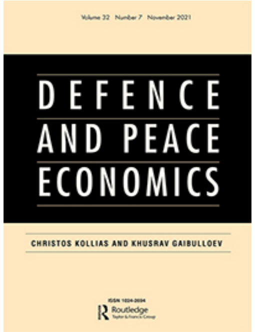

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Measuring Spillover Effects from Defense to Civilian Sectors – A Quantitative Approach Using LinkedIn

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ABSTRACT

Spillover effects describe the process of a company benefiting from the R&D activities of another one and thereby gaining an economic advantage. One prominent approach for measuring spillover effects is based on the analysis of patent citation networks. Taking social media analytics and knowledge economics into account, this paper presents a complementary approach to quantify spillover effects from defense to civilian research and development, analyzing 513 employment biographies from the social network LinkedIn. Using descriptive network analysis, we investigate the emigration of personnel of the German defense industry to other civilian producers. Thereby, our study reveals that in the last decade, employees of defense suppliers have changed positions significantly less often, with 3.24 changes on average than professionals who have worked more than 50% of their jobs in the civilian sector, having changed 4.61 times on average. Our work illustrates the churn behavior and how spillover effects between defense and civilian sectors can be measured using social career networks such as LinkedIn.

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Spillover; dual-use; LinkedIn; social media analytics; JEL: O33, H56

Introduction

Progress in science and technology influences the dynamics of peace and security (Reuter et al. 2020). Among other scientific and technical disciplines (physics, biology, chemistry) many areas of computer science (e.g. artificial intelligence) are currently of rising importance (Reuter 2019) due to the disciplines' involvements into the research and development of dual-use technologies. Dual-use technologies have an impact on the assessment of international and national security, as do their spillover effects (Acosta, Coronado, and Marín 2011; Acosta et al. 2017). The measurement of technological and innovation spillover is relevant for the effective regulative control of certain high-risk industries. Dual-use, in more general terms, is on the one hand all items that can either be used in a beneficial or harmful way or have civilian or military applications (Oltmann 2015). The latter, traditional understanding has been accompanied by more recent conceptual discussions about beneficial and harmful use (Oltmann 2015). This conceptualization of dual-use takes into consideration technological usage by transnational actors, which may have a negative impact on people's lives and that negative effects of a dual-use item may not necessarily have to be due to the use of fatal weaponry (Riebe and Reuter 2019). Thus, focusing on this distinction of societally beneficial and (potential) harmful use allows considering various advantages and threats regarding human security (Brundage et al. 2018). Especially for emerging dual-use technologies such as Artificial Intelligence (AI), understanding the diffusion of innovation is crucial for risk government

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(Tucker 2012). Still, our work follows a traditional understanding of dual-use, focusing on both civilian and defense industries. This is plausible as we are not interested in a diversified sample of technologies, incorporating specific knowledge or technologies of the life or computer sciences. Rather, our research is motivated by industrial spillovers, focusing on German companies most active in conventional arms sales.

Public funds for research and development (R&D) in the defense sector are often argued to lead to a backflow of know-how in the form of spillover effects in the civilian sector (Brzoska 2006; Acosta et al. 2017). Other scholars have assumed that innovation from the defense sector diffuses less due to idiosyncratic factors, such as the culture, market structure, and policy environment of the defense industry (Molas-Gallart 1997; Schmid 2017, 3).

On the other hand, developing and producing emerging dual-use technologies for both potential civilian and defense applications can lower production costs and is therefore in many fields desirable for companies. Even though spillover effects on an economic productivity scale are difficult to measure (Sempere 2018), this is certainly part of the European Commission's discussion concerning the new European Defence Fund (European Commission 2017) and the procurement of defense-related goods (European Commission 2004).

Naturally, measurement of spillovers depends on the item's operationalization; for example, it is based on patents (Acosta et al. 2017) or labor mobility (Fujiwara 2017). Acosta et al. focus on patent citations (2011, 2017) as well as Kim, Lee, and Sohn (2016), who quantify spillover effects from the development of unmanned aerial vehicles (UAVs) into other industrial sectors. The location of the R&D industry has shown to be an important factor regarding the spillover of technology (Keller 2004), reflected by a geographical concentration in Western countries (Keller 2004; Jaffe, Trajtenberg, and Henderson 1993) and more recently Asian countries like China (WIPO 2019).

