Name
Advertising and media	Ravensburger AG
Advertising and media	Rheinisch-Bergische Verlagsgesellschaft mbH
Advertising and media	Service Innovation Group GmbH
Advertising and media	Serviceplan Gruppe für innovative Kommunikation GmbH & Co. KG
Advertising and media	Sky Deutschland GmbH
Advertising and media	Springer Nature AG & Co. KGaA
Advertising and media	Ströer SE & Co. KGaA
Advertising and media	Süddeutscher Verlag GmbH
Advertising and media	Südwestdeutsche Medien Holding GmbH
Advertising and media	Verlagsgesellschaft Madsack GmbH & Co. KG
Advertising and media	Verlagsgruppe Georg von Holtzbrinck GmbH
Advertising and media	Verlagsgruppe Passau GmbH
Automotive	Adam Opel GmbH
Automotive	AGCO Holding GmbH
Automotive	Airbus Operations GmbH
Automotive	Bayerische Motoren Werke AG
Automotive	Bombardier Transportation GmbH
Automotive	Borgers SE & Co. KGaA
Automotive	BorgWarner Europe GmbH
Automotive	BOS GmbH & Co. KG
Automotive	Brose Fahrzeugteile GmbH & Co. KG
Automotive	Daimler AG
Automotive	DB Fahrzeuginstandhaltung GmbH
Automotive	Dura Automotive Holding GmbH & Co. KG
Automotive	Eberspächer Gruppe GmbH & Co. KG
Automotive	Eissmann Automotive Deutschland GmbH
Automotive	ElringKlinger AG
Automotive	EvoBus GmbH
Automotive	Faurecia Automotive GmbH
Automotive	Ford-Werke GmbH
Automotive	GRAMMER AG
Automotive	Hella KGaA Hueck & Co.
Automotive	Huf Hülsbeck & Fürst GmbH & Co. KG
Automotive	Joyson Safety Systems
Automotive	Kirchhoff Automotive
Automotive	Kromberg & Schubert GmbH & Co. KG Kabel-Automobiltechnik
Automotive	MAHLE GmbH
Automotive	MAN Truck & Bus AG
Automotive	NOVEM Beteiligungs GmbH
Automotive	Robert Bosch GmbH
Automotive	VOLKSWAGEN AG
Automotive	Webasto SE
Banking and Finance	Aareal Bank AG
Banking and Finance	BayernLB

Knowledge-Intensive Sector	Firm Name
Banking and Finance	Berliner Volksbank
Banking and Finance	Commerzbank AG
Banking and Finance	DekaBank Deutsche Girozentrale
Banking and Finance	Deutsche Apotheker- und Ärztebank eG
Banking and Finance	Deutsche Bank AG
Banking and Finance	Deutsche Börse AG
Banking and Finance	Deutsche Kreditbank AG
Banking and Finance	Deutsche Postbank AG
Banking and Finance	Deutsche Sparkassen Leasing AG & Co. KG
Banking and Finance	DZ Bank AG Deutsche Zentral-Genossenschaftsbank
Banking and Finance	Hamburger Sparkasse AG
Banking and Finance	HSBC
Banking and Finance	HSH Nordbank AG
Banking and Finance	ING-DiBa AG
Banking and Finance	Kreissparkasse Köln
Banking and Finance	Landesbank Baden-Württemberg
Banking and Finance	Landesbank Hessen-Thüringen
Banking and Finance	NordLB
Banking and Finance	Oldenburgische Landesbank AG
Banking and Finance	Santander Consumer Bank AG
Banking and Finance	Sberbank Europe AG
Banking and Finance	Sparkasse KölnBonn
Banking and Finance	Sparkasse Nürnberg
Banking and Finance	State Street Bank International GmbH
Banking and Finance	Targobank AG & Co. KGaA
Banking and Finance	UniCredit Bank AG
Banking and Finance	Union Investment Privatfonds GmbH
Banking and Finance	Wüstenrot Bausparkasse AG
Chemical & pharmaceutical	Aenova Group
Chemical & pharmaceutical	ALTANA AG
Chemical & pharmaceutical	BASF SE
Chemical & pharmaceutical	Bayer AG
Chemical & pharmaceutical	Berlin-Chemie AG
Chemical & pharmaceutical	Biotest AG
Chemical & pharmaceutical	Boehringer Ingelheim Pharma GmbH & Co. KG
Chemical & pharmaceutical	Continental AG
Chemical & pharmaceutical	Covestro AG
Chemical & pharmaceutical	CSL Behring AG
Chemical & pharmaceutical	Evonik Industries AG
Chemical & pharmaceutical	FUCHS PETROLUB SE
Chemical & pharmaceutical	Gelita AG
Chemical & pharmaceutical	Gerresheimer AG
Chemical & pharmaceutical	Grünenthal Pharma GmbH & Co. Kommanditgesellschaft
Chemical & pharmaceutical	Heinz-Glas GmbH & Co. KGaA

