Cross-Border Commuters and Knowledge Diffusion*

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Abstract

Patents disclose knowledge, yet this disclosure is often insufficient for the knowledge to be put into practice and used for cumulative innovation. Firms rely on workers possessing tacit knowledge or specific skills to effectively build on the ideas of others. In this study, we examine the effects of expanding Swiss firms' access to the German labor market on the diffusion of knowledge developed in Germany to Switzerland. We investigate the impact of a reform implemented in 2002, which eliminated the restrictions Swiss firms previously faced in hiring German cross-border commuters. We find that following the reform's implementation, German patents originating from locations within close commuting distance to the Swiss-German border are more heavily cited by Swiss applicants. Moreover, we observe an increase in the number of new Swiss patents that are textually similar to patents from the German border region. Knowledge diffusion effects are particularly pronounced for cumulative innovation at an intermediate technological distance to the original German invention. Such inventions introduce at least one new technology field of application while having at least one common field. Additionally, we find that the effects are concentrated in fields where Switzerland is relatively closer to the knowledge frontier than the neighboring German regions.

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1. Introduction

Patents disclose knowledge; however, this disclosure alone is often not sufficient for the knowledge to be put into practice and used by others for cumulative innovation. This is due to several factors: certain aspects of knowledge remain tacit and not explicitly documented, specific skills are necessary to effectively apply certain knowledge components, and some knowledge may not immediately appear valuable or applicable to potential users (Rogers 1983, Arora 1996, Foray 2004, Maurseth and Svensson 2020). Labor markets help overcome this problem by enabling firms to search for and hire individuals who possess the tacit knowledge or skills required or who identify previously unacknowledged technological opportunities (Arrow 1962, Almeida and Kogut 1999, Rosenkopf and Almeida 2003, Singh and Agrawal 2011). Nevertheless, quantifying the impact of labor markets on firms' capacity to build on external knowledge has proven difficult, mainly because hiring decisions are endogenous to changes in the research focus of firms and because changes in transportation or communication networks that affect labor market access also have direct effects on knowledge diffusion (Agrawal et al. 2017, Catalini et al. 2020, Furman et al. 2021, Hanley et al. 2022, Wernsdorf et al. 2022).

In this paper, we examine the impact of the expansion of Swiss firms' access to the German labor market on the diffusion of knowledge developed in Germany to Switzerland. We investigate the effects of the Agreement on the Free Movement of Persons (AFMP), which, starting in 2002, eliminated the restrictions faced by Swiss firms to hire EU workers. We leverage the reform's initial phase, during which the first group of workers who Swiss firms had easier access to were cross-border commuters, foreigners commuting to Switzerland to work from their residences in its neighboring countries. We focus on German cross-border workers around the Swiss-German border, which separates two of the most patenting-intensive European regions.

Our analysis is based on a difference-in-differences strategy. We identify German inventions that were patented before the AFMP introduction in locations within close commuting distance to the Swiss-German border in the state of Baden-Württemberg ("border region"). We then track their diffusion in the inventions of Swiss firms, before and after the AFMP introduction. Next, we compare them with other German patents, also developed in Baden-Württemberg but in locations too distant from the border to allow for cross-border commuting ("non-border region"). By focusing on cohorts of patents filed before the reform was enacted, we can control for time-invariant technical characteristics that influence diffusion, thereby isolating the effects attributed to the AFMP introduction.

We employ two distinct measures to gauge diffusion. First, we use the number of citations received by German patents from Swiss patents, a commonly used diffusion measure in the literature. Second, we track the number of new Swiss patents that are textually similar to German patents. We infer similarity by comparing either the patents' abstracts or their full technical description. Using textual similarity can reveal associations between patents that are not captured by citations, such as the use of a common method in the production of an invention. It also extends our ability to measure diffusion as virtually all German patents have at least a moderately similar Swiss counterpart, in contrast to citations, which are relatively rare in our sample.

Our findings indicate that following the removal of restrictions on Swiss firms hiring German cross-border commuters, citations by Swiss firms to patents originating from the German border region increase by about 53.7%. The number of patents filed by Swiss firms with similar abstracts to patents from the German border region increases by about 3.4% to 7.6%, depending on the specific similarity threshold adopted. Using full text similarity, the number of similar patents filed by Swiss firms increases by about 14.5% to 25.7%.

We examine the direct involvement of German cross-border workers in the diffusion process by identifying them among the inventors of Swiss patents that cite or are textually similar to a German patent. We identify Swiss firms and Swiss municipalities where inventing cross-border workers ("cross-border inventors") are employed, and then compare knowledge diffusion effects by their varying presence. While this is primarily a descriptive analysis, we interpret it as indicative of how effects depend on such direct and indirect links to cross-border inventors. We find that the presence of cross-border inventors in Swiss firms or in Swiss municipalities intensifies the observed increase in diffusion. Beyond their direct involvement in cumulative innovation, they seem to foster spillovers to other inventors in the firms they work for.

We deepen our investigation of this diffusion phenomenon with two additional analyses. First, we examine whether access to the labor market influences the direction of cumulative innovation by tracking the knowledge diffusion effects by the technological distance between the original German inventions and the possibilities for subsequent follow-on work. We posit that as this distance increases, the need to acquire knowledge beyond that disclosed in the patent text increases. We measure technology distance by the overlap in technological classes (International Patent Classification (IPC) main groups), corresponding to different fields of application, between the original German patent and the Swiss patents.

Second, we examine whether the knowledge diffusion effects are more pronounced in fields where Baden-Württemberg was closer to the knowledge frontier than Switzerland before the reform or in fields where Switzerland held a position closer to the knowledge frontier. On the one hand, the reform might have helped Swiss firms to "catch up" in fields where they were previously lagging behind. On the other hand, high absorptive capacity in fields where Swiss firms excelled may have enabled them to better exploit the knowledge brought in by cross-border workers. To determine this, we calculate the citation lag from patents to scientific articles. For each technical field, we then rank the two regions based on the distribution of their patents' lag to science.

We find an inverted-U relationship in the dependence of the knowledge diffusion effect on technology distance, using textual similarity as the diffusion measure. The effects are strongest for cumulative innovations at intermediate distances, which introduce at least one new field of application relative to the original invention but also share at least one common field of application with the original invention. Knowledge diffusion effects are pronounced in technical fields where Switzerland is closer to the knowledge frontier than Baden-Württemberg, and the strength of this effect seems to increase with the size of the advantage. In fields where Baden-Württemberg is closer to the frontier, the effects are absent.

Our study provides substantial new evidence on the role of labor markets in enabling knowledge diffusion. In our research setting, labor movements are triggered by an exogenous legal change in the permission to hire workers. This addresses concerns about the endogenous nature of hiring and allows us to distinguish the effect of labor market access from confounding factors—such as changes in transportation networks or in knowledge-sharing infrastructure—that affect diffusion and correlate with labor mobility (see, e.g., Agrawal et al. 2017, Catalini et al. 2020, Furman et al. 2021, Hanley et al. 2022, Wernsdorf et al. 2022). The paper also builds on previous studies showing how labor movements predict subsequent diffusion (Almeida and Kogut 1999, Rosenkopf and Almeida 2003, Singh and Agrawal 2011). Our policy experiment addresses the concern that such movements are partially explained by changes in the research focus of hiring firms, thereby providing causally valid estimates. Moreover, our study is also among the first to use textual similarity as a diffusion measure (another study is Buenstorf and Heinisch 2020).[1] Our results uncover a previously unrecognized mechanism: the influence of labor market access on knowledge diffusion varies based on the technological distance.

This paper is also one of the few to examine the effects of an immigration reform on knowledge

[1] Buenstorf and Heinisch (2020) compare the textual similarity of a firm's patents and the dissertations of its recently hired PhDs. Another application is Myers and Lanahan (2022), who use textual similarity to identify technical areas where they track R&D grant spillovers.

diffusion.[2] Understanding the effects of such reforms is crucial for policymakers and for gaining insight into the consequences of the growing integration of labor markets across borders. Previous research has focused on leading scientists and inventors migrating across continents, who might be expected to bring along previously unrecognized ideas (Borjas and Doran 2012, Moser et al. 2014, Ganguli 2015). We show that knowledge diffusion effects also occur for a reform that primarily affected the mobility of a younger and much less established group of scientists and engineers, over a much shorter distance.