While patent citation analysis has many advantages, it also has limitations (for a discussion see Belderbos and Mohnen 2013). Especially regarding emerging technologies, which may not have developed an established output of patents yet, other indicators of the spillover of innovations may prove necessary. Additionally, not all innovations lead to patents; thus, some spillovers might not be measurable by patent citations, but rather by focusing on knowledge transfer via workforce mobility and local networks. Social media, for instance, is currently used in many different ways, ranging from personal conversations to business networking – and emerging data are analyzed for business purposes, but also in context for crises and conflicts (Reuter and Kaufhold 2018). Social Media Analytics (SMA) (Stieglitz et al. 2018; Russel 2018) provides a set of approaches taking advantage of the evolution of networks, work biographies, skills, accomplishments, and interests. Furthermore, SMA, more specifically, Social Network Analysis (Leistner 2012) can provide insights into the centrality of actors and the density of a network, giving additional insight into skills of highly educated employees (Geyik et al. 2018; Ha-Thuc et al. 2015; Russel 2018) involved in the research and development of dual-use technologies and related (informal) knowledge transfers among individual users (Havakhor, Soror, and Sabherwal 2018; Leistner 2012).

Emerging and high-technologies are developed in interdisciplinary teams, which involves the exchange of ideas and information. As part of job changes, the knowledge is used in other teams and companies (Branstetter, Gandal, and Kuniesky 2017). Measuring spillover based on individual actions, this approach does not focus on patents or technologies, but rather on individuals as they transfer knowledge between companies and job positions using a career network analysis (Stieglitz et al. 2018; Russel 2018). Thus, we are interested in the methodological and empirical question:

What are the Spillover Effects that Can Be Measured Using Career-network Analysis?

Assuming SMA can be used to investigate spillover effects, similar effects should be measured that confirm studies which focused on knowledge spillovers based on patent data. Schmid (2017) argues that 'the distinctive culture, policy environment, and market structure of the defense-servicing sector impede the diffusion of technologies developed therein', thereby functioning as a limitation to the flow of knowledge from the defense industry to the civilian sectors. Therefore, we assume that the spillover of knowledge is lower from the defense to the civilian sector (H1).

Counting nearly 675 million users, of which 211 million are in Europe, LinkedIn is the career network with the highest number of users worldwide (LinkedIn 2020a) and thus selected as a data source for professional networks. However, due to LinkedIn's purpose of matching companies and employees, its matching algorithm is steadily adjusted (Geyik et al. 2018). This imposes limitations due to access restrictions and data protection policy (LinkedIn 2020b).

The work is structured as follows: Section 2 describes our theoretical background, referring to related work of knowledge economics (2.1), and patent analysis (2.2). Section 3 then introduces the method of our SMA approach, the data collection (3.1), and the coding of the companies (3.2). In section 4, the data is analyzed in terms of their churn behavior (4.1). Subsection 4.2 describes the limitations of the approach. Put in relation to the traditional methodological approach of patent analysis, Section 5 discusses the results of this work in comparison to other approaches. The conclusion and outlook on the further development of the research approach are presented in the last Section 6.

State of Research

Scholars of knowledge economics have focused on economies, knowledge, and technology transfer and conducted theoretical work with respect to spillovers, knowledge transfer in social networks, or innovation by industrial districts (Cerulli and Potì 2009; Costantini, Mazzanti, and Montini 2013; Audretsch and Vivarelli 1996; Tappi 2001). Thus, this section presents related work of knowledge economics and sheds light on research regarding the measurement of spillover effects by patent analysis.