Knowledge-Intensive Sector	Firm Name
Chemical & pharmaceutical	Henkel AG & Co. KGaA
Chemical & pharmaceutical	Hutchinson GmbH
Chemical & pharmaceutical	LANXESS Deutschland GmbH
Chemical & pharmaceutical	MERCK KGaA
Chemical & pharmaceutical	Merz Pharma GmbH & Co. KGaA
Chemical & pharmaceutical	Messer Group
Chemical & pharmaceutical	MICHELIN Reifenwerke AG & Co. KGaA
Chemical & pharmaceutical	Procter & Gamble Manufacturing GmbH
Chemical & pharmaceutical	Roche Diagnostics GmbH
Chemical & pharmaceutical	Sanofi-Aventis Deutschland GmbH
Chemical & pharmaceutical	SCHOTT AG
Chemical & pharmaceutical	STADA Arzneimittel AG
Chemical & pharmaceutical	Stahlgruber Otto Gruber AG
Chemical & pharmaceutical	Wacker Chemie AG
Computer hardware	ads-tec GmbH
Computer hardware	ADTRAN GmbH
Computer hardware	Avaya GmbH & Co. KG
Computer hardware	BDT Media Automation GmbH
Computer hardware	Beckhoff Automation GmbH & Co. KG
Computer hardware	BÖWE SYSTEC GmbH
Computer hardware	Cherry GmbH
Computer hardware	COMPAREX AG
Computer hardware	Dell GmbH
Computer hardware	Diebold Nixdorf AG
Computer hardware	Fujitsu Technology Solutions GmbH
Computer hardware	HESS Cash Systems GmbH & Co. KG
Computer hardware	HP Deutschland GmbH
Computer hardware	IBM Deutschland GmbH
Computer hardware	IDEMIA Germany GmbH
Computer hardware	IDS Imaging Development Systems GmbH
Computer hardware	in-tech GmbH
Computer hardware	Interflex Datensysteme GmbH
Computer hardware	Kontron AG
Computer hardware	MCQ TECH GmbH
Computer hardware	Océ Printing Systems GmbH & Co. KG
Computer hardware	Primion Technology AG
Computer hardware	REWE Systems GmbH
Computer hardware	Ricoh Deutschland GmbH
Computer hardware	SLM Solutions Group AG
Computer hardware	SPIE Fleischhauer GmbH
Computer hardware	Swiss Post Solutions GmbH
Computer hardware	TA Triumph-Adler GmbH
Design, architecture, and media engineering	AGROLAB GmbH
Design, architecture, and media engineering	AKKA Technologies Group

Knowledge-Intensive Sector	Firm Name
Design, architecture, and media engineering	Altran Group
Design, architecture, and media engineering	Bertrandt AG
Design, architecture, and media engineering	Bilfinger SE
Design, architecture, and media engineering	Brunel GmbH
Design, architecture, and media engineering	Centrotec Sustainable AG
Design, architecture, and media engineering	Dorsch Gruppe
Design, architecture, and media engineering	Drees & Sommer SE
Design, architecture, and media engineering	EDAG Engineering GmbH
Design, architecture, and media engineering	ESG Elektroniksystem- und Logistik-GmbH
Design, architecture, and media engineering	Euro engineering AG
Design, architecture, and media engineering	FERCHAU Engineering GmbH
Design, architecture, and media engineering	Fichtner GmbH & Co. KG
Design, architecture, and media engineering	Formel D GmbH
Design, architecture, and media engineering	Framatome GmbH
Design, architecture, and media engineering	HOCHTIEF AG
Design, architecture, and media engineering	IAV GmbH Ingenieurgesellschaft Auto und Verkehr
Design, architecture, and media engineering	Mitsubishi Hitachi Power Systems Europe GmbH
Design, architecture, and media engineering	Müller-BBM GmbH
Design, architecture, and media engineering	OHB SE
Design, architecture, and media engineering	P3 group GmbH
Design, architecture, and media engineering	R+S Group AG
Design, architecture, and media engineering	RLE International Produktentwicklungsgesellschaft mbH
Design, architecture, and media engineering	Rud. Otto Meyer Technik Ltd. & Co. KG
Design, architecture, and media engineering	Scholpp Holding GmbH
Design, architecture, and media engineering	SGS Germany GmbH
Design, architecture, and media engineering	Sonic Healthcare
Design, architecture, and media engineering	SPIE SAG Group GmbH
Design, architecture, and media engineering	WESSLING GmbH
Electronics	ABB Ltd
Electronics	Diehl Stiftung & Co. KG
Electronics	Dr. Johannes Heidenhain GmbH
Electronics	E.G.O. Blanc und Fischer & Co. GmbH
Electronics	Endress + Hauser
Electronics	Enercon GmbH
Electronics	FESTO Beteiligungen GmbH & Co KG
Electronics	Friedhelm Loh Group
Electronics	Fritz Dräxlmaier GmbH & Co. KG
Electronics	GEA Group AG
Electronics	Hager Group
Electronics	ifm electronic
Electronics	Infineon Technologies AG
Electronics	ista group
Electronics	KION Group
Electronics	Lear Corporation GmbH