Our study also relates to the literature on the geographical determinants of knowledge diffusion (Jaffe et al. 1993; Thompson and Fox-Kean 2005; Peri 2005; Breschi and Lissoni 2009; Singh and Marx 2013; Belenzon and Schankerman 2013). In a seminal contribution, Jaffe et al. (1993) pioneer the use of patent citations to measure knowledge flows and show they are geographically localized. Peri (2005) and Singh and Marx (2013) show that national and sub-national borders constrain technical knowledge flows beyond simple geographic distance. Our study identifies the contribution of labor market segmentation to this phenomenon.[3]

Last, our paper is associated to more specific research evaluating the effects of the AFMP introduction for cross-border workers on Switzerland (Beerli et al. 2021; Ariu 2022; Cristelli and Lissoni 2020; Oswald-Egg and Siegenthaler 2021) and its neighboring countries (Hafner 2021; Dicarlo 2021). Beerli et al. (2021) illustrate how the AFMP induced a large positive supply shock of cross-border workers in Swiss regions close to the international border, increasing the productivity of Swiss firms and the wages of highly educated Swiss workers. Cristelli and Lissoni (2020) show that many of these commuters were inventors employed in Swiss R&D labs, whose greater

[2] Another study in the context of the EU enlargement is by Fackler et al. (2020), who examine the effect on knowledge remittances to the new EU member states.

[3] This literature focuses chiefly on the diffusion of technical knowledge embodied in patents and scientific articles. Abramitzky and Sin (2014) study the international diffusion of knowledge embodied in books after the collapse of the Soviet Union. Giorcelli (2019) examines the diffusion of management knowledge and technology from the United States to Italy during the Marshall Plan.

supply post-AFMP increased patenting in Swiss regions near the border as well as the productivity of incumbent inventors directly collaborating with foreign commuters. In contrast to these two studies, our identification strategy leverages the proximity to the border within the cross-border commuters' region of origin rather than within Switzerland. Our units of observation are not Swiss regions, firms, or inventors, but German patents, allowing us to examine how diffusion is affected for a particular piece of technological knowledge while also exploiting patent-specific variation in technological distance to the follow-on work or technical field.[4]

The paper proceeds as follows. The next section reports essential details about the AFMP introduction for cross-border commuters across the Swiss-German border. Section describes the construction of the dataset and the textual similarity measures. Section discusses the empirical strategy. Sections 5 and 6 present the results, and Section 7 concludes.

2. Context

2.1. The Agreement on the Free Movement of Persons

On June 21, 1999, Switzerland and the EU signed the Agreement on the Free Movement of Persons (AFMP). Gradually implemented during the following years, the AFMP lifted all restrictions to immigration from the EU to Switzerland (and vice versa). Its negotiation had started in 1994 as part of a series of treaties regulating EU-Swiss relationships, after Switzerland's attempt to join the European Economic Area was rejected by Swiss voters via a 1992 referendum. The outcome of the negotiations remained uncertain until common ground was achieved in 1998, and the AFMP introduction was certain only after the positive result of a Swiss confirmatory referendum held on May 21, 2000.

[4] Notably, our approach does not rely on ex-ante assumptions about diffusion patterns within Switzerland. Spillovers to regions within Switzerland that are too distant from the Baden-Wüerttemberg border to attract German cross-border workers are captured in our analysis. For example, an applicant in Lausanne, which is 2.5 hours from the border, might learn from an applicant in Basel, just 10 minutes away.

The first category of immigrants to benefit from the AFMP introduction were cross-border workers, foreigners employed in Swiss areas close to the international border and residing in nearby areas in Switzerland's neighboring countries. Before the AFMP implementation, cross-border commuting to Switzerland was regulated by a series of bilateral treaties. The treaty between Germany and Switzerland, signed in 1970, designated the German areas whose residents were eligible to apply for a Swiss cross-border worker permit called a "G-permit," as well as the Swiss regions where they were allowed to obtain employment.[5] G-permits were limited and difficult to obtain. Sponsoring employers in Switzerland had to undergo a costly and time-consuming application process, which included demonstrating that they had searched and failed to find a native worker with the required skills. Once a cross-border worker obtained a permit, they had to renew it every year, and it was tied to the sponsoring employer. The worker also had to commute back to their country of residence on a daily basis.

The AFMP progressively lifted these restrictions. Immediately after the treaty was signed in 1999, particularly after the confirmatory referendum in 2000, the procedures for firms to obtain G-permits were informally simplified (Beerli et al. 2021). Then, after the official introduction of the AFMP on June 1, 2002, the duration of G-permits was extended to five years and no longer tied to the employer. In addition, the compulsory daily commute was transformed into a weekly one, and the six-month across-the-border residence requirement was suppressed. In 2004 all residual restrictions for G-permit holders were lifted except the requirement to be employed only in certain Swiss areas, as indicated by the pre-AFMP bilateral treaties. This changed in 2007, when resident immigrants from EU-15 and European Free Trade Association countries also gained full freedom to work in Switzerland.

[5] State Secretariat for Migration, `https://www.sem.admin.ch/sem/de/home/publiservice/weisungen-kreisschreiben/auslaenderbereich.html`

2.2. *Cross-Border Commuters and Inventors*

The AFMP introduction generated a large positive supply shock of cross-border commuters, almost exclusively directed to Switzerland and residing in adjacent areas in its neighboring countries. Beerli et al. (2021) illustrate how the majority of these incoming cross-border commuters were highly educated and employed in high-paying occupations. Cristelli and Lissoni (2020) show that among those commuters were many "cross-border inventors," scientists and engineers residing in Switzerland's neighboring countries but working and patenting for a Swiss firm.

We use data from the Swiss Central Migration Information System (ZEMIS) register to characterize German cross-border workers hired by Swiss firms after the AFMP introduction. ZEMIS provides data on all foreigners working in Switzerland, including their permit types, residence and work locations, and nationalities, starting from 2002 onward. Among them, we can identify cross-border workers patenting for a Swiss firm, which we define as "cross-border inventors," using data from Cristelli and Lissoni's (2020) dataset, linking inventors listed on European Patent Office (EPO) patents to their ZEMIS profiles.[6]

We count 107,838 German cross-border workers entering Switzerland in the wake of the AFMP introduction. They tended to be hired in the early stages of their professional careers, displaying a modal, median, and mean age at arrival of 26, 33, and 34.7 years old, respectively. Among them, we identify 1,304 cross-border inventors, around (1.2% of the total). They also enter Switzerland at the beginning of their careers. Their modal, median, and mean age at arrival are 31, 34, and 35.2 years old, respectively, which is close to the average age of first-time inventors indicated by the literature (Jones 2009; Breschi et al. 2020; Kaltenberg et al. 2023). Only 13% of them had filed a patent before entering the Swiss labor market. However, their integration within the Swiss R&D

[6] Inventor records are linked to their profiles in the ZEMIS register using a supervised machine learning strategy first proposed by Feigenbaum (2016), based on name similarity and corresponding geographic information. Details on the linkage procedure can be found in the Online Appendix of Cristelli and Lissoni (2020).

system was fast: around 50% filed their first patent in Switzerland during their first three years in the country, and 75% did so by their first six years.

2.3. Patenting and Wages in Baden-Württemberg and Switzerland

The AFMP introduction for cross-border commuters between Germany and Switzerland affected two of the most patenting-intensive areas in Europe. Appendix Figure A7 shows the average number of yearly filings to the EPO in European NUTS-3 areas during the 1990s. Most of the areas in Baden-Württemberg and Switzerland are ranked above the 75th patenting percentile, and several are in the top 90th. While Stuttgart and its metropolitan area display the highest patenting rates in Baden-Württemberg (top 95th and top 99th percentile), NUTS-3 areas closer to Switzerland do not lag far behind, reporting yearly patenting outputs either between the 75th–90th or the 90th–95th percentile in Europe. In Switzerland, many top innovative areas are contiguous to the German border (e.g., Zurich and Basel), although the surrounding Swiss regions report high patenting outputs as well.

Although Baden-Württemberg and Switzerland display comparable patenting productivity, workers' compensation levels differed starkly when the AFMP was introduced. Appendix Figure A6 shows the average gross yearly salary for NUTS-2 areas in Baden-Württemberg and Switzerland in 2002. All Swiss regions exhibit considerably higher figures, with those adjacent to Baden-Württemberg reporting more than twice the average annual salary of areas on the German side of the border. This salary differential (and equivalently different price levels) likely explains the Germany-to-Switzerland direction of cross-border workers' flows. When the AFMP lifted immigration restrictions, it became a particularly strong pull factor for the residents of an area with almost one million inhabitants (Appendix Figure A8).

