

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.

Keywords: Location pattern ■ employment relocation ■ employment growth ■ origin-destination analysis ■ knowledge economy ■ Germany

Wo leben Beschäftigte der Wissensökonomie in Deutschland? Eine Fallstudie mit Daten zur Arbeitsmigration in der deutschen Wissensökonomie von 2012 bis 2021

Zusammenfassung

In Deutschland konzentriert sich die Beschäftigung in der Wissensökonomie zunehmend auf urbane Räume, vor allem durch dort angesiedelte Unternehmen, die um die qualifiziertesten und am besten geeigneten Arbeitskräfte konkurrieren. Dieser Beitrag befasst sich mit dem Umzugsverhalten von Wissensarbeiterinnen und Wissensarbeitern und wie sich Umzugsmuster auf unterschiedlichen räumlichen Ebenen unterscheiden. Mit einer innovativen Herkunft-Ziel-Analyse untersuchen wir arbeitsplatzbezogene Beschäftigtenumzüge zwischen 186 funktionalen urbanen Räumen in Deutschland im Zeitraum von 2012 bis 2021. Hierfür nutzen wir offizielle Beschäftigungsdaten von 480 Mehrbetriebsunternehmen, die einer von drei

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Wissensbasen zugeordnet werden: analytisch, synthetisch und symbolisch. Diese Klassifizierung hilft zu erklären, wie Unternehmen Wissen in ihren Innovationsprozessen erzeugen und nutzen, und ermöglicht uns, die Umzugsmuster der Beschäftigten zu differenzieren. Unsere Ergebnisse liefern eine detaillierte, multiskalare Perspektive auf die deutsche Wissensökonomie: Zwischen 2012 und 2021 hat sich die räumliche Verteilung wissensintensiver Beschäftigung stärker auf die größten funktionalen urbanen Räume wie München oder Berlin konzentriert. Allerdings unterscheiden sich die Umzugsmuster je nach Wissensbasis, weshalb wir die zugrunde liegende Dynamik dieser Konzentration aufdecken können. Arbeitskräfte in synthetischen Wissensbasen ziehen überwiegend in großem Maßstab in die größten Funktionsbereiche sowie zwischen diesen und dezentraleren funktionalen urbanen Räumen um. Dies deutet darauf hin, dass die räumliche Nähe bei arbeitsplatzbezogenen Umzügen möglicherweise eine untergeordnete Rolle spielt. Im Gegensatz dazu ziehen Beschäftigte in analytischen und symbolischen Wissensbasen seltener in andere funktionale urbane Räume. Sie ziehen stattdessen auf kleinräumigerer Ebene um, meist zwischen benachbarten oder räumlich näher gelegenen funktionalen urbanen Räumen.

Schlüsselwörter: Standortmuster ■ Arbeitsmigration ■ Beschäftigungszuwachs ■ Herkunfts-Ziel-Analyse ■ Wissensökonomie ■ Deutschland

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 (Niedomysl/Hansen 2010; Dorfman/Partridge/Galloway 2011; Tippel/Plöger/Becker 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/Neffke/O'Clery 2018). Therefore, a causal relationship exists between firm locations and the number of employees (e.g. Heidinger/Fuchs/Thierstein 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 (Zhao/Bentlage/Thierstein 2017; Heidinger/Fuchs/Thierstein 2024). For example, firms in industries classified as having a symbolic or synthetic knowledge base, such as consultancy or advertising, rely on face-to-face in-

teraction for effective knowledge creation and hence tend to be located in regions with a high concentration of workers who possess the necessary knowledge (Wood 2002; Bathelt/Malmberg/Maskell 2004). 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: 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/De Laurentis/Tödtling et al. 2007: 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.¹ 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 2, we introduce the conceptual background of the study by defining knowledge-intensive employment and discussing the 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.

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.

2.1 Knowledge-intensive firms

Research continuously explores where firms (co-)locate or cluster (Asheim/Gertler 2005; Storper 2011; Barlet/Briant/Crusson 2013; Duvivier/Cazou/Truchet-Aznar et al. 2021; Rozenblat 2021; Smętkowski/Celińska-Janowicz/Wojnar 2021). Over the last decades, driven by processes of deregulation and liberalisation, multinational firms have emerged as key drivers of globalisation (Cooke/De Laurentis/Tödtling et al. 2007; Bathelt/Glückler 2011). 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/Balland/Burger et al. 2014; van Meeteren/Neal/Derudder 2016). Firms in the knowledge economy thus use knowledge sources to improve a product or service, effectively offering knowledge as a product (Cooke/De Laurentis/Tödtling 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 (2005) 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: 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/Hammer/McCann 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 (Roesler/Broekel 2017; Arant/Fornahl/Grashof et al. 2019). Additionally, firms depend on various location factors, such as accessibility to regional and global networks through a well-developed train system or airports (Andersson/Karlsson 2004; Heidinger/Wenner/Sager et al. 2023). 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

¹ cf. <https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Qualitaet-Arbeit/Dimension-4/dauer-beschaeftigung-aktuell-Arbeitgeber.html> (24.04.2025).

much-needed tacit knowledge (Parr 2004; Storper/Venables 2004; Boschma 2005).

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 (2005) 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 2005; 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/Boschma/Cooke 2011; de Bok/van Oort 2011; Harris/Moffat/Evenhuis 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/Boschma/Cooke 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/Gertler 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 2005). 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, Bentlage and Thierstein (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.