Knowledge-Intensive Sector	Firm Name
Electronics	LEONI AG
Electronics	Leopold Kostal GmbH & Co. KG
Electronics	Lindner Group KG
Electronics	Nordex SE
Electronics	Osram Licht AG
Electronics	Pepperl + Fuchs GmbH
Electronics	Phoenix Contact GmbH & Co. KG
Electronics	Rittal GmbH & Co. KG.
Electronics	SEW-EURODRIVE GmbH & Co. KG
Electronics	SICK AG
Electronics	Siemens AG
Electronics	TDK Electronics
Electronics	TRILUX GmbH & Co. KG
Electronics	Zollner Elektronik AG
Information and communication services	1&1 Versatel GmbH
Information and communication services	All for One Steeb AG
Information and communication services	Atos IT Solutions and Services GmbH
Information and communication services	Bechtle AG
Information and communication services	BITMARCK Holding GmbH
Information and communication services	Computacenter AG & Co. oHG
Information and communication services	CTDI GmbH
Information and communication services	DATAGROUP SE
Information and communication services	DATEV
Information and communication services	DAVASO GmbH
Information and communication services	DB Systel GmbH
Information and communication services	Deutsche Telekom AG
Information and communication services	Fiducia & GAD IT AG
Information and communication services	Finanz Informatik GmbH & Co. KG
Information and communication services	freenet AG
Information and communication services	Google Germany GmbH
Information and communication services	Hönigsberg & Düvel Datentechnik GmbH
Information and communication services	Lufthansa Systems GmbH & Co. KG
Information and communication services	Microsoft Deutschland GmbH
Information and communication services	ORACLE Deutschland B.V. & Co. KG
Information and communication services	PSI Software AG
Information and communication services	QSC AG
Information and communication services	Ratiodata GmbH
Information and communication services	SAP SE
Information and communication services	Software AG
Information and communication services	Teleperformance Germany S.à r.l. & Co. KG
Information and communication services	Tintschl AG
Information and communication services	United Internet AG
Information and communication services	Unitymedia GmbH
Information and communication services	Vodafone GmbH

Knowledge-Intensive Sector	Firm Name
Insurance	Allianz SE
Insurance	Alte Leipziger Lebensversicherung aG
Insurance	ARAG SE
Insurance	AXA Konzern AG
Insurance	Barmenia Krankenversicherung aG
Insurance	Basler Versicherung AG
Insurance	Concordia AG
Insurance	Continentale Krankenversicherung aG
Insurance	DAK - Gesundheit
Insurance	Debeka Lebensversicherungsverein aG
Insurance	Deutsche Rentenversicherung Knappschaft-Bahn-See
Insurance	Deutsche Rentenversicherung Westfalen
Insurance	DEVK Deutsche Eisenbahn Versicherung Sach- und HUK-Versicherungsverein aG Betriebliche Sozialeinrichtung der Deutschen Bahn
Insurance	ERGO Group AG
Insurance	Generali Versicherung AG
Insurance	Gothaer Versicherungsbank VVaG
Insurance	Hannover Rück SE
Insurance	HDI Haftpflichtverband der Deutschen Industrie VVaG
Insurance	HUK-COBURG Haftpflicht-Unterstützungs-Kasse kraftfahrender Beamter Deutschlands a.G.
Insurance	IDUNA Vereinigte Lebensversicherung aG für Handwerk, Handel und Gewerbe
Insurance	IDUNA Vereinigte Lebensversicherung aG für Handwerk, Handel und Gewerbe (Aignal Iduna)
Insurance	INTER Versicherungsverein aG
Insurance	Landschaftliche Brandkasse Hannover
Insurance	Landschaftliche Brandkasse Hannover (VGH)
Insurance	LVM Landwirtschaftlicher Versicherungsverein Münster aG
Insurance	Münchener Rückversicherungs-Gesellschaft AG
Insurance	Nürnberger Lebensversicherung AG
Insurance	R+V Versicherung AG
Insurance	SV SparkassenVersicherung
Insurance	SV SparkassenVersicherung Holding AG
Insurance	Techniker Krankenkasse
Insurance	VHV Vereinigte Hannoversche Versicherung aG
Insurance	WWK Lebensversicherung aG
Law	Allen & Overy
Law	Baker & McKenzie
Law	Becker Büttner Held
Law	Beiten Burkhardt
Law	BOEHMERT & BOEHMERT
Law	Brinkmann & Partner
Law	Clifford Chance
Law	CMS Hasche Sigle
Law	DGB Rechtsschutz GmbH
Law	DLA Pieper