Knowledge Economics and the Italian School

Works of knowledge economics (Westeren 2012) may be associated with the contemporary 'industrial society' experiencing a 'profound transformation' which has been reflected by 'increasing importance of intellectual property rights, [...] "human capital"' or the erosion of former sources of growth (Stehr and Mast 2005, 17). Within this context, various scholars focus on knowledge or technology[1] spillovers as innovation-inducing factors (Aghion and Jaravel 2015). Conceptually, spillover grasps the process of transferring (technological) knowledge, often originating within companies and subsequently published by, e.g. patents or passing it on to other actors (van Oort and Raspe 2012; Aghion and Jaravel 2015). Additionally, there has been a focus on labor mobility as initiating knowledge spillover (Audretsch and Keilbach 2005). In this regard, the measurement of knowledge transfers has been discussed in more detail, differentiating between codified and tacit knowledge and focusing on geographical proximities as well as on transfers of informal knowledge across social networks (Panahi, Watson, and Partridge 2013; Audretsch and Keilbach 2005). Besides the economic centrality of knowledge, literature of knowledge economies is dedicated to the relevance of entities like universities as well as spillover-related issues of actors' proximities and geographical agglomerations (Agasisti, Barra, and Zotti 2019; de Marchi and Grandinetti 2013; Westeren 2012). Departing from the work of the economist Alfred Marshall, the so-called Italian School coined the industrial district as a unit of analysis, disregarding common units of investigation like firm, state, or (solely technologically determined) industries (Sforzi 2015; Marshall 1920). Instead, the industrial district is characterized by a variety of firms, which may share relationships with each other (Morrison 2008; Tappi 2001). At the same time, these firms are not the only relevant actors, but, as theorized by scholars of the Italian School (Becattini 1991), the network of respective firms is embedded in a social system (Tappi 2001). Academic contributions conducting research of the Northern Italian leather or wine industrial districts or clusters, respectively (Morrison and Rabellotti 2009; Randelli and Lombardi 2014), facilitated a network-centric perspective in knowledge economics, taking personal relationships into account as well (Owen-Smith and Powell 2004; Carbonara 2018).

Here, we remain focused on firms and disregard an examination of entities comprising an entire industrial district. Thus, we do not strictly focus on the relationships among 'relatively *small firms* [. . .] [constituting] a set of *vertically disintegrated networks*' (Tappi 2001, 2, emphasis in original). Yet, we take the perspective of connectedness among firms through people, i.e. individual agents which are socially embedded, into account. While the individuals may not personally know each other, their paths may be connected by working for the same firm, conducting similar working activities, learning or transferring the same tacit or explicit knowledge (P. L. Robertson and Jacobson 2011; Belussi and Pilotti 2002). Our work does, in contrast to approaches of the Italian School, not specifically focus on human beings' sociability or socio-economic laws of productivity increase (Becattini 2002). LinkedIn does not constitute a typical industrial district, which is defined by a characterizing commodity within a certain territorial space and incorporating all relevant actors of the production and consumption process (Becattini 2002). Yet, our sample based on LinkedIn profile data reflects the most important companies of the German defense industry, comprised of various individuals of different working positions. Furthermore, these individuals are connected by their employing firm(s) and reflect the importance of humans' economic force and neighboring industrial clusters, defined by other commodities (Becattini 2002). In our view, LinkedIn (profiles) partly represent the network characteristics of the Italian School's propagated industrial districts and thus allow for studying linkages among network-relevant firms with a focus on spillovers from the defense to the civilian industries, initiated by job changes of individual agents, entailing knowledge transfer.

Measuring Spillover Effects by Patent Referencing and Labor Mobility

To distinguish between defense and civilian R&D is challenging due to some companies being active in both areas, especially when producing dual-use items (Acosta et al. 2017). An example is Airbus, which is represented in the civilian sector with the brand 'Airbus Aircrafts' and in the defense sector with 'Airbus Defence and Space'. Enterprises create subdivisions to be able to serve both the civilian and defense market segments (Markusen 1992; Acosta et al. 2017). Spillover effects describe the process in which a company gains benefits from the R&D activities of another company and obtains an economic advantage (Jaffe, Trajtenberg, and Henderson 1993).

A method for examining and quantifying spillover effects uses citations of patents or references of scientific literature in patents of interest to understand the relationships between technological inventions (Acosta, Coronado, and Marín 2011; Acosta et al. 2017; Kim, Lee, and Sohn 2016). This 'paper-trail approach' (Kim, Lee, and Sohn 2016, 141) takes advantage of the fact that in order to maintain a patent, it is necessary to restrict its scope to the citations of other patent texts in such a way that it clearly indicates which part constitutes the patentable innovation. Acosta, Coronado and Marín (2011), Breschi and Lissoni (2005), and Schmid (2017) used this data source to conduct analyses on the flow of knowledge between industries and countries. They understand the relationships created by citations as ways of knowledge transfer. Thereby, it is assumed that an invention, which is applied for patenting, profits from past inventions, i.e. patented knowledge, when referring to them. Thus, usually knowledge transfer and diffusion are measured according to patent citations while the specific spillover effect of creating economic advantages is, for example, derived considering the patent applicants' firm size, sales of the respective technology (Acosta et al. 2017) or geographical proximities (Ferreira, Dana, and Ratten 2016).