3. Data and Measurement

3.1. Sample Construction and Citations

We extract all patent applications originating from the German state of Baden-Württemberg that were filed with the European Patent Office (EPO) or the German Patent and Trademark Office (DPMA) between 1990 and 2000 (Worldwide Patent Statistical Database PATSTAT, version 2019b).[7] We geocode all addresses of inventors and applicants at the municipality level and calculate the driving distance to the Swiss-German border by car.[8] Next, we extract all patent applications filed by Swiss applicants with the EPO or the DPMA, as well as those filed with the Swiss Federal Institute of Intellectual Property (IGE), between 1990 and 2015.[9] Since the same invention may have been filed with multiple intellectual property offices, we aggregate applications at the DOCDB patent family level, which we henceforth refer to as "patents" for ease of exposition.

Our final dataset contains 65,787 patents filed in Baden-Württemberg between 1990 and 2000. We track the citations they received from 147,491 patents filed in Switzerland between 1990 and 2015. The citation year is dated by the earliest filing date of the citing Swiss patent application. We do not differentiate by citation-generating authority, citation category, or whether the citation was added by an examiner.

[7]For a patent application to be included in this sample, we require that both the applicant and at least one of the inventors have an address in Baden-Württemberg. From this set, we further exclude all patent applications that also list an inventor with a Swiss address (besides the German ones) and those that list a Swiss applicant besides the German one. Some patents may list other co-inventors and co-applicants from outside Baden-Württemberg and Switzerland, but they are not further considered in our analysis.

[8]Addresses found on EPO patent applications are provided by PATSTAT. For DPMA patent applications, we supplement our data with address information from DPMA's homepage. Driving distances are calculated as commuting times in September 2020 to the nearest Swiss municipality under typical traffic conditions on a Monday at 8:00 am, using the Google Maps Geolocation API. In robustness checks, we consider travel times by train.

[9]To be included in this sample, we require that there be at least one applicant with an address in Switzerland. We allow for co-applicants and co-inventors from Baden-Württemberg as their presence on Swiss patents could be an endogenous result of the reform. We do not check the applicant's legal status; they could be individual inventors without a business who cannot hire cross-border workers. However, we assume that the prevalence of such cases is negligible.

3.2. *Textual Similarity*

In addition to citations, we track the diffusion of patents from Baden-Württemberg via the emergence of textually similar patents from Switzerland. It should be noted that this analysis is limited to patents filed with the EPO, which account for 46.0% of patents from Baden-Württemberg and 75.6% of patents from Switzerland within our sample. We rely on two approaches. First, we calculate the textual similarity between patent abstracts. Second, we assess the textual similarity between the full text bodies of patents. The patent abstract is a 150-word summary of the invention's description and is for disclosure purposes only (European Patent Convention (EPC), Art. 85).[10] The full text body describing the invention is in principle unlimited in length and averages about 7,000 words. It must meet the standard of disclosure sufficient to reproduce the invention.[11]

The first approach follows the algorithm developed by Younge and Kuhn (2016).[12] We use all patents from Baden-Württemberg filed between 1990 and 2000 and all patents from Switzerland filed between 1990 and 2010 at the EPO and extract their English-language abstracts.[13] Starting from the words found in the abstracts in the sample (i.e., the corpus), we construct a vocabulary of terms defining the vector space model dimensions. We pre-process the corpus by tokenizing the text; stemming term variants with a Porter stemmer; and removing numbers, alphanumeric terms, terms with less than 3 characters and more than 25 characters, and a list of natural-language stop words. The resulting vocabulary consists of around 30,000 terms.

[10]According to rule 47 of the EPC implementing regulation, "[it should allow] the clear understanding of the technical problem, the gist of the solution of that problem through the invention, and the principal use or uses of the invention."

[11]The EPO states, based on Art. 83 of the EPC, that "a detailed description of at least one way of carrying out the invention must be given. [..][However,] it is neither necessary nor desirable that details of well-known ancillary features are given, but the description must disclose any feature essential for carrying out the invention in sufficient detail to render it apparent to the skilled person how to put the invention into practice. A single example may suffice, [unless] the claims cover[s] a broad field[.]"

[12]Younge and Kuhn (2016) construct a vector space model to calculate the textual similarity between the description of all US Patent and Trademark Office (USPTO) patents filed since 1976.

[13]We do not consider patent families that only comprise applications with the national offices (DPMA or IGE) but not with the EPO, as they do not have an English-language abstract available. We restrict to the filing years preceding (and including) 2010 for Swiss applicants to reduce the computational burden.

We represent each patent as a vector in the vocabulary space, constructed using the term frequency of each term in each patent abstract scaled by the inverse document frequency of each term across the entire corpus. This technique, commonly known as "tf-idf," evaluates the relevance of a term in a patent abstract by considering its recurrence across the entire corpus, thus reducing the weight of common terms that provide less information about the unique features of a given invention.[14] The textual similarity score is calculated as the cosine of the angle separating a given pair of vectors (patents) in the space and ranges between 0 and 1, with 1 indicating the highest similarity level.

The second approach is based on the patents' full text body. We use a sophisticated, proprietary text-mining algorithm integrated within the commercial tool *octimine*, which is primarily designed for prior art search. This algorithm, as described in Natterer (2016) and used in Brachtendorf et al. (2020), is trained on a much larger text corpus than our abstract similarity algorithm, including the universe of patents filed with the EPO, USPTO, and World Intellectual Property Organization (WIPO). It encompasses pre-processing techniques such as stop word removal, stemming, and term reduction; automatic language correction; and a weighting scheme based on term frequency and entropy.

Each patent is represented in a vector space model, where the dimensions capture words with similar latent semantic meanings. The algorithm provides cosine similarity scores ranging from 0 to 1. A limitation of the algorithm is that it only returns similarity scores for the 1,000 most similar patents worldwide for each patent analyzed. As a result, each patent has a different truncation point when identifying similar patents. For example, if the 1,000th most similar patent has a score of 0.16, we only observe patents with similarity scores exceeding this value. In our analysis, patent fixed effects account for these differences.

[14] Formally, tf-idf is calculated as $\textit{tf-idf}\ (t, d, D) = f_{t,d} \times log(N/n_t)$, where $f_{t,d}$ is the frequency of term t in document d, N is the total number of documents, and n_t is the number of documents with term t.

For each patent filed at the EPO from Baden-Württemberg, we compute the yearly number of patents subsequently filed (either in the same year or in the years following the filing of the patent from Baden-Württemberg) at the EPO by Swiss applicants between 1990 and 2010. We consider those whose textual similarity to the original patent exceeds a given threshold, evaluating separately for abstract and full text similarity. Because the vector representations in the abstract model and the full text model are completely different, the cosine similarity values obtained with the two models are not comparable.

Conceptually, textual similarity and citations may capture different types of knowledge associations. Citations primarily indicate that a cited patent prejudices the novelty or inventiveness of a claimed invention, representing the state-of-the-art knowledge against which a new invention is compared.[15] Conversely, textual similarity between the patents' abstracts or technical descriptions indicates a commonality in the characteristics of two inventions.[16] Therefore, textual similarity can trace the adoption and dissemination of shared knowledge inputs, such as specific methods, which may not be adequately captured by citations alone.

Table 1 presents descriptive statistics for both citations and textual similarity. On average, a patent from Baden-Württemberg receives 0.0089 citations per year from Swiss applicants (between 1990 and 2010). Swiss applicants file an average of 85.038 patents per year, where the cosine similarity of the abstract to the Baden-Württemberg patent exceeds 0.1. When raising the abstract similarity threshold to 0.2, 0.3, and 0.4, the average number of similar patents filed by Swiss applicants drops to 13.355, 2.825, and 0.575 per year, respectively. Using full text similarity, the average number of similar patents filed by Swiss applicants per year amounts to 1.6663, 1.0479, 0.1607, and 0.018 for cosine similarity thresholds of 0.1, 0.2, 0.3, and 0.4, respectively.

[15] Patent offices generally allow citations to prior art that may not directly impact legal patentability (e.g., citation categories like "T" for theories and underlying principles in the case of the EPO). However, these citations are highly incomplete as examiners and applicants do not have the incentive to uncover or record them.

[16] For example, Bryan et al. (2020) show that the patent descriptions often contain references to scientific sources that are not included among the front-page citations.

4. Empirical Strategy

Our empirical strategy examines the effects of the AFMP introduction on the diffusion of patented inventions from Baden-Württemberg among Swiss firms, using a difference-in-differences approach. We compare the diffusion of patented inventions that were developed within close commuting distance of the Swiss-German border (border regions) with the diffusion of those developed in locations that are too far away to allow for cross-border commuting (non-border regions). We assume that the knowledge of inventions from border regions, or the relevant knowledge for their implementation, is more likely to be transmitted into Switzerland after the AFMP introduction due to the presence of cross-border workers familiar with those technologies developed near their source locations.