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; Mossig 2011; Heider/Siedentop 2020; Wagner/Growe 2023). As a result, firms must either relocate to regions with appropriate workers or open subsidiaries there (Storper/Scott 2009; Balland/Rigby 2017). 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/Klinger/Barabasi et al. 2007; Storper 2010; Stoyanov/Zubakov 2012; Serafinelli 2019). 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/Reshef/Toubal 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/Li/Shi 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 (Tippel/Plöger/Becker 2017; Carlino/Saiz 2019). 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 (Berry/Glaeser 2005; van Meeteren/Neal/Derudder 2016; Balland/Jara-Figueroa/Petralia et al. 2020).

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: 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.

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 avail-

able 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.

3 Data and methodology

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 2011). 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, Bentlage and Thierstein (2017). The complete list of subsectors and their corresponding knowledge bases are available upon request. We then used Dun & Bradstreet data² 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 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.

² Dun & Bradstreet is a business analytics database that provides various commercial information on firm locations such as size, age, and revenue.

Table 1 Summary statistics of job-related relocations

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

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/Ersoy/Telea 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 direc-

tionality. 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)³ 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, 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.⁴ 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/Derudder 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. Tab. 1 shows the summary

³ <https://www.bbsr.bund.de/BBSR/DE/forschung/raumb Beobachtung/Raumabgrenzungen/deutschland/regionen/siedlungsstrukturelle-regionstypen/regionstypen.html> (24.04.2025).

⁴ The only functional urban area that we assigned manually was the functional urban area Berlin, as it is monocentric.

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).

4 Findings

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 Fig. 1 and Fig. 2. In analytical high-tech, as shown in Fig. 1, 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 Fig. 2, 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.

4.2 Advanced Producer Services knowledge bases

Synthetic Advanced Producer Services are displayed in Fig. 3 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/Fleischman/Rebitzer 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

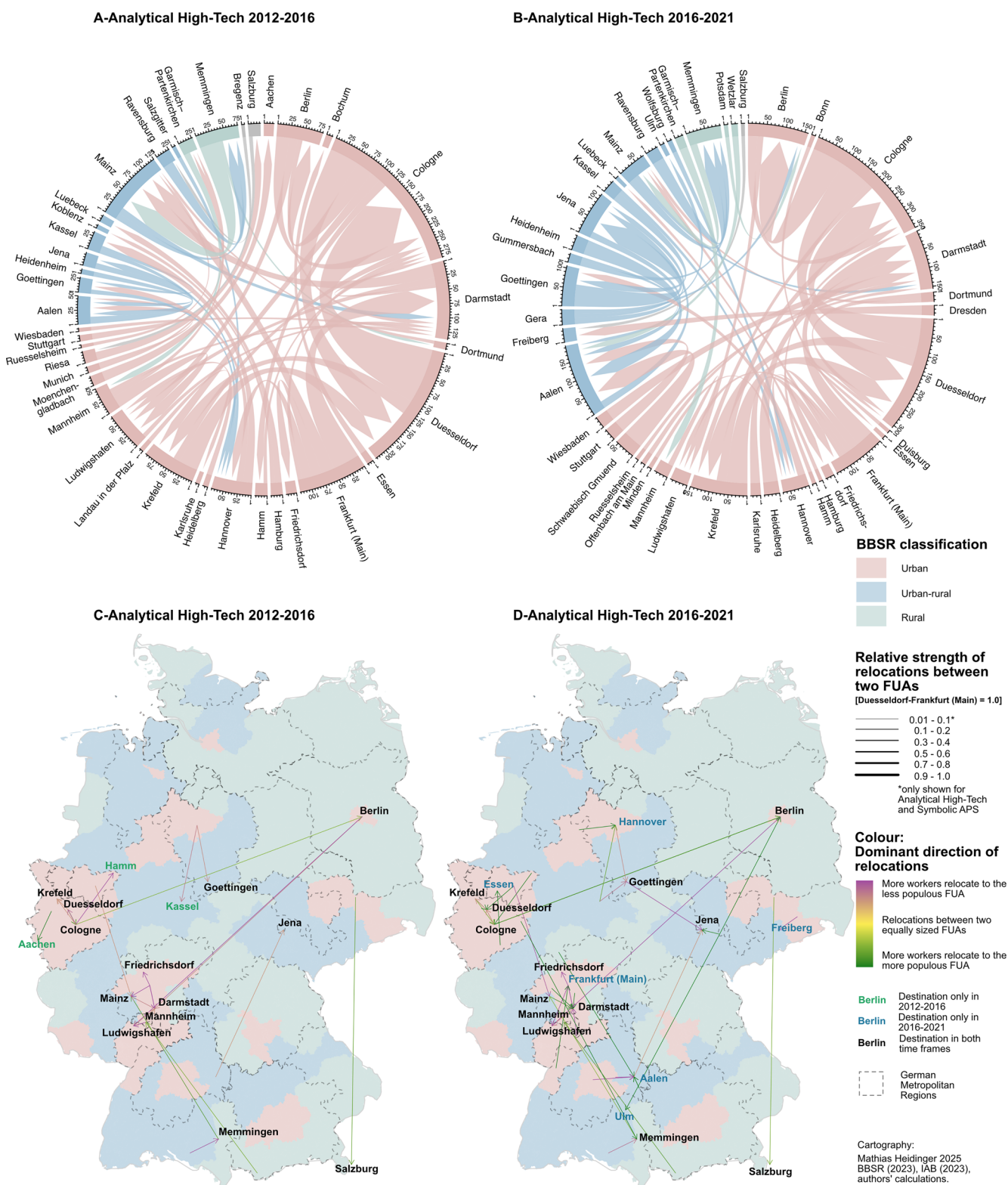


Fig. 1 Chord diagrams and maps illustrating job-related relocations for analytical high-tech across both time spans