Approaches that focus on patent citation focus on technologies that are already fully developed and therefore easier to assess. Technologies, on the other hand, that are in earlier stages of their research and development need an early assessment for tailored and informed policy risk assessment (Tucker 2012). Using the data provided by SMA yields insight on social networks and relevant knowledge spillovers that may precede patent publication.

Due to the rise of social networks such as Facebook and LinkedIn, the field of SMA has emerged, which intends to combine, extend, and adapt methods for the analysis of social media data (Stieglitz et al. 2018). These methods include content, sentiment, social network, statistical, and trend analyses, amongst others. Taking advantage of SMA is an explorational approach to measure spillover effects, as applied in a study of cyber-military capabilities of the US Cyber reserve using keyword search for skill analysis in LinkedIn profiles of a selected population (Porche et al. 2017). Skill analysis is an often-used approach of SMA in LinkedIn, mostly to match the supply and demand of the employers and employees (Ramanath et al. 2018; Ha-Thuc et al. 2015; Geyik et al. 2018). At the same time, SMA based on LinkedIn data allows grasping employed users' job change histories, indicating occurrences of knowledge transfer (Audretsch and Keilbach 2005).

Methodology: Analyzing the LinkedIn Profile Data

Sample and Case Selection

To analyze spillovers from the German defense to civilian industry using SMA, data from LinkedIn were retrieved manually. Therefore, a profiling account was used. We analyzed 513 profiles of employees, working or having worked for the three arms companies with the highest revenue in Germany[2] (Table 1) over the last 10 years. The sample was built on an advanced search on LinkedIn, combining the research terms 'Germany', 'Hensoldt', 'Krauss-Maffei Wegmann', 'Rheinmetall Group', and 'Rheinmetall Defence'. The companies have been selected based on the SIPRI Arms Industry Database Top 100 from 2002–17, focusing on German companies (Fleurant et al. 2017). From the 1100 results on LinkedIn, the first 513 have been coded. Only job positions that have been held for longer than 6 months were counted, excluding internships. To ensure the possibility of job change-(s), the sample comprises solely profiles of people who have graduated their latest educational program until 2016.

Within the last 10 years (from January 2009 until March 2019), the 513 sample employees held 1926 different positions in 113 companies, including the subsidiary companies. Incomplete profiles were excluded from the dataset. In general, profile information showed rare spelling errors and career-interruptive blank spots. Thus, it is plausible to assume that the profile information has been chosen carefully and represents the actual career paths of respective individuals. Due to the sensitivity of the data, we anonymized profile information and summarized companies which occurred only once across the entire sample under the labels civilian or defense for reasons of clarity. Personalized descriptions of freelancers were also anonymized instead of being excluded from the sample. The manual process of data retrieval allowed for a well-thought assessment of the data's saturation with respect to our research interest. Choosing a European country with a comparatively strong defense industry legitimizes the case selection of Germany. At the same time, focusing on respective firms allows for a suitable representation of the relevant actors of the German defense market. Compared to other countries, like the US, R&D for military ends is commonly not heavily funded in cooperation with research institutes or universities or at least this is not publicly transparent. While there is governmental funding of military R&D, e.g. research projects by the Fraunhofer Institute of Optronics, System Technologies and Image Exploitation (Fraunhofer IOSB 2020; German Federal Ministry of Defense 2017), some German universities have signed the *Zivilklausel*, committing them to non-proliferation through civilian research (von Massenbach 2020). The German case stresses the plausibility of our way of conduct with regards to our interest in spillovers induced by knowledge transfer through individuals' job changes within the context of

Table 1. Distribution of defense company in the sample.