Our analysis is restricted to patent cohorts from Baden-Württemberg filed before the reform's implementation. This approach allows us to examine changes in diffusion occurring after the AFMP introduction while keeping constant all time-invariant factors that might also influence diffusion. If the diffusion patterns of the two groups diverge following the reform, we interpret this as evidence that the removal of work restrictions for cross-border commuters had a causal effect on the diffusion of knowledge developed in Germany to Switzerland.

Focusing on cohorts of patents from Baden-Württemberg filed between 1990 and 2000, we assign each patent a treatment intensity based on its inventors' driving distance to the Swiss-German border. In our main specifications, we assign the share of inventors residing in municipalities lying within a 45-minute commute to the border, our designated border region in Baden-Württemberg. Although we use the inventors' addresses to assign the patented invention its treatment status, we do not assume that the inventors are necessarily responsible for the diffusion of the invention in Switzerland. Rather, we assume that their locations are a proxy for whether the invention was developed in the border region or in the non-border region of Baden-Württemberg. Figure 1 (upper panel) presents a map of driving distance to the Swiss-German border for municipalities in Baden-Württemberg.

We corroborate our research design with data from ZEMIS linked to EPO inventor records. Figure 1 (middle panel) shows the spatial distribution of residential addresses of German cross-border workers who appear as inventors (cross-border inventors) in Baden-Württemberg by district. About 84.9% of cross-border inventors reside in districts that are within a 45-minute drive of the Swiss border (using the minimum driving distance across municipalities in the district). Furthermore, 64.7% reside in the three closest districts (Lörrach, Waldshut, and Konstanz).

Using place of birth data, we show that many cross-border inventors not only reside in areas close to Switzerland but also originate from there. The bottom panel of Figure 1 shows the spatial distribution of cross-border inventors' place of birth by district. We see that 76.6% of cross-border inventors were born in districts that are within a 45-minute drive of the Swiss border, while 49.1% were born in the three closest districts. Appendix Figure A1 shows corresponding maps using the entire population of cross-border workers, not just inventors. The places of residence and birth appear to be even more concentrated near the Swiss border for this sample. It is therefore likely that many cross-border workers were already living in areas close to Switzerland even before seeking employment as cross-border commuters.

Our research design has two potential complications. First, few workers may have still moved from non-border regions within Baden-Württemberg to the border region to take up employment as cross-border commuters in response to the reform. This would introduce a negative, and hence conservative, bias on our estimates. Second, since the patents from Baden-Württemberg were filed in the 1990s while the reform is not implemented until 2002, it is possible that workers may have moved between the border and non-border regions during that period. This would introduce measurement error and thus a conservative attenuation bias.

We estimate the event study specification of a Poisson difference-in-differences model, at the patent level. The conditional mean satisfies

$$
\begin{aligned}
E\left[y_{i,t}|X_{i,t}\right] = \exp\Big[\alpha_i + (&\beta_1 I_{t\leq 1994} + \beta_2 I_{t=1995,1996} + \beta_3 I_{t=1997,1998} + \beta_4 I_{t=2001,2002} + \\
&\beta_5 I_{t=2003,2004} + \beta_6 I_{t=2005,2006} + \beta_7 I_{t=2007,2008} + \beta_8 I_{t=2009,2010} + \\
&\beta_9 I_{t=2011,2012} + \beta_{10} I_{t\geq 2013}) \times BorderBW_i + \delta_{t^*(i),t}\Big]
\end{aligned} \tag{1}
$$

where $y_{i,t}$ is the diffusion outcome for patent i from Baden-Württemberg in year t (e.g., the number of citations from Swiss patents), for all years after the year of filing of patent i; α_i is the patent fixed effect, which captures time-invariant characteristics of each patent that affect diffusion; and $\delta_{t^*(i),t}$ is a patent-cohort (i.e., year of filing) $\times$ citation year fixed effect. $BorderBW_i$ is the patent's treatment status, which in the main specification is given by the share of inventors who reside within a 45-minute commute to the Swiss-German border. $I_{t\in T}$ are indicators equal to 1 for years that fall in the designated period T and equal 0 otherwise. We aggregate individual years into two-year periods to increase the precision of our estimates, and the base period is 1999–2000. The β coefficients are our estimates of interest. They are interpreted as the relative differences in diffusion in the given period between patents with all inventors located in the border region and patents with none of their inventors located in the border region. For inference, we cluster the standard errors at the patent level.

Assuming a one-year lag between the start of inventive activity and patenting (Hall et al. 1986; de Rassenfosse and Jaffe 2018), the coefficient for 2001–2002 captures diffusion outcomes during the phase when procedures were informally simplified in anticipation of the reform (discussed in Section 2). The coefficients from 2003 onward represent diffusion outcomes under the fully implemented cross-border worker regime until 2007, the year in which free movement was introduced.[17]

We also estimate a corresponding fixed effects difference-in-differences specification. The conditional mean satisfies

$$E[y_{i,t}|X_{i,t}] = \exp\left[\alpha_i + \beta(AFMP_t \times BorderBW_i) + \delta_{t^*(i),t}\right] \tag{2}$$

where all definitions from Equation 1 apply. $AFMP_t$ is a function that captures the reform's timing. To account for the gradual simplification of procedures between 2000 and 2002, we model this function as gradually increasing. We select a linearly increasing treatment intensity of one-third for the year 2001, two-thirds for 2002, and one for the years thereafter. β is our coefficient of interest. The percentage increase in the outcome variable due to the reform for patents with all inventors located in the border region is given by $\exp(\beta) - 1$.In our analysis we focus primarily on effects up to 2007. When examining effects after 2007, we also set a treatment intensity of one for the years after 2007. For inference, we cluster the standard errors at the patent level.

Figure A2 shows the average number of citations by Swiss applicants for patents developed in border and non-border regions of Baden-Württemberg. Figure A3 shows the average number of new Swiss patents that are textually similar, using either abstract similarity or full text similarity with a cosine similarity threshold of 0.2. The graphs indicate that between 2003 and 2007, patents with at least one inventor residing in the border region exhibit a relative increase in diffusion among Swiss applicants compared to patents where all inventors reside in the non-border region.

[17] The coefficient for 2007–2008 therefore captures diffusion outcomes for one year that falls in the AFMP implementation period and one year that falls under the subsequent free movement regime.

5. The Effect of the AFMP Introduction on Knowledge Diffusion

5.1. *Patent Citations Results*

Figure 2 presents the estimation results of the event study specification (Equation 1), using the number of citations by Swiss patents as the dependent variable. The estimated coefficients for the periods before 1998 are close to zero and not statistically significant, suggesting a common trend in citations for patents developed in border and non-border regions before the AFMP introduction. Similarly, the coefficient is close to zero and not statistically significant for the period 2001–2002. However, once the restrictions to cross-border workers are lifted, our estimated coefficients become positive and statistically significant, implying an increase in Swiss citations for patents from border regions in the periods 2003–2004 and 2005–2006. For the periods after 2007, the coefficients decrease and become statistically insignificant.

In Table 2, we report the estimation results of the fixed effects difference-in-differences specification (Equation 2). The estimate in column 1 suggests that between 2001 and 2007, the removal of work restrictions for cross-border commuters increased the number of citations from Swiss patents to patents developed in the German border region, or more precisely, to patents with all inventors located in the border region, by about $\exp(0.430) - 1 = 53.7\%$ ($p < 0.001$).[18] In column 2, extending the outcome period to 2015, we find an average effect of about 25.2% ($p = 0.035$).

It is worth noting that citations by Swiss applicants are quite rare. The mean of our dependent variable is only about 0.0089 (see Table 1), and only 4,520 patents from Baden-Württemberg, corresponding to about 6.9% of the sample, are cited at least once by a Swiss applicant (when measured up to 2007). Therefore, our results imply an absolute increase of about 0.0048 additional citations per year and per patent due to the reform, with the gains accruing to a rather small subset of patents.

[18] All reported p-values refer to the two-sided test for the treatment coefficient; i.e., $p = 2 * \Phi(-|\hat{\beta}/\hat{\sigma}|)$.