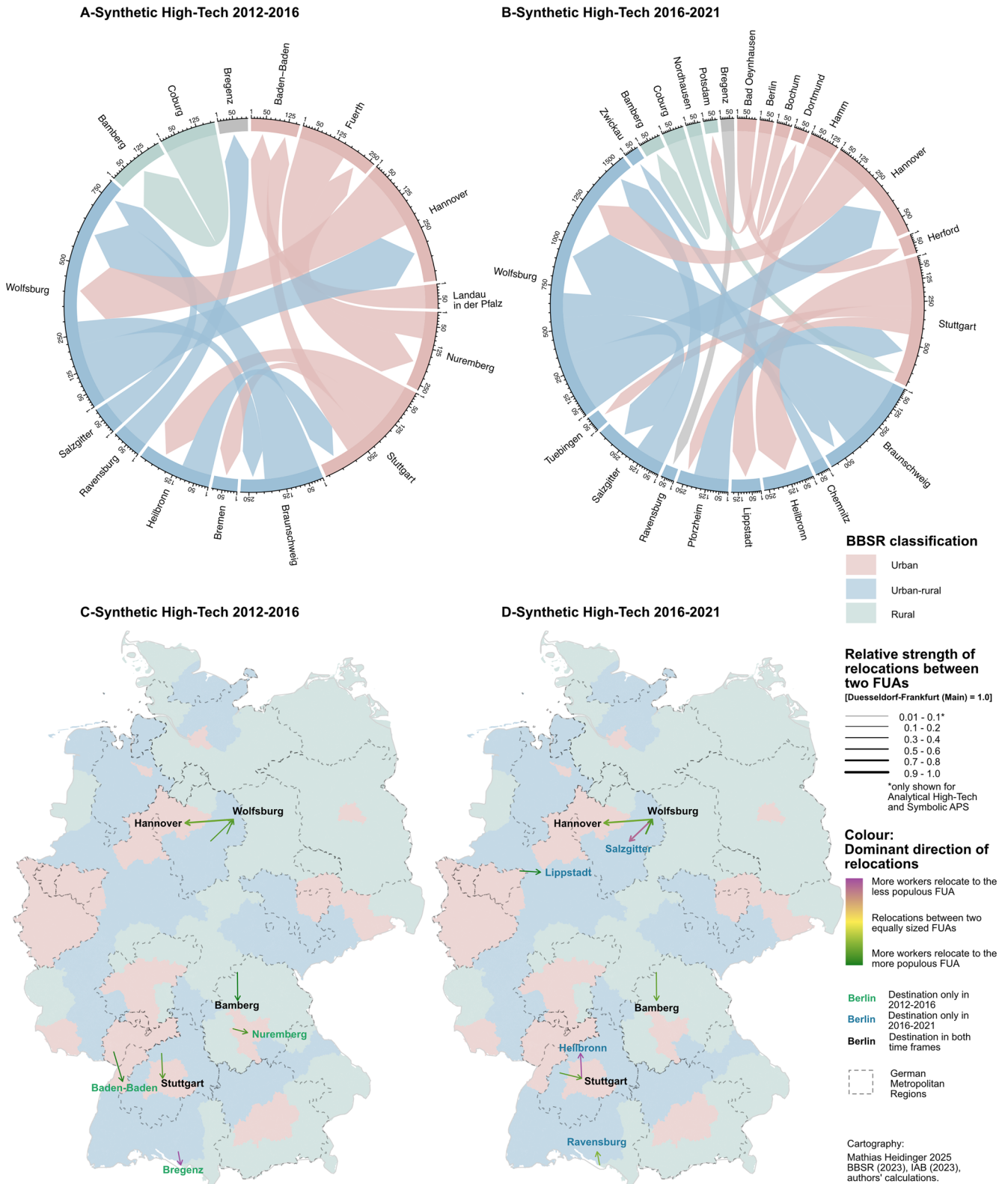


Fig. 2 Chord diagrams and maps illustrating job-related relocations for synthetic high-tech across both time spans