Knowledge-Intensive Sector	Firm Name
Law	Flick Gocke Schaumburg
Law	Freshfields Bruckhaus Deringer
Law	Gleiss Lutz
Law	Görg
Law	Hengeler Mueller
Law	Heuking Kühn Lüer Wojtek
Law	Hogan Lovells
Law	Kapellmann und Partner
Law	Kübler, Danko, Breitenbücher, Laboga
Law	Latham & Watkins
Law	Linklaters
Law	Luther
Law	Noerr
Law	P+P Pöllath + Partners
Law	Pluta
Law	Rödl & Partner
Law	SKW
Law	Taylor Wessing
Law	White & Case
Law	Wilmer Cutler Pickering Hale and Dorr LLP
Management and IT consulting	Aareon AG
Management and IT consulting	Accenture GmbH
Management and IT consulting	adesso AG
Management and IT consulting	Batten & Company GmbH
Management and IT consulting	BearingPoint GmbH
Management and IT consulting	CANCOM SE
Management and IT consulting	Capgemini Deutschland GmbH
Management and IT consulting	CGI Deutschland Ltd. & Co. KG
Management and IT consulting	COMPAREX AG
Management and IT consulting	CompuGroup Medical SE
Management and IT consulting	Deloitte Consulting GmbH
Management and IT consulting	Droege Group AG
Management and IT consulting	Elektrobit Automotive GmbH
Management and IT consulting	GfK SE
Management and IT consulting	GFT Technologies SE
Management and IT consulting	Itelligence AG
Management and IT consulting	Materna GmbH Information & Communications
Management and IT consulting	McKinsey & Company Inc.
Management and IT consulting	MHP Management- und IT-Beratung GmbH
Management and IT consulting	msg group GmbH
Management and IT consulting	msg systems AG
Management and IT consulting	Nemetschek SE
Management and IT consulting	NTT Data Deutschland GmbH
Management and IT consulting	Roland Berger GmbH

Knowledge-Intensive Sector	Firm Name
Management and IT consulting	SELLBYTEL Group GmbH
Management and IT consulting	SNP Schneider-Neureither & Partner SE
Management and IT consulting	Sopra Steria GmbH
Management and IT consulting	SQS Software Quality Systems AG
Management and IT consulting	Tata Consultancy Services Deutschland GmbH
Management and IT consulting	The Boston Consulting Group GmbH & Co. KG
Management and IT consulting	Vector Informatik GmbH
Mechanical engineering	Alfred Kärcher GmbH & Co. KG
Mechanical engineering	Claas KGaA mbH
Mechanical engineering	DMG MORI AG
Mechanical engineering	Dürr AG
Mechanical engineering	Georgsmarienhütte Holding GmbH
Mechanical engineering	Grohe AG
Mechanical engineering	Groz-Beckert KG
Mechanical engineering	Heidelberger Druckmaschinen AG
Mechanical engineering	Hörbiger Automotive Komfortsysteme GmbH
Mechanical engineering	Ideal Standard Produktions-GmbH
Mechanical engineering	John Deere GmbH & Co. KG
Mechanical engineering	Knorr-Bremse AG
Mechanical engineering	Koenig & Bauer AG
Mechanical engineering	KRONES AG
Mechanical engineering	KSB SE & Co KGaA
Mechanical engineering	KUKA AG
Mechanical engineering	Luftschiffbau Zeppelin GmbH
Mechanical engineering	MAN Energy Solutions SE
Mechanical engineering	Mann + Hummel International GmbH
Mechanical engineering	MTU Aero Engines AG
Mechanical engineering	Rheinmetall AG
Mechanical engineering	Rolls-Royce plc
Mechanical engineering	Salzgitter AG
Mechanical engineering	Sartorius AG
Mechanical engineering	Schaeffler AG
Mechanical engineering	ThyssenKrupp AG
Mechanical engineering	TRUMPF GmbH + Co. KG
Mechanical engineering	Voith GmbH & Co. KGaA
Mechanical engineering	WILO SE
Mechanical engineering	ZF Friedrichshafen AG
Medical & optical instruments	B. Braun Melsungen AG
Medical & optical instruments	Bauerfeind AG
Medical & optical instruments	Baxter International Inc.
Medical & optical instruments	Beurer GmbH
Medical & optical instruments	BIOTRONIK SE & Co. KG
Medical & optical instruments	Brainlab AG
Medical & optical instruments	Carl Zeiss AG