5.2. *Textual Similarity Results*

Figure 3 (top panel) shows event study estimates when our dependent variable is the number of new Swiss patents whose abstract has a cosine similarity of at least 0.2 relative to the abstract of the focal Baden-Württemberg patent. The coefficients are negative, close to zero, and, with the exception of 1997–1998, statistically insignificant before the AFMP introduction. There is a slight increase for 2001–2002, where the coefficient becomes positive and statistically significant. After 2003, the coefficients substantially increase and remain significant. Unlike the estimates using citations as the dependent variable, we do not find any evidence of a decline in the diffusion effect after 2007. Event study estimates based on different abstract similarity thresholds are presented in Appendix Figure A4.

Table 3, Panel A reports the results from the fixed effects difference-in-differences specification. The estimates indicate that by 2007, the AFMP introduction increased the number of Swiss patents with similar abstracts to those developed in the border region by about 3.4%, using an abstract similarity threshold of 0.1 (column 1, $p < 0.001$), by about 7.6% using an abstract similarity threshold of 0.2 (column 3, $p < 0.001$), and by about 6.0% using an abstract similarity threshold of 0.3 (column 5, $p < 0.001$). Using an abstract similarity threshold of 0.4, the estimated coefficient is close to zero and insignificant (2.2%, column A7, $p = 0.785$). In columns 2, 4, 6, and 8, we extend the outcome period to 2010, which yields very similar results. In Appendix Table A1, instead of choosing a threshold, we divide the range of cosine similarity values for abstracts into even intervals. We find significant diffusion effects for the intermediate ranges of 0.2 to 0.3 and 0.3 to 0.4 but not for the upper (0.4 to 1) or lower (0.1 to 0.2) ends of the spectrum.

Despite the smaller estimated coefficients compared to citations, these results imply economically large diffusion effects. Given that patents with a textually similar abstract are common (see the mean of the dependent variable in Table 1), the estimates indicate an increase of about 2.89, 1.01, and 0.17 similar patents per year for each patent from the German border region, using cosine similarity thresholds of 0.1, 0.2, and 0.3, respectively. In interpreting these effects, it is useful to consider the potential counterfactuals that are implicit in our quasi-experiment: if the reform had not occurred, the missing similar Swiss patents could either not exist at all or exist but with a different text, covering an invention that possibly has different characteristics. As we raise the similarity threshold, the estimates are likely to capture greater changes in the abstract's text, and perhaps inventions that would have not been developed in the absence of the AFMP introduction.

Figure 3, Panel B presents event study estimates that are based on the number of new Swiss patents with a full text cosine similarity of at least 0.2. The results mirror our previous findings. Before the AFMP introduction, the estimated coefficients are close to zero and, except for 1997–1998, not statistically significant. The coefficients increase after 2000 and are positive and statistically significant after 2003. After 2007, they decrease in size but remain statistically significant (for different thresholds, see Appendix Figure A4).

Table 3, Panel B shows that the AFMP introduction increased the number of similar Swiss patents by about 14.5%–25.7% (columns 1–6, all p-values < 0.001), depending on whether we use a full text similarity threshold of 0.1, 0.2, or 0.3 or whether we measure our diffusion outcome up to 2007 or up to 2010. We observe no increase in the number of textually similar patents when the cosine similarity is 0.4 or higher (columns 7–8). Similar to our estimates based on abstracts, Appendix Table A1 shows that diffusion effects appear only for intermediate ranges of cosine similarity (0.2 to 0.3 and 0.3 to 0.4).

Given the mean of the dependent variable (Table 1), the estimates imply absolute increases in the number of Swiss patents whose full text is similar to those developed in Baden-Wüerttemberg's border region of about 0.24, 0.24 and 0.041 per year and per patent using full text similarity thresholds of 0.1, 0.2, and 0.3, respectively.

5.3. *Robustness Checks*

In Appendix Table A2, we present results for alternative definitions of the German patent's treatment status. In column 1, we assign to the patent the share of its applicants located within 45 minutes of the Swiss-German border, which results in slightly larger estimated coefficients. In columns 2–4, we use the inventors' locations but consider different cutoffs (30–60 minutes) for the driving time to the Swiss-German border. To keep the control group constant in this exercise, we only consider patents that are (at least partially) treated and those for which none of their inventors reside within 60 minutes of the border. We find positive and statistically significant diffusion effects in line with our main results, except for the specification based on citations as the diffusion measure and a cutoff of 30 minutes for driving time, where the coefficient is not statistically significant.

In column 5, we allow for commuting by train or a combination of car and train.[19] Our results in this case are very similar to our main results. In column 6, we transform the dependent variable using the inverse hyperbolic sine and estimate the model with Ordinary Least Squares. The estimates of the diffusion effect are highly significant. However, when using textual similarity as the diffusion measure, we observe relatively smaller implied elasticities (58.7% for citations, 4.4% when using an abstract similarity threshold of 0.2, and 8.8% when using a full text similarity threshold of 0.2).

5.4. *Evidence on the Involvement of Cross-Border Workers*

We first examine the heterogeneity of diffusion effects based on the distance of Swiss applicants from the Swiss-German border. If these effects are driven by the influx of cross-border workers due to the AFMP, we would expect stronger effects for patents filed by firms based in areas closer to the border due to a higher prevalence of such workers. Nonetheless, even distant regions might

[19] Commuting times by train are given by the fastest travel time from the municipality's train station to a train station in Switzerland. Car/train commute times are calculated as the sum of the travel time from the municipality of origin to the train station (in another municipality), plus the train commute time, plus five minutes for changing between car and train.

benefit from internal Swiss spillovers. For instance, an applicant in Lausanne, which is 2.5 hours from the Swiss-German border, might gain insights from an applicant in Basel, whose city limits border directly with Germany.

Appendix Table A3 shows the results of our fixed effects difference-in-differences specification (Equation 2). In columns 1, 3, and 5, the dependent variable is the number of citations or the number of textually similar new patents by Swiss applicants located in municipalities within a 45-minute commute to the border.[20] We find diffusion effects of about 63.8% ($p = 0.004$) using citations, 19.1% ($p < 0.001$) using abstract similarity, and 41.1% ($p < 0.001$) using full text similarity (in both cases, we use a cosine similarity threshold of 0.2). However, for locations beyond a 45-minute drive, the effects are close to zero and insignificant (see columns 2 and 4) except for full text similarity, where the effect is smaller yet significant (11.4%, $p < 0.001$; see column 6).

We then examine the heterogeneity of diffusion effects through the involvement of cross-border inventors. For each citing or textually similar patent filed by a Swiss applicant located within 45 minutes of the border, we identify German cross-border inventors (i.e., German cross-border workers observed patenting for a Swiss applicant) who appear directly on the patent, cross-border inventors who patent for the same Swiss applicant, and cross-border inventors who patent for Swiss applicants in the same Swiss municipality. We do this using a method that, while not relying on ZEMIS, produces highly congruent results in identifying cross-border inventors. The method can be linked to our full dataset, which ZEMIS cannot, and allows us to identify cross-border inventors even before the reform.[21] For the period 2002–2007, we calculate the share of cross-border inventors relative to all inventors patenting for a given Swiss applicant as well as the share of cross-border

[20] In this section, we track Swiss citations only from applications at the EPO but not for patent applications filed at the DPMA or at the IGE. This is because we only have Swiss-geocoded addresses available for EPO patent applications.

[21] We do so by comparing the address of individual inventors to that of their patent applicant, defining cross-border inventors all those who reside in a G-permit-designated area in Baden-Württemberg and patent for a Swiss-based applicant.

inventors relative to all inventors patenting in a given municipality.

In Appendix Table A4, columns 1, 3, and 5, we use as the dependent variable the number of citations received by Swiss patents—or the number of similar Swiss patents—with a cross-border inventor directly on the patent. We find increased diffusion through this channel for patents originating from the German border region. Although an inherent selection bias exists with inventor teams that include cross-border workers, precluding causal interpretations, we interpret this as indicative that a portion of the diffusion effect is attributed to cross-border inventors' direct involvement in cumulative innovation.[22]

Conversely, the results in columns 2, 4, and 6 show that diffusion also increases substantially and significantly among inventor teams that do not include a cross-border inventor. This suggests that knowledge spillovers from German cross-border workers, whether inventors or non-inventors, to other inventors in Switzerland are partly responsible for the diffusion effect. We try to delineate these spillovers below, focusing on cross-border inventors. However, it is important to note that non-inventors may also account for part of the diffusion effect and we cannot distinguish their presence from the presence of cross-border inventors.