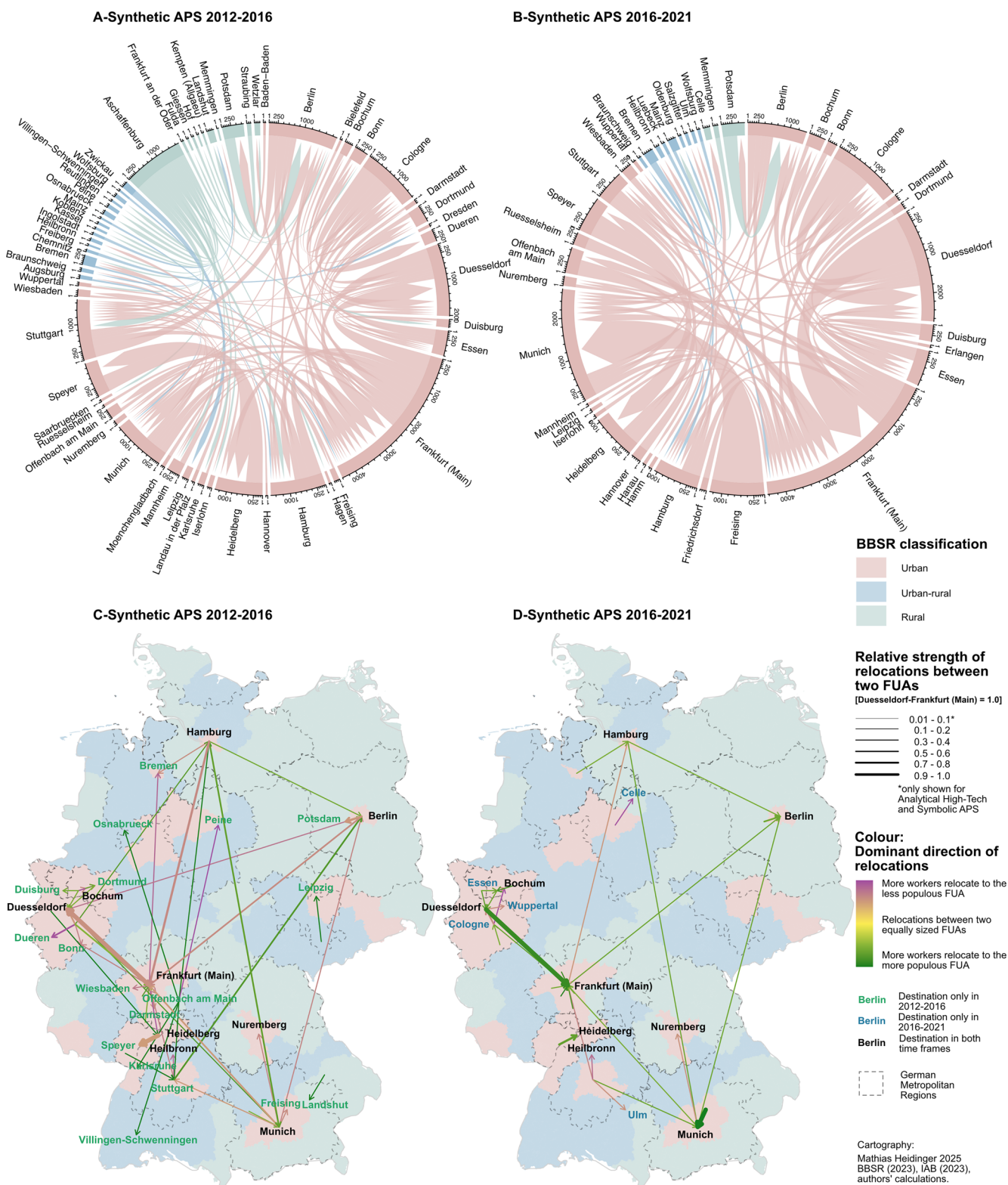


Fig. 3 Chord diagrams and maps illustrating job-related relocations for synthetic Advanced Producer Services across both time spans