Frequency of job positions	1,926	100 %
Hensoldt	336	17.45
Krauss-Maffei Wegmann	65	3.37
Rheinmetall	406	21.08
Total	807	41.90

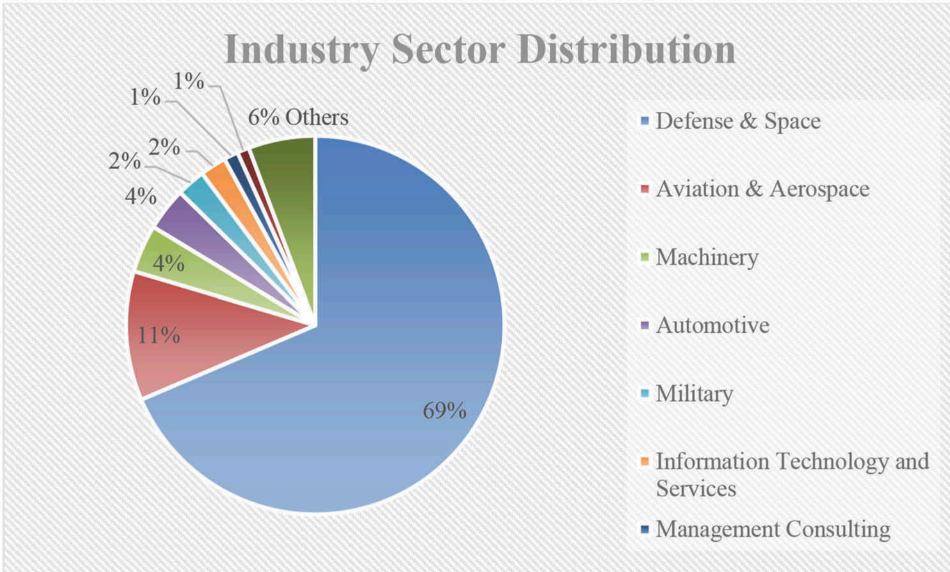

Figure 1. Industry sector distribution in sample in 2019.

a network of companies (in contrast to concentrating on governmental defense funding or R&D policies with a strong focus on the defense industry as initiators of innovation).

Coding the Companies

The unit of analysis is the job position, which is coded as civilian or defense based on the company's business model. Companies have been coded as having a mainly civilian business model when they have had more than 50% of total sales in the civilian sector and as belonging to the defense industry with more than 50% or more than 840 Mio USD turnover by sales in the military sector, thus belonging to the top 100 arms-producing companies worldwide (Fleurant et al. 2017), such as Rheinmetall Group and Thales. In case numbers were not accessible online, companies' profiles were qualitatively assessed with reference to declared industries of activity, partners, as well as the range of products with respect to their field of application (defense or civilian).

Extracting data from LinkedIn was done manually, selecting the first 513 profiles from the selected companies which are located in Germany (LinkedIn 2020b). LinkedIn users can assign an industry sector to their current position. The distribution of the sectors is shown in Figure 1. As high as 69%of the sample work in Defense and Space at the time of the inquiry. However, professionals might work for defense R&D, but assign themselves to other industry sectors, such as Aviation & Aerospace (11%), Machinery (4%), and Automotive (4%), and others.

To review the results of the LinkedIn search, a control group was sampled (n = 62). The control group was selected searching for civilian R&D companies in Germany.

Empirical Results

The professionals changed their jobs on average 3.75 times between 2009 and 2019, with a standard variation of 1.76 and a median of 3 (see Table 2). The standard variation is relatively high, being a result of the individual differences in the position changes in the sample. As all professionals in the sample are currently working or have recently worked for one of the defense companies, the sample consists of 70.92% job positions in the defense industry and 29.08% civilian positions.

Table 2. Job mobility between 2009–2019.

Number of jobs between 2009-2019	1,926
Professionals	513
Average position change pP	3.75
SD	1.76
Median	3

Data regarding job changes show significant differences in the behavior of the professionals depending on the industry they are predominantly part of. Conducting descriptive statistics of the sample, the distribution of military to civilian jobs is indicated, showing that 257 people worked exclusively for defense-oriented companies within the last 10 years (Figure 2). This supports the hypothesis that spillover of knowledge from the defense industry is low due to idiosyncratic features of national defense industries (see Schmid 2017). Figure 2 further shows that the ratio-values are normally distributed between the people who have changed between civilian and defense sectors.