In Appendix Table A5 and Table A6, we examine if a notable presence of cross-border inventors—whether within the Swiss applicant or the applicant's municipality—intensifies the observed increase in diffusion.[23] Although this analysis cannot be given a causal interpretation due to selection bias, it may support the notion that cross-border workers drive diffusion effects in the firms and municipalities where they are employed.

[22]For the period 2002–2007, we find that for 15.4% of citations to patents from the German border region, a German cross-border inventor is listed on the citing patent. For textually similar patents, this share is 4.6% for abstract similarity and 10.7% for full text similarity.

[23]For 22.9% (30.3% and 16.8%) of citations (patents that are similar in abstract or full text, respectively) to patents from the German border region, we find a significant presence of cross-border inventors (of at least 5%) in the Swiss applicant. For 53.8% (37.3% and 41.4%) of citations (patents that are similar in abstract or full text, respectively) to patents from the German border region, we find a significant presence of cross-border inventors (of at least 5%) in the Swiss applicant's municipality.

In Table A5, columns 1, 3, and 5, we use as the dependent variable the number of citations or textually similar patents by Swiss applicants located within 45 minutes of the border and with at least 5% cross-border inventors between 2002 and 2007. We find that the number of citations received from, and the number of new textually similar patents filed by, this group increases considerably, with the lowest point estimate being 50.5%. The estimated increases are mostly statistically significant ($p < 0.001$) except for citations, where $p = 0.085$. For the remaining applicants within the same 45-minute boundary, using either citations or abstract similarity as the diffusion measure yields smaller and insignificant increases (columns 2 and 4). However, when using full text similarity (column 6), we continue to find significant increases that are similar in magnitude to our previous estimates, possibly indicating spillovers that are not captured by our other diffusion measures.

In Table A6, we repeat this exercise but instead use the share of cross-border inventors in the applicant's municipality. Again, we focus on applicants in municipalities within 45 minutes of the border and distinguish locations with less than 1%, 1%–5%, and more than 5% of cross-border inventors.[24] We find that diffusion effects tend to increase with the share of cross-border inventors within a municipality. The number of citations received from, and the number of new textually similar patents filed by, Swiss applicants in municipalities with the highest share of cross-border inventors increases strongly and statistically significantly, with the lowest point estimate being 23.1%. By contrast, for municipalities with the lowest share of cross-border inventors, the increase in diffusion is close to zero and insignificant for all diffusion measures, including full text similarity.

5.5. Diffusion Within Corporate Groups, Firm Collaborations, and Inventor Self-Citations

In this section we attempt to shed light on some other channels underlying the overall diffusion effect. First, we try to identify pairs of citing/cited and similar patents where the applicants on the

[24] For municipalities, the range of 1% to 5% in the cross-border inventor share is more densely populated when compared to the distribution for applicants, allowing us to further graduate the outcomes.

Swiss and German sides of the border are members of the same corporate group.[25] A limitation is that we can only observe ownership links in 2007, i.e., after the reform. Second, we examine whether diffusion effects can be partly attributed to new cross-border collaborations between firms, as indicated by the citing patent having both Swiss and German co-applicants. Third, we identify instances of inventor self-citations.[26] In our context, this would suggest that Swiss firms hire established inventors from Baden-Württemberg and have them do "follow-up work" that builds on their own earlier inventions.

Appendix Table A7 shows the results. Overall, we find that occurrences of all three types of linkages are very rare, and they do not appear to contribute much to the overall effect. We do find positive diffusion effects within corporate groups, sometimes statistically significant and sometimes not, depending on the measure we use. Our conclusion is that diffusion appears to occur primarily between corporate groups, predominantly outside of firm collaborations, and in inventor teams that do not include the original patent's inventor.

6. Additional Results

6.1. Effects by Technology Distance

In this section, we investigate whether the diffusion effects resulting from labor market access depend on the technological distance between the original invention and the possibilities for subsequent follow-on work. Our hypothesis posits that an increase in this distance necessitates the acquisition of knowledge beyond what the patent discloses, and such knowledge may be held by cross-border commuters.

To illustrate this point, consider an example from pharmaceuticals: a general compound used

[25] We first assign patents to firms using Orbis IP (version 2020) and then examine their ownership links using the Orbis Historical Ownership Snapshot of 2007. We assume that two firms are part of the same group if they have the same "global ultimate owner."

[26] We mark as "self-citations" when the same inventor name appears on both the citing and the cited patent.

for a specific disease. The patent would reveal key information, most importantly its chemical formula, making it easier for subsequent inventors to reproduce it. Some intricate details might be omitted, such as solubility or the addition of specific acids to increase efficacy. With this knowledge, others can modify the compound to treat related conditions. However, the patent does not disclose whether the compound can be repurposed to other disease categories. During the compound's initial development and up to its patent disclosure, the original inventors likely explored many such alternative uses. This knowledge is typically reserved for the initial development team and perhaps a broader circle within the company. It is also possible that to adeptly reproduce compounds developed by firms in Baden-Württemberg and apply them to other diseases, one must have a profound understanding of compound synthesis techniques prevalent in those firms.

To measure technological distance, we assign patents to "main groups" in the IPC system, similar to Hegde et al. (2022). Each main group represents different applications of an invention within a broader technological area, or differences in the characteristics of a particular invention. Since a patent is usually assigned to several main groups, we calculate the technological distance between pairs of citing/cited patents and textually similar patents by determining the overlap in IPC main groups. Our measure, denoted as $Dist_{ij}$, is computed as $1-\#(IPC_i^S \cap IPC_j^{BW})/\#IPC_j^S$, where IPC_j^S represents the IPC main groups of a Swiss patent j and IPC_i^{BW} represents the IPC main groups of a Baden-Württemberg patent i. In simpler terms, our technology distance measure is one minus the share of overlapping IPC main groups, or equivalently, the share of IPC main groups present in the Swiss patents but not in the Baden-Württemberg patent.

We divide the range of our technology distance measure and let the dependent variable in Equation 2 be the number of textually similar patents, based on either their abstract or full text that fall within the specified range of technology distance. We consider an outcome period until 2007. Figure 4 reports the results.

Using an abstract similarity threshold of either 0.2 or 0.3, when the dependent variable is the number of similar Swiss patents with perfect overlap in IPC main groups (i.e., $Dist = 0$), the estimates are very close to zero, allowing us to rule out even modest increases above 2.0% and 2.2%, respectively, at the 5% confidence level (middle panel).[27] In contrast, we find large and statistically significant effects—ranging from 26.7% to 67.0% (all p-values below 0.0011)—when the dependent variable is the number of similar Swiss patents at an intermediate technological distance ($0 < Dist < 1/3$,$1/3 \leq Dist < 2/3$, or $2/3 \leq Dist < 1$) that add at least one new IPC main group relative to the original patent but also share at least one common IPC main group with the original patent. When the dependent variable is the number of similar Swiss patents with no overlap in IPC main groups (i.e., $Dist = 1$), the estimates suggest smaller increases of about 10.3%–17.4%, which are statistically significant or insignificant, depending on the abstract similarity threshold used (p-values of 0.175 and 0.0006, respectively).

We observe similar patterns when using a full text similarity threshold of 0.2. For similar Swiss patents with an intermediate technological distance, we estimate strong diffusion effects (bottom panel, 35.0% to 53.1%, all p-values below 0.0098). When the dependent variable is the number of similar Swiss patents with perfect overlap in IPC main groups, the point estimate of the effect is about 6.6 to 11.6 standard deviations lower (13.9%, $p < 0.001$). For similar Swiss patents with no overlap in IPC main groups, the estimated effect is 18.1% ($p = 0.0075$). Using a full text similarity threshold of 0.3, the estimates become noisier. However, even in this specification, when aggregating all intermediate distances, we find large and significant increases in the number of similar Swiss patents at a technological distance of $0 < Dist < 1$ (47.1%, $p < 0.001$) and small insignificant increases for similar Swiss patents with perfect or no overlap in IPC main groups (16.9% and 9.0%, respectively).

[27] Appendix Table A8 provides tabulated regression results.

Our results using citations are shown in the top panel of Figure 4 and appear inconclusive. The estimates for the increase in citations by Swiss patents with perfect overlap in IPC main groups and for citations by Swiss patents at an intermediate technological distance range between 46.4% and 146.6% (p-values between $p = 0.025$ and $p = 0.090$) and are generally found to be within the 95% confidence interval of each other. For Swiss patents with no overlap in IPC main groups, the estimated effect is 32.5% which is not statistically significant ($p = 0.264$).