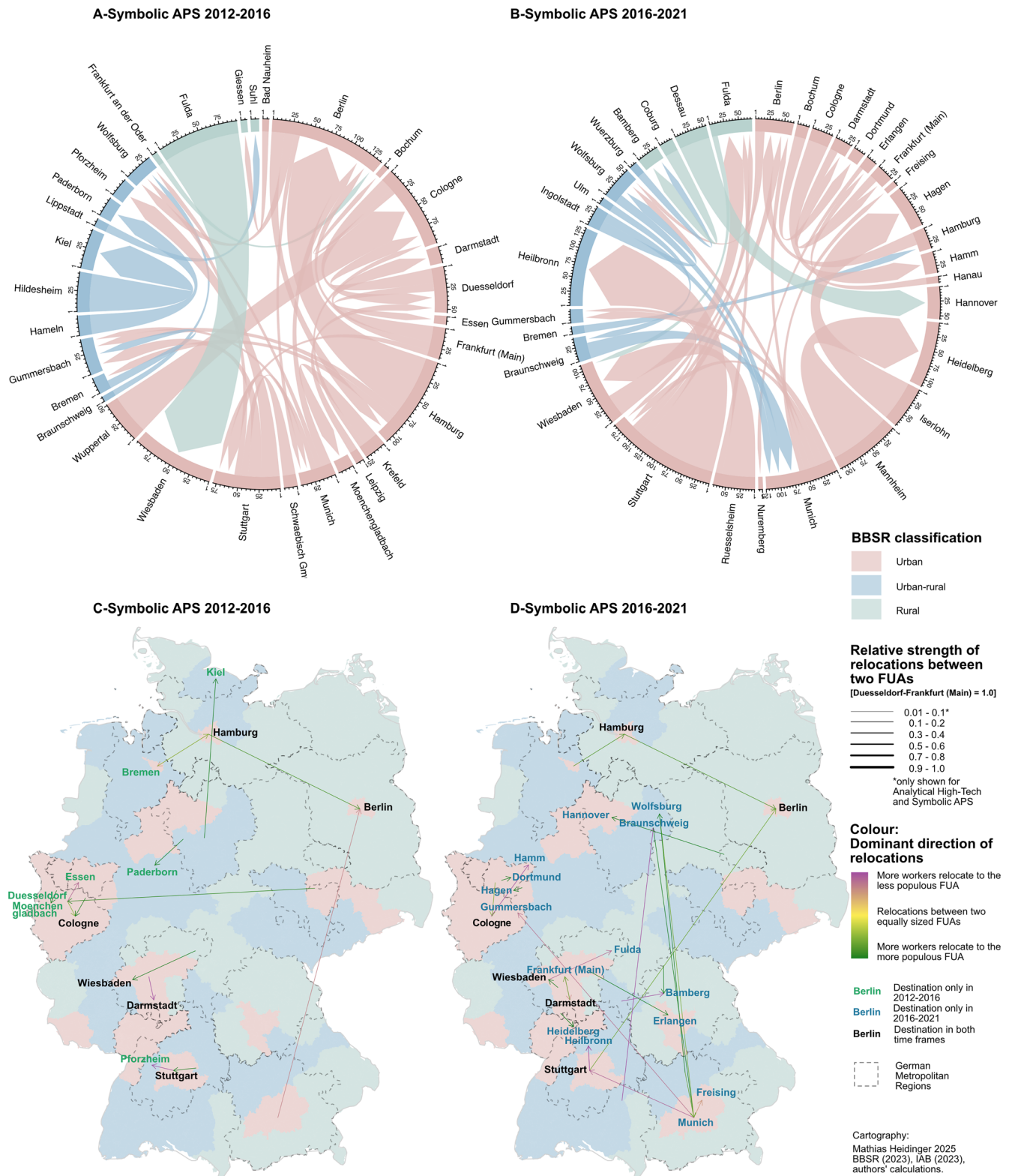


Fig. 4 Chord diagrams and maps illustrating job-related relocations for symbolic Advanced Producer Services across both time spans

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 Fig. 2, 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 Fig. 4. 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.

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/Boschma/Cooke 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/Boschma/Cooke 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 exter-

nal 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 interconnectiveness 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/Derudder et al. 2016) or complement each other's capabilities (Baland/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 Dueseldorf 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/Klinger/Barabasi 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 Figs 1 and 2). 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 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 2005). 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/Jara-Figueroa/Petralia 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/

Bentlage/Thierstein 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 2011), 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/Hendrikse/Lai 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/Trincado-Munoz/Rubin 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 (Trincado-Munoz/van Meeteren/Rubin et al. 2023; Bassens/Hendrikse/Lai et al. 2024). 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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References

- Alcacer, J.; Zhao, M. (2010): Local R&D Strategies and Multi-Location Firms: The Role of Internal Linkages. Boston. = Harvard Business School Strategy Unit Working Paper 10-064. <https://doi.org/10.2139/ssrn.1550099>
- Andersson, M.; Karlsson, C. (2004): The Role of Accessibility for the Performance of Regional Innovation Systems. In: Karlsson, C.; Flensburg, P.; Hörte, S.Å. (eds.): Knowledge Spillovers and Knowledge Management. Cheltenham, 283–310. <https://doi.org/10.4337/9781781958605.00018>
- Arant, W.; Fornahl, D.; Grashof, N.; Hesse, K.; Söllner, C. (2019): University-Industry Collaborations – The Key to Radical Innovations? In: Review of Regional Research 39, 2, 119–141. <https://doi.org/10.1007/s10037-019-00133-3>
- Asheim, B.; Boschma, R.; Cooke, P. (2011): Constructing Regional Advantage: Platform Policies Based on Related Variety and Differentiated Knowledge Bases. In: Regional Studies 45, 7, 893–904. <https://doi.org/10.1080/00343404.2010.543126>
- Asheim, B.; Gertler, M.S. (2005): The Geography of Innovation: Regional Innovation Systems. In: Fagerberg, J.; Mowery, D.C.; Nelson, R.R. (eds.): The Oxford Handbook of Innovation. Oxford, 291–317.
- Asheim, B.; Hansen, H.K. (2009): Knowledge Bases, Talents, and Contexts: On the Usefulness of the Creative Class Approach in Sweden. In: Economic Geography 85, 4, 425–442. <https://doi.org/10.1111/j.1944-8287.2009.01051.x>