Churn Behavior between the Defense and Civilian Industries

The data show three groups within the sample: group one (D) with the ratio $v = 1$, meaning that they have exclusively worked for defense companies ($N = 257$), group two (DC,), consisting of people that have predominantly worked in the defense sector ($v \geq 0.5$), and group three (C) of people that have worked more often in the civilian sector than the defense sector ($v < 0.5$) (see Figure 2). Among the persons who have worked at least once outside of the defense industry ($v < 1$), the values are almost normally distributed with a mean *M* of 0.49 and a standard deviation (*SD*) of 0.17 with a tendency towards positions in the civilian sector (see Figure 2).

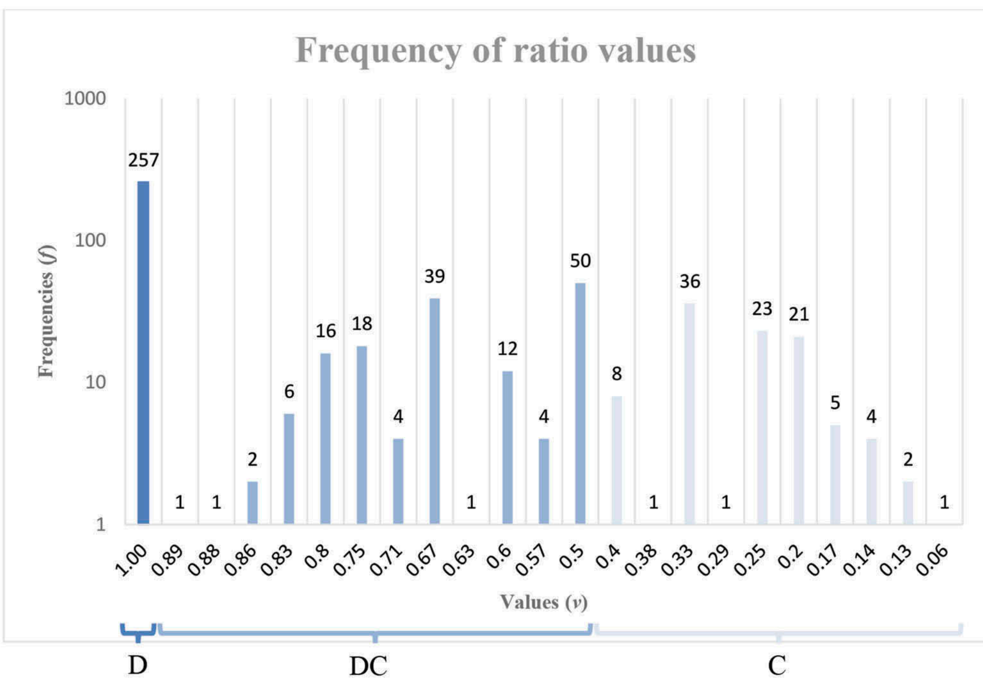

Figure 2. Frequency of ratio values v (N_{total} = 513, $M_{DC\ and\ C}$ = 0.49, $SD_{DC\ and\ C}$ = 0.17).

Thus, for further detailed analysis of significant variables on job changes, we categorized three groups: *v(D)* = 1 (100% positions in the defense sector), *v(DC)* ≥ 0.5 (50% or more positions in the defense sector) and *v(C)* < 0.5 (more than 50% positions in the civilian sector).

To test the hypothesis (H1), t-Tests for job changes and the ANOVA – in combination with post-hoc tests (Tukey's HSD-Test with Bonferroni correction) were conducted using R (Bühner and Ziegler 2007; Luhmann 2011). Testing for the significance of these differences, the ANOVA showed a significant result ($F(3,509) = 18.13$, $p = 0.0071$, $\alpha = 0.05$). Thus, the job changes and the groups 1–3 correlate significantly overall. In line with the mean values for *v(D)* 3.242, *v(C)* 4.608, and *v(DC)* 4.019, the subsequent Tukey's test showed significant differences in job change behavior of group 1 (D) to both group 2 (DC) and 3 (C) ($p < 0.05$). Professionals change their jobs less often, the more positions they have had in the defense industry than in the civilian sector (Table 3).