Knowledge-Intensive Sector	Firm Name
Medical & optical instruments	Dentsply Sirona
Medical & optical instruments	Dr. Schumacher GmbH
Medical & optical instruments	Drägerwerk AG & Co. KGaA
Medical & optical instruments	Dürr Dental AG
Medical & optical instruments	Fresenius SE & Co. KGaA
Medical & optical instruments	Gebr. Brasseler GmbH & Co. KG
Medical & optical instruments	Hama Hamaphot Hanke & Thomas GmbH & Co. KG
Medical & optical instruments	IPG Photonics Corporation
Medical & optical instruments	JENOPTIK AG
Medical & optical instruments	Joh. Stiegelmeyer & Co. GmbH
Medical & optical instruments	Karl Storz GmbH & Co. KG
Medical & optical instruments	KaVo Dental GmbH
Medical & optical instruments	Lohmann & Rauscher
Medical & optical instruments	Löwenstein Medical GmbH & Co.KG
Medical & optical instruments	MDH AG Mamisch Dental Health
Medical & optical instruments	MMM Münchener Medizin Mechanik GmbH
Medical & optical instruments	Ottobock SE & Co. KGaA
Medical & optical instruments	Paul Hartmann AG
Medical & optical instruments	Qioptiq Photonics GmbH & Co. KG
Medical & optical instruments	Richard Wolf GmbH
Medical & optical instruments	Rodenstock GmbH
Medical & optical instruments	Sarstedt AG & Co. KG
Medical & optical instruments	Vetter Pharma-Fertigung GmbH & Co. KG
Telecommunications	albis-elcon system Germany GmbH
Telecommunications	Axians GA Netztechnik GmbH
Telecommunications	Beyerdynamic GmbH & Co.
Telecommunications	d & b audiotechnik GmbH
Telecommunications	DFMG Deutsche Funkturm GmbH
Telecommunications	Ericsson GmbH
Telecommunications	FUBA Automotive Electronics GmbH
Telecommunications	Funkwerk AG
Telecommunications	GFTD-mbH Gesellschaft für Telekommunikation Deutschland
Telecommunications	Gigaset AG
Telecommunications	GSP Sprachtechnologie GmbH
Telecommunications	Hirschmann Car Communication GmbH
Telecommunications	KEYMILE GmbH
Telecommunications	Lautsprecher Teufel GmbH
Telecommunications	LogMeIn Germany GmbH
Telecommunications	Medion AG
Telecommunications	Motorola Solutions Germany GmbH
Telecommunications	Nokia Solutions and Networks GmbH & Co. KG
Telecommunications	Omexom Hochspannung GmbH
Telecommunications	Preh Car Connect GmbH
Telecommunications	Riedel Communications GmbH & Co. KG

Knowledge-Intensive Sector	Firm Name
Telecommunications	Rohde & Schwarz GmbH & Co. KG
Telecommunications	S.Siedle & Söhne Telefon- und Telegrafenwerke OHG
Telecommunications	Sennheiser electronic GmbH & Co. KG
Telecommunications	Tech Mahindra GmbH
Telecommunications	TechniSat Digital GmbH
Telecommunications	Telefonbau Arthur Schwabe GmbH & Co. Kommanditgesellschaft
Telecommunications	Thales Deutschland GmbH
Telecommunications	Verizon Deutschland GmbH
Telecommunications	Wagner Group GmbH
Telecommunications	WISI Communications GmbH & Co. KG und WISI Automotive GmbH & Co KG