- Balland, P.-A.; Boschma, R. (2021): Complementary Interregional Linkages and Smart Specialisation: An Empirical Study on European Regions. In: *Regional Studies* 55, 6, 1059–1070. <https://doi.org/10.1080/00343404.2020.1861240>
- Balland, P.-A.; Jara-Figueroa, C.; Petralia, S.G.; Steijn, M.P.A.; Rigby, D.L.; Hidalgo, C.A. (2020): Complex Economic Activities Concentrate in Large Cities. In: *Nature Human Behaviour* 4, 3, 248–254. <https://doi.org/10.1038/s41562-019-0803-3>
- Balland, P.-A.; Rigby, D. (2017): The Geography of Complex Knowledge. In: *Economic Geography* 93, 1, 1–23. <https://doi.org/10.1080/00130095.2016.1205947>
- Barlet, M.; Briant, A.; Crusson, L. (2013): Location Patterns of Service Industries in France: A Distance-Based Approach. In: *Regional Science and Urban Economics* 43, 2, 338–351. <https://doi.org/10.1016/j.regsciurbeco.2012.08.004>
- Bassens, D.; Hendrikse, R.; Lai, K.P.Y.; van Meeteren, M. (2024): World Cities under Conditions of Digitization and Platform Capitalism: Updating the Advanced Producer Services Complex. In: *Geoforum* 152, 104021. <https://doi.org/10.1016/j.geoforum.2024.104021>
- Bathelt, H.; Glückler, J. (2011): *The Relational Economy: Geographies of Knowing and Learning*. Oxford.
- Bathelt, H.; Malmberg, A.; Maskell, P. (2004): Clusters and Knowledge: Local Buzz, Global Pipelines and the Process of Knowledge Creation. In: *Progress in Human Geography* 28, 1, 31–56. <https://doi.org/10.1191/0309132504ph469oa>
- Berry, C.R.; Glaeser, E.L. (2005): The Divergence of Human Capital Levels across Cities. In: *Papers in Regional Science* 84, 3, 407–444. <https://doi.org/10.1111/j.1435-5957.2005.00047.x>
- Boschma, R. (2005): Proximity and Innovation: A Critical Assessment. In: *Regional Studies* 39, 1, 61–74. <https://doi.org/10.1080/0034340052000320887>
- Boschma, R.A.; Fritsch, M. (2009): Creative Class and Regional Growth: Empirical Evidence from Seven European Countries. In: *Economic Geography* 85, 4, 391–423. <https://doi.org/10.1111/j.1944-8287.2009.01048.x>
- Broekel, T.; Balland, P.-A.; Burger, M.; van Oort, F. (2014): Modeling Knowledge Networks in Economic Geography: A Discussion of Four Methods. In: *The Annals of Regional Science* 53, 2, 423–452. <https://doi.org/10.1007/s00168-014-0616-2>
- Brunow, S.; Hammer, A.; McCann, P. (2020): The Impact of KIBS' Location on Their Innovation Behaviour. In: *Regional Studies* 54, 9, 1289–1303. <https://doi.org/10.1080/00343404.2019.1684463>
- Carlino, G.A.; Saiz, A. (2019): Beautiful City: Leisure Amenities and Urban Growth. In: *Journal of Regional Science* 59, 3, 369–408. <https://doi.org/10.1111/jors.12438>
- Cooke, P.; De Laurentis, C.; Tödtling, F.; Trippel, M. (2007): *Regional Knowledge Economies*. Cheltenham.
- de Bok, M.; van Oort, F. (2011): Agglomeration Economies, Accessibility and the Spatial Choice Behavior of Relocating Firms. In: *Journal of Transport and Land Use* 4, 1, 5–24. <https://doi.org/10.5198/jtlu.v4i1.144>
- Deng, L.; Li, H.; Shi, W. (2022): Willingness for Different Job Mobility Types and Wage Expectations: An Empirical Analysis Based on the Online Resumes. In: *Papers in Regional Science* 101, 1, 135–162. <https://doi.org/10.1111/pirs.12636>
- Diodato, D.; Neffke, F.; O'Clery, N. (2018): Why Do Industries Coagglomerate? How Marshallian Externalities Differ by Industry and Have Evolved over Time. In: *Journal of Urban Economics* 106, 1–26. <https://doi.org/10.1016/j.jue.2018.05.002>
- Dorfman, J.H.; Partridge, M.D.; Galloway, H. (2011): Do Natural Amenities Attract High-Tech Jobs? Evidence From a Smoothed Bayesian Spatial Model. In: *Spatial Economic Analysis* 6, 4, 397–422. <https://doi.org/10.1080/17421772.2011.610811>
- Duvivier, C.; Cazou, E.; Truchet-Aznar, S.; Brunelle, C.; Dubé, J. (2021): When, Where, and for What Industries Does Broadband Foster Establishment Births? In: *Papers in Regional Science* 100, 6, 1377–1402. <https://doi.org/10.1111/pirs.12626>
- ESPON (2004): ESPON Project 1.1.1. Potentials for polycentric development in Europe. Project Report. Urban Areas as Nodes in a Polycentric Development. <https://archive.espon.eu/programme/projects/espon-2006/thematic-projects/urban-areas-nodes-polycentric-development> (07.05.2025).
- Fallick, B.; Fleischman, C.A.; Rebitzer, J.B. (2006): Job-Hopping in Silicon Valley: Some Evidence Concerning the Microfoundations of a High-Technology Cluster. In: *The Review of Economics and Statistics* 88, 3, 472–481. <https://doi.org/10.1162/rest.88.3.472>
- Gehrke, B.; Fritsch, R.; Neuhäusler, P.; Rammer, C. (2013): Neuabgrenzung Forschungsintensiver Industrien und Güter. NIW/ISI/ZEW-Listen 2012. Hannover. = Studien zum deutschen Innovationssystem 8-2013.
- Gertler, M.S. (2003): Tacit Knowledge and the Economic Geography of Context, or The Undefinable Tacitness of Being (There). In: *Journal of Economic Geography* 3, 1, 75–99. <https://doi.org/10.1093/jeg/3.1.75>
- Ghosh, S.; Grassi, E. (2020): Overeducation and Over-skilling in the Early Careers of PhD Graduates: Does International Migration Reduce Labour Market Mis-