Our findings from textual similarity analysis show an inverted-U relationship between labor mobility and technology distance. Additional textually similar Swiss patents resulting from a labor market access reform tend to introduce at least one new IPC main group relative to the original patent while sharing at least one common IPC main group. This suggests that changes in the adaptation process leading to completely unrelated applications, as reflected by great technological distance, require knowledge beyond that of cross-border commuters. In the case of pharmaceuticals, this knowledge may involve testing for other disease indications that were not previously considered or possessing a deeper understanding of the underlying scientific principles.

6.2. Effects by Relative Distance to the Knowledge Frontier

In this section we examine the impact of the AFMP introduction on the diffusion of German technological knowledge based on the relative distance of Switzerland and Baden-Württemberg to the knowledge frontier in a particular technological field. On the one hand, the reform might have presented an opportunity for Swiss firms to "catch up" in fields where they were previously lagging behind. On the other hand, high absorptive capacity in fields where Swiss firms excelled may have enabled them to better exploit the knowledge brought in by cross-border workers.

We measure the relative distance of Switzerland and Baden-Württemberg to the knowledge frontier in the 35 technical fields defined by Schmoch (2008), comparing citation lags to the scientific literature for patents filed within those locations. This choice is motivated by recent studies showing that patents referencing scientific articles are associated with higher forward citation rates (Ahmadpoor and Jones 2017), higher value (Poege et al. 2019), and greater novelty (Watzinger et al. 2021). For patents filed at the EPO between 1990 and 2000, we compute the share $S_{f,r}(t)$ citing a scientific article published no more than t years before the patent's filing year in technical field f and region r.[28] We suppose that Switzerland is "closer to the knowledge frontier" in field f if $S_{f,S}(t) \geq S_{f,BW}(t)$ for all lags $t \leq 10$ and that Baden-Württemberg is closer to the frontier if the opposite holds true. To measure the magnitude of the advantage that Switzerland may have, we compute the average difference in field f as $RLS_f = \frac{1}{10}\sum_{y=0}^{10}[S_{f,S}(t) - S_{f,BW}(t)]$, which we refer to as the "relative lag to science (RLS)."[29]

Columns 1, 3, and 5 of Table 4 show that the point estimates are negative when we track the diffusion effects for German patents filed in fields where Baden-Württemberg is closer to the frontier. They are positive for those filed in fields where Switzerland is moderately ahead ($0 < RLS_f \leq$ 1.7 percentage points) and are even more positive for patents filed in fields where Switzerland is much closer to the frontier ($RLS_f >$ 1.7 percentage points).[30] This pattern holds consistently across all of our diffusion measures. We also find that the difference in the diffusion effect between patents filed in fields where Baden-Württemberg is closer to the frontier and patents filed in fields where Switzerland is much closer to the frontier is statistically significant for all diffusion measures (all p-values below 0.008). In columns 2, 4, and 6, we include the relative lag to science RLS_f as a linear predictor and confirm the positive relationship between the size of the diffusion effect in a field and the advantage of Switzerland in that field in terms of their citation lag to science.

[28] Data on references to scientific articles are taken from Poege et al. (2019).

[29] We identify 16 technical fields where Swiss applicants are closer to the frontier (e.g., textiles, chemical engineering, and biotechnology) and 6 technical fields where applicants from Baden-Württemberg are closer (e.g., surface technology/coating, metallurgy, and telecommunications). In the remaining 13 fields, the two regions cannot be ranked because $S_{f,S}(t)$ and $S_{f,BW}(t)$ overlap (e.g., pharmaceuticals, semiconductors, and machine tools). Appendix Figure A5 shows RLS plots for selected fields.

[30] The median value of RLS_f among fields in which Switzerland is ahead is 1.7 percentage points.

6.3. *Reverse Knowledge Flows*

In this section, we examine whether there is evidence that German cross-border commuters transferred Swiss technological knowledge back to Baden-Württemberg. It should be noted that due to higher prices and wages in Switzerland compared to Baden-Württemberg (discussed in Section 2), cross-border commuting is almost exclusively from Baden-Württemberg to Switzerland. Hence, we assume that any increase in the diffusion of Swiss patents originating from locations close to the German-Swiss border in the patents of Baden-Württemberg firms is due to German cross-border workers, either passing knowledge acquired in Switzerland through their professional network or after returning to a German employer.

We closely replicate the methodology used in Section 3.1 to construct our sample. We consider the set of patent applications filed in Switzerland between 1990 and 2000 with the EPO, and track their diffusion in patent applications from Baden-Württemberg filed between 1990 and 2010.[31] We then re-estimate model (2), where the treatment status for each Swiss patent is determined by the proportion of inventors residing within a 45-minute commute to the border. The dependent variable is the number of citations received by patents from Baden-Württemberg, filed either with the EPO or the DPMA, or the number of new patents from Baden-Württemberg with a full text cosine similarity of at least 0.2 or 0.3, filed with the EPO.[32]

Table A9 presents the results and shows that the point estimates of the reverse diffusion effect are negative. Our estimates allow us to reject increases in citations of above 0.1% (until 2007, in a one-sided test at the –5% significance level). Moreover, they indicate decreases in the number of patents that are similar in full text of at least -1.1% or of at least -4.9% (until 2007), depending on

[31] We only have Swiss geocodes available for EPO patent applications but not for patent applications filed at the DPMA or at the IGE. In analogy to Section 3.1, we require that both the applicant and at least one of the inventors have an address in Switzerland, and we further exclude all EPO patent applications that also list an inventor or an applicant from Baden-Württemberg. For German patents, we require that there be at least one applicant with an address in Baden-Württemberg.

[32] We do not have abstract similarity measures available for patents from Baden-Württemberg filed in the years 2001–2010.

the cosine similarity threshold. Extending the outcome period to 2010 does not change this finding. Overall, our findings do not support the existence of reverse knowledge flows. If anything, the loss of cross-border workers may have slightly reduced the ability of firms in Baden-Württemberg to build on technological knowledge originating from border regions in Switzerland. However, it is important to note that we only examine the dissemination of Swiss patents filed before the reform. It is possible that cross-border workers transmit back knowledge to Baden-Württemberg from Swiss patents filed after the reform (and after their arrival).

7. Conclusion

To effectively leverage external knowledge, firms depend on hiring workers who possess tacit knowledge, specific skills, and an understanding of technological opportunities. This study investigates a reform that eliminated restrictions on Swiss firms' hiring of cross-border workers. Our objective is to analyze the extent to which the use of technological knowledge in new inventions depends on firms' access to the labor market from which this knowledge originates.

We find notable changes after the reform was implemented. Citations by Swiss firms to patents originating from locations within commuting distance of the border (on the German side) increase by about 53.7%, the number of patents filed by Swiss firms with similar abstracts increases by 3.4% to 7.6% (depending on the specific similarity thresholds used), and the number of patents that are similar in the patent's full text increases by about 14.5% to 25.7%. Knowledge diffusion effects are strongest for cumulative innovations at an intermediate technological distance, which introduce at least one new field of application relative to the original invention but also share at least one common field of application with the original invention. Increases in diffusion are limited to technical areas where Switzerland is closer to the knowledge frontier compared to Baden-Württemberg.

Our study provides substantial new evidence on the role of labor markets in knowledge diffusion.

In our design, labor movements are triggered by an exogenous legal change in hiring permissions, allowing us to distinguish this effect from changes in firms' research focus that explain hiring decisions and from changes in confounding factors, such as transportation networks, that correlate with both knowledge diffusion and labor mobility.

Our findings have practical implications. For firms, their choices regarding the labor markets in which they operate affect their access to locally produced knowledge. The knowledge flows quantified in our study contribute to the agglomeration benefits of innovative hubs with thick, cohesive labor markets (see, e.g., Moretti 2021). Moreover, our study highlights the employment contract's unique role as a facilitator of knowledge transfer (compared to other arrangements that were already possible before the reform). Firms may find it difficult to replicate this level of knowledge transfer through alternative contractual arrangements, such as consulting agreements or collaborations.

Policies that facilitate the integration of geographically segmented labor markets, such as the AFMP, affect how knowledge is diffused and, likely, the direction of cumulative innovation. Subsequent inventions that deviate in scope from the original invention may rely disproportionately on knowledge transfer through the labor market. In our setting, integrating the Swiss labor market with that of Baden-Württemberg appears to have been beneficial for cumulative innovation in areas of knowledge in which Switzerland excelled.