Limitations of the Approach

The sample is focused on German companies and thus the only representative for similarly structured economies (Verspagen 1997). In addition, it is not known how many employees of the investigated companies are logged in to LinkedIn. To counteract this problem, only companies of which several thousand employees had profiles on LinkedIn were investigated. The approach also assumes that the information provided by the LinkedIn members is correct. It is trusted that social control leads people to specify a correct employment biography in their profiles. In the process of manual data retrieval, close attention was paid to the degree of accuracy and reliability, while incomplete profiles were excluded.

Second, the coding of a company as being located in the civil or military sector used in this work, as described in 3.2, has been proven challenging due to the dual-use character of some companies, as well as the difficulty to analyze the revenue of smaller companies, that are not among the SIPRI Top 100 arms producers and military services (Fleurant et al. 2017). While the alternatives of relying on LinkedIn industries, with 'Defense and Space' inherently introducing a dual-use type of industry, or categorization based on patent classification systems like the International Patent Classification (IPC) or Cooperative Patent Classification (CPC) (European Patent Office 2020), do not suggest a more plausible solution, our coding process tried to take empirical realities of the German economic landscape into account and was reassured by very detailed descriptions of job positions or projects. At the same time, departing from numerical indicators in cases of absence to qualitative assessment suggests a reasonable way of conduct.

Our approach offers insights into job changes, implicating knowledge spillovers. Yet, offering a first illustration of measurement of spillovers based on career-network information, future work may provide more insight into the directions of job changes. To grasp the entire process of spillover effects, future work may further complement the analysis of knowledge transfers with analysis of companies' innovations or turnovers. Still, our results, offering an overview of individuals' tendencies of job types as well as insights into correlations of groups and frequency of job changes, indicate that there is little evidence for spillovers from defense to civilian industries. Further, despite LinkedIn profiles showed standardized information regarding skills, it is not possible to derive points of time when an individual's knowledge, i.e. skills, did expand (e.g. after changing their job). Also, we could not quantify the amount of knowledge being transferred by job change. Although results indicate little knowledge transfer within the defense

Table 3. Means and results of Tukey's test.

D	DC	C	Variables	Difference	*p*
M = 3.24	*M* = 4.02	*M = 4.61*	C-D	1.37b	0.000
			DC-D	0.78b	0.000
			DC-C	−0.59a	0.031

a$p \leq 0.05$.
b$p \leq 0.001$.

industry due to lower labor mobility, the concrete amount of knowledge may only be measured when taking the type of job changes (from one business area to another or within the same area of activity) into consideration. Thereby, it would be possible to retrieve users' job titles that have mainly stayed in their area of expertise as an indicator of a higher level of knowledge transfer. This may be due to employees changing their areas of activities to undergo a learning process and having fewer options to apply knowledge, at least when it comes to explicit, specific knowledge. Additionally, one may consider the time span over which a job position was held to approach the amount of transferred knowledge. Approaching knowledge transfers from a temporal perspective requires the assessment of job titles and project changes. However, the privacy of the social network users needs to be protected, and even with anonymized datasets declaration of job titles, the combination of job changes or skills might lead to public identification of employees and their biographies (Hoser and Nitschke 2010).

Comparison of the Approaches

This paper aims to answer the question '*What are the spillover effects that can be measured using career-network analysis?*'

The empirical results of the churn rates between defense and civilian job positions in LinkedIn of 513 persons showed that the fewer people changed the industry, the less they changed job positions. This finding supports the hypothesis (H1) that spillovers are less likely between defense and civilian sectors and even indicates that churn rates in the defense sector are much lower than in the civilian sector. In the sample, we had a high rate of people only working in the defense sector (50%, Group D, see Figure 2), while the other half of the sample had a higher percentage of positions in defense companies (group DC, equal and more than 50% of their positions) and the other had a lower percentage (group C, less 50% of their positions).

Comparing our results of reluctant flow of defense innovation into the civilian sector to the patent study of Acosta et al. (2017), the results are similar: Germany has the second-highest rate of military registered patents (22% of all patents) worldwide. At the same time, the civilian use of these patents is rather low, with 16.8% of citations by other patents in civilian classifications (Acosta, Coronado, and Marín 2011, 341). The most cited kind of patents were dual-use patents. Therefore, in future research, SMA of companies that produce dual-use technologies may provide useful insights with respect to potentially critical knowledge spillovers.