- match? In: *Papers in Regional Science* 99, 4, 915–945. <https://doi.org/10.1111/pirs.12509>
- Growe, A. (2012): Emerging Polycentric City-Regions in Germany. Regionalisation of Economic Activities in Metropolitan Regions. In: *Erdkunde* 66, 4, 295–311. <https://doi.org/10.3112/erdkunde.2012.04.02>
- Gu, Z.; Gu, L.; Eils, R.; Schlesner, M.; Brors, B. (2014): Circlize Implements and Enhances Circular Visualization in R. In: *Bioinformatics* 30, 19, 2811–2812. <https://doi.org/10.1093/bioinformatics/btu393>
- Harrigan, J.; Reshef, A.; Toubal, F. (2021): The March of the Techies: Job Polarization Within and Between Firms. In: *Research Policy* 50, 7, 104008. <https://doi.org/10.1016/j.respol.2020.104008>
- Harris, R.; Moffat, J.; Evenhuis, E.; Martin, R.; Pike, A.; Sunley, P. (2019): Does Spatial Proximity Raise Firm Productivity? Evidence from British Manufacturing. In: *Cambridge Journal of Regions, Economy and Society* 12, 3, 467–487. <https://doi.org/10.1093/cjres/rsz017>
- Heider, B.; Siedentop, S. (2020): Employment Suburbanization in the 21st Century: A Comparison of German and US City Regions. In: *Cities* 104, 102802. <https://doi.org/10.1016/j.cities.2020.102802>
- Heidinger, M.; Fuchs, M.; Thierstein, A. (2024): The contribution of knowledge-intensive firms to employment growth: A Granger causality approach for German regions. In: *Regional Studies, Regional Science* 11, 1, 103–121. <https://doi.org/10.1080/21681376.2024.2312186>
- 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. In: *Review of Regional Research* 43, 1, 101–124. <https://doi.org/10.1007/s10037-023-00183-8>
- Hidalgo, C.A.; Klinger, B.; Barabasi, A.-L.; Hausmann, R. (2007): The Product Space Conditions the Development of Nations. In: *Science* 317, 5837, 482–487. <https://doi.org/10.1126/science.1144581>
- Holten, D.; van Wijk, J.J. (2009): Force-Directed Edge Bundling for Graph Visualization. In: *Computer Graphics Forum* 28, 3, 983–990. <https://doi.org/10.1111/j.1467-8659.2009.01450.x>
- Hurter, C.; Ersoy, O.; Telea, A. (2012): Graph Bundling by Kernel Density Estimation. In: *Computer Graphics Forum* 31, 3pt1, 865–874. <https://doi.org/10.1111/j.1467-8659.2012.03079.x>
- Kloosterman, R.C.; Lambregts, B. (2001): Clustering of Economic Activities in Polycentric Urban Regions: The Case of the Randstad. In: *Urban Studies* 38, 4, 717–732. <https://doi.org/10.1080/00420980120035303>
- Krabel, S.; Flöther, C. (2014): Here Today, Gone Tomorrow? Regional Labour Mobility of German University Graduates. In: *Regional Studies* 48, 10, 1609–1627. <https://doi.org/10.1080/00343404.2012.739282>
- Krätke, S. (2007): Metropolisation of the European Economic Territory as a Consequence of Increasing Specialisation of Urban Agglomerations in the Knowledge Economy. In: *European Planning Studies* 15, 1, 1–27. <https://doi.org/10.1080/09654310601016424>
- Legler, H.; Frietsch, R. (2006): Neuabgrenzung der Wissenswirtschaft – Forschungsintensive Industrien und wissensintensive Dienstleistungen. Hannover = Studien zum deutschen Innovationssystem 22-2007.
- LeSage, J.P. (2014): What Regional Scientists Need to Know About Spatial Econometrics. <https://doi.org/10.2139/ssrn.2420725>
- Meijers, E. (2005): Polycentric Urban Regions and the Quest for Synergy: Is a Network of Cities More than the Sum of the Parts? In: *Urban Studies* 42, 4, 765–781. <https://doi.org/10.1080/00420980500060384>
- Mossig, I. (2011): Regional Employment Growth in the Cultural and Creative Industries in Germany 2003–2008. In: *European Planning Studies* 19, 6, 967–990. <https://doi.org/10.1080/09654313.2011.568807>
- Neffke, F.; Henning, M. (2013): Skill Relatedness and Firm Diversification: Skill Relatedness and Firm Diversification. In: *Strategic Management Journal* 34, 3, 297–316. <https://doi.org/10.1002/smj.2014>
- Niedomysl, T.; Hansen, H.K. (2010): What Matters More for the Decision to Move: Jobs versus Amenities. In: *Environment and Planning A: Economy and Space* 42, 7, 1636–1649. <https://doi.org/10.1068/a42432>
- Parr, J. (2004): The Polycentric Urban Region: A Closer Inspection. In: *Regional Studies* 38, 3, 231–240. <https://doi.org/10.1080/003434042000211114>
- Pitoski, D.; Lampoltshammer, T.J.; Parycek, P. (2021): Network Analysis of Internal Migration in Austria. In: *Digital Government: Research and Practice* 2, 3, 1–24. <https://doi.org/10.1145/3447539>
- Polanyi, M. (1958): *Personal Knowledge. Towards a Post-Critical Philosophy*. London.
- Roesler, C.; Broekel, T. (2017): The Role of Universities in a Network of Subsidized R&D Collaboration: The Case of the Biotechnology-Industry in Germany. In: *Review of Regional Research* 37, 2, 135–160. <https://doi.org/10.1007/s10037-017-0118-7>
- Rozenblat, C. (2021): Intracity and Intercity Networks of Multinational Firms, 2010-2019. In: Neal, Z.P.; Rozenblat, C. (eds.): *Handbook of Cities and Networks*. Cheltenham, 511–556.
- Serafinelli, M. (2019): “Good” Firms, Worker Flows, and Local Productivity. In: *Journal of Labor Economics* 37, 3, 747–792. <https://doi.org/10.1086/702628>