The approach focuses on the embodiment of knowledge through human professionals that change their positions and share their knowledge within their teams. While this allows for an approximation of knowledge flows, it does not guarantee growth-inducing spillover. Turnover-oriented studies focusing on national or international domestic growth (Belderbos and Mohnen 2013; Cuvero et al. 2018) prioritize such an interest, potentially disregarding multicausality. Having a closer look at the flow of working forces may support the hypotheses of innovation-led growth. The evaluation of formal knowledge transfers by examining patent references (Hur 2017; Acosta, Coronado, and Marín 2011; Acosta et al. 2017) necessarily excludes those that are informal and taking place through other institutional channels. With respect to the theoretical background of knowledge economies or industrial districts (Carbonara 2018; Tappi 2001), which are characterized by interactional relationships among actors, this work stands out in relation to patent analysis due to its empirical source of the social network LinkedIn. As a reliable representation of relevant industrial actors, envisaging the case as a network seems less constructed than rather abstract patent networks. It needs to be considered that sometimes, a patent citation is motivated by reasons other than relying on the formerly formulated knowledge. This includes tendencies to cite historically important patents as well as the necessity to refer to related patents while not considering them more specifically. Further, there is always the option of secret patents, prohibiting insight into knowledge transfers between both civilian and defense industries, especially in defense research with national security interests (German Patent and Trade Mark Office 2017). Compared to patent network analysis, an investigation of individuals' job movements does not exclude tacit knowledge a priori (P. L. Robertson and Jacobson 2011). Detailed project descriptions on respective profiles reassured the knowledge-based character of jobs. Further, our study allows for an economically interested analysis of civilian and defense enterprises. Usually, in patent analysis, the type of industry (civilian vs. defense) is operationalized according to the patent family, categorizing an invention as a weapon or as a technology for civilian use. In contrast, our approach includes not only the type of technology, considering a company's share of arms sales or main business activities. It also considers that knowledge transfer does not mainly take place from one patented invention to the other, but that companies are the places where knowledge is created intra-organizationally and passed on to other socioeconomically embedded actors. With the assumption of working forces embodying both tacit and explicit knowledge, there is a legitimate focus on labor mobility with respect to spillover-inducing knowledge transfers.

Conclusion

In this work, it has been shown how spillover effects between defense and civilian sectors can be measured using social career-networks, such as LinkedIn. Our approach did not only confirm the assumption on churn behavior but also provides insight into the networks of the professionals. Thus, social media analytics can be used for further network analysis, such as skill-oriented approaches (Ramanath et al. 2018), the investigation of centrality of actors in networks (Mutschke 2008), or users' contacts, among which (tacit) knowledge transfers may take place, e.g. during conversation or visits of same events (Leistner 2012). Yet, Social Network Analysis of immediate relationships (Leistner 2012), in contrast to connections via employing companies, yields research ethical controversies due to the analysis of data which might be taken out of the context of consent the users agreed to or even violate the privacy of the users (Hoser and Nitschke 2010). In this regard, patent analysis proves to pose fewer challenges of ethical research as databases offering public access are well known, and there is less focus on individual inventors, who are usually aware of the publication of their involvement (Bradbury 2011). Thus, one may analyze patent information, including its content, to gain a deeper insight into the features of knowledge being transferred without potentially identifying individuals by analyzing their characteristic skills or biographies. Being aware of ethical issues regarding anonymity or informed consent is crucial in conducting social media research (Quan-Haase and Lori 2016); the latter offering new ways of approaching spillover dynamics based on knowledge transfer via social and job networks.

Notes

1. Meunier and Bellais (2019) define technology as the 'application of knowledge for practical ends', implicating the foundational character of knowledge and its potential materialization into technology.
2. ThyssenKrupp has been ranked as the second most active German company in arms sales (Fleurant et al. 2017). Yet, as its share of arms sales in relation to total sales makes out 'only' 4% percent, the company mainly has a civilian profile. Hence, the sample was saturated before such additional inclusion, and we aimed for Hensoldt, Rheinmetall, and Krauss-Maffei Wegmann, representing the German arms market in SIPRI's Top 100.

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