- Simmie, J. (2003): Innovation and Urban Regions as National and International Nodes for the Transfer and Sharing of Knowledge. In: *Regional Studies* 37, 6–7, 607–620. <https://doi.org/10.1080/0034340032000108714>
- Smętkowski, M.; Celińska-Janowicz, D.; Wojnar, K. (2021): Location Patterns of Advanced Producer Service Firms in Warsaw: A Tale of Agglomeration in the Era of Creativity. In: *Cities* 108, 102937. <https://doi.org/10.1016/j.cities.2020.102937>
- Storper, M. (2010): Why Does a City Grow? Specialisation, Human Capital or Institutions? In: *Urban Studies* 47, 10, 2027–2050. <https://doi.org/10.1177/0042098009359957>
- Storper, M. (2011): Why Do Regions Develop and Change? The Challenge for Geography and Economics. In: *Journal of Economic Geography* 11, 2, 333–346. <https://doi.org/10.1093/jeg/lbq033>
- Storper, M.; Scott, A.J. (2009): Rethinking Human Capital, Creativity and Urban Growth. In: *Journal of Economic Geography* 9, 2, 147–167. <https://doi.org/10.1093/jeg/lbn052>
- Storper, M.; Venables, A.J. (2004): Buzz: Face-to-Face Contact and the Urban Economy. In: *Journal of Economic Geography* 4, 4, 351–370. <https://doi.org/10.1093/jnecg/lbh027>
- Stoyanov, A.; Zubanov, N. (2012): Productivity Spillovers Across Firms through Worker Mobility. In: *American Economic Journal: Applied Economics* 4, 2, 168–198. <https://doi.org/10.1257/app.4.2.168>
- Tambe, P.; Hitt, L.M. (2014): Job Hopping, Information Technology Spillovers, and Productivity Growth. In: *Management Science* 60, 2, 338–355. <https://doi.org/10.1287/mnsc.2013.1764>
- Taylor, P.J. (2004): *World City Network: A Global Urban Analysis*. London.
- Tippel, C.; Plöger, J.; Becker, A. (2017): ‘I Don’t Care about the City’: The Role of Connections in Job-Related Mobility Decisions of Skilled Professionals. In: *Regional Studies, Regional Science* 4, 1, 94–108. <https://doi.org/10.1080/21681376.2017.1315611>
- Trincado-Munoz, F.; van Meeteren, M.; Rubin, T.H.; Vorley, T. (2023): Digital Transformation in the World City Networks’ Advanced Producer Services Complex: A Technology Space Analysis. In: *Geoforum* 151, 103721. <https://doi.org/10.1016/j.geoforum.2023.103721>
- van Meeteren, M.; Neal, Z.; Derudder, B. (2016): Disentangling Agglomeration and Network Externalities: A Conceptual Typology. In: *Papers in Regional Science* 95, 1, 61–81. <https://doi.org/10.1111/pirs.12214>
- van Meeteren, M.; Poorthuis, A.; Derudder, B.; Witlox, F. (2016): Pacifying Babel’s Tower: A Scientometric Analysis of Polycentricity in Urban Research. In: *Urban Studies* 53, 6, 1278–1298. <https://doi.org/10.1177/0042098015573455>
- van Meeteren, M.; Trincado-Munoz, F.; Rubin, T.H.; Vorley, T. (2022): Rethinking the Digital Transformation in Knowledge-Intensive Services: A Technology Space Analysis. In: *Technological Forecasting and Social Change* 179, 121631. <https://doi.org/10.1016/j.techfore.2022.121631>
- Wagner, M.; Growe, A. (2023): Patterns of Knowledge Bases in Large City Regions in Germany: Comparison of Cores and Their Surrounding Areas. In: *Geografiska Annaler: Series B, Human Geography* 105, 3, 284–304. <https://doi.org/10.1080/04353684.2022.2141131>
- Wood, P. (2002): Knowledge-Intensive Services, Consultancy and Innovation. In: Wood, P. (ed.): *Consultancy and Innovation: The Business Service Revolution in Europe*. London, 1–14.
- Yeung, H.W. (2024): From Regional to Global and Back Again? A Future Agenda for Regional Evolution and (De)Globalised Production Networks in Regional Studies. In: *Regional Studies* 58, 7, 1480–1491. <https://doi.org/10.1080/00343404.2024.2316856>
- Zhao, J.; Bentlage, M.; Thierstein, A. (2017): Residence, workplace and commute: Interrelated spatial choices of knowledge workers in the metropolitan region of Munich. In: *Journal of Transport Geography* 62, 197–212. <https://doi.org/10.1016/j.jtrangeo.2017.05.012>