We acknowledge several limitations. First, we cannot determine whether the observed effects capture changes in Swiss inventions that would have otherwise taken a different form, e.g., Swiss patents that would be textually dissimilar to German patents in the absence of the reform or additional innovation that would not have occurred without the reform. Our findings do not imply an overall increase in the innovative activity of Swiss firms; rather, they indicate an increased reliance on German technological knowledge.[33]

Second, our geographic setting of Switzerland and the German state of Baden-Württemberg is peculiar in that they are similarly innovative regions, but Switzerland has higher wages and prices. This feature implies that the reform presumably triggered stronger labor mobility responses than would have occurred in a different setting and should be considered when generalizing the results to other contexts.

Third, the reform represents a change from a regime of restricted to unrestricted labor market access. Presumably, the most highly skilled cross-border workers, for whom the Swiss firms were willing to incur the regulatory costs, were already present. Thus, our estimates likely represent a lower bound on the full effect of integrated labor markets. The group that became mobile due to the reform might not be the target of some selective immigration policies that demand employer sponsorship or set high minimum wages for highly skilled foreign workers (e.g., the H-1B in the US, the EU Blue Card, or Australia's Global Talent Program). However, our results indicate that this group possesses valuable expertise and knowledge.

[33] It is worth mentioning that other studies have suggested an overall increase in innovative activity for Swiss firms following the AFMP introduction (see Beerli et al. 2021 and Cristelli and Lissoni 2020).

References

Abramitzky, R. and I. Sin (2014): "Book translations as idea flows: The effects of the collapse of Communism on the diffusion of knowledge," *Journal of the European Economic Association*, 12, 1453–1520.

Agrawal, A., A. Galasso, and A. Oettl (2017): "Roads and Innovation," *The Review of Economics and Statistics*, 99, 417–434.

Ahmadpoor, M. and B. F. Jones (2017): "The dual frontier: Patented inventions and prior scientific advance," *Science*, 357, 583–587.

Almeida, P. and B. Kogut (1999): "Localization of Knowledge and the Mobility of Engineers in Regional Networks," *Management Science*, 45, 905–917.

Ariu, A. (2022): "Foreign workers, product quality, and trade: Evidence from a natural experiment," *Journal of International Economics*, 139, 103686.

Arora, A. (1996): "Contracting for tacit knowledge: the provision of technical services in technology licensing contracts," *Journal of Development Economics*, 50, 233–256.

Arrow, K. J. (1962): *Economic Welfare and the Allocation of Resources for Invention*, Princeton: Princeton University Press, 609–626.

Beerli, A., J. Ruffner, M. Siegenthaler, and G. Peri (2021): "The Abolition of Immigration Restrictions and the Performance of Firms and Workers: Evidence from Switzerland," *American Economic Review*, 111, 976–1012.

Belenzon, S. and M. Schankerman (2013): "Spreading the Word: Geography, Policy, and Knowledge Spillovers," *The Review of Economics and Statistics*, 95, 884–903.

Borjas, G. J. and K. B. Doran (2012): "The Collapse of the Soviet Union and the Productivity of American Mathematicians," *The Quarterly Journal of Economics*, 127, 1143–1203.

Brachtendorf, L., F. Gaessler, and D. Harhoff (2020): "Truly Standard-Essential Patents? A Semantics-Based Analysis," *CEPR Discussion Paper No. DP14726.*

Breschi, S. and F. Lissoni (2009): "Mobility of Skilled Workers and Co-invention Networks: an Anatomy of Localized Knowledge Flows," *Journal of Economic Geography*, 9, 439–468.

Breschi, S., F. Lissoni, and E. Miguelez (2020): "Return Migrants' Self-Selection: Evidence for Indian Inventors," in *The Roles of Immigrants and Foreign Students in US Science, Innovation, and Entrepreneurship*, ed. by I. Ganguli, S. Kahn, and M. MacGarvie, Univ. of Chicago Press.

Bryan, K. A., Y. Ozcan, and B. Sampat (2020): "In-text patent citations: A user's guide," *Research Policy*, 49, 103946.

Buenstorf, G. and D. P. Heinisch (2020): "When do firms get ideas from hiring PhDs?" *Research Policy*, 49, 103913.

Catalini, C., C. Fons-Rosen, and P. Gaulé (2020): "How do travel costs shape collaboration?" *Management Science*, 66, 3340–3360.

Cristelli, G. and F. Lissoni (2020): "Free Movement of Inventors: Open-Border Policy and Innovation in Switzerland," *Mimeo*.

de Rassenfosse, G. and A. B. Jaffe (2018): "Econometric Evidence on the Depreciation of Innovations," *European Economic Review*, 101, 625–642.

Dicarlo, E. (2021): "How Do Firms Adjust to Negative Labor Supply Shocks? Evidence from Migration Outflows," *Mimeo*.

Fackler, T. A., Y. Giesing, and N. Laurentsyeva (2020): "Knowledge Remittances: Does Emigration Foster Innovation?" *Research Policy*, 49, 103863.

Feigenbaum, J. J. (2016): "Automated Census Record Linking: A Machine Learning Approach," *Mimeo*.

Foray, D. (2004): *Economics of Knowledge*, MIT press.

Furman, J. L., M. Nagler, and M. Watzinger (2021): "Disclosure and subsequent innovation: Evidence from the patent depository library program," *American Economic Journal: Economic Policy*, 13, 239–70.

Ganguli, I. (2015): "Immigration and Ideas: What did Russian Scientists "Bring" to the United States?" *Journal of Labor Economics*, 33, S257–S288.

Giorcelli, M. (2019): "The long-term effects of management and technology transfers," *American Economic Review*, 109, 121–152.

Hafner, F. (2021): "Labor Market Competition, Wages and Worker Mobility," *Mimeo.*

Hall, B. H., Z. Griliches, and J. A. Hausman (1986): "Patents and R and D: Is There a Lag?" *International Economic Review*, 27, 265–283.

Hanley, D., J. Li, and M. Wu (2022): "High-speed railways and collaborative innovation," *Regional Science and Urban Economics*, 93, 103717.

Hegde, D., K. F. Herkenhoff, and C. Zhu (2022): "Patent publication and innovation," *NBER WP 29770, National Bureau of Economic Research.*

Jaffe, A. B., M. Trajtenberg, and R. Henderson (1993): "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *The Quarterly Journal of Economics*, 108, 577–598.

Jones, B. F. (2009): "The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?" *The Review of Economic Studies*, 76, 283–317.

Kaltenberg, M., A. B. Jaffe, and M. E. Lachman (2023): "Invention and the life course: Age differences in patenting," *Research policy*, 52, 104629.

Maurseth, P. B. and R. Svensson (2020): "The Importance of Tacit Knowledge: Dynamic Inventor Activity in the Commercialization Phase," *Research Policy*, 49, 104012.

Moretti, E. (2021): "The effect of high-tech clusters on the productivity of top inventors," *American Economic Review*, 111, 3328–3375.

Moser, P., A. Voena, and F. Waldinger (2014): "German Jewish Émigrés and US Invention," *American Economic Review*, 104, 3222–3255.

Myers, K. R. and L. Lanahan (2022): "Estimating spillovers from publicly funded R&D: Evidence from the US Department of Energy," *American Economic Review*, 112, 2393–2423.

Natterer, M. (2016): *Ähnlichkeit von Patenten: Entwicklung, empirische Validierung und ökonomische Anwendung eines textbasierten Ähnlichkeitsmaßes*, Verlag für Nationalökonomie, Management und Politikberatung (NMP).

Oswald-Egg, M. E. and M. Siegenthaler (2021): "Train Drain? Access to Skilled Foreign Workers and Firms? Provision of Training," *KOF Working Papers*, 495.

Peri, G. (2005): "Determinants of Knowledge Flows and their Effect on Innovation," *Review of Economics and Statistics*, 87, 308–322.

Poege, F., D. Harhoff, F. Gaessler, and S. Baruffaldi (2019): "Science quality and the value of inventions," *Science Advances*, 5, eaay7323.

Rogers, E. (1983): *The Diffusion of Innovations*, Free Press, New York.

Rosenkopf, L. and P. Almeida (2003): "Overcoming local search through alliances and mobility," *Management Science*, 49, 751–766.

Schmoch, U. (2008): "Concept of a Technology Classification for Country Comparisons," *WIPO Technical Report*.

Singh, J. and A. Agrawal (2011): "Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires," *Management Science*, 57, 129–150.

Singh, J. and M. Marx (2013): "Geographic Constraints on Knowledge Spillovers: Political Borders vs. Spatial Proximity," *Management Science*, 59, 2056–2078.

Thompson, P. and M. Fox-Kean (2005): "Patent Citations and the Geography of Knowledge Spillovers: A Reassessment," *American Economic Review*, 95, 450–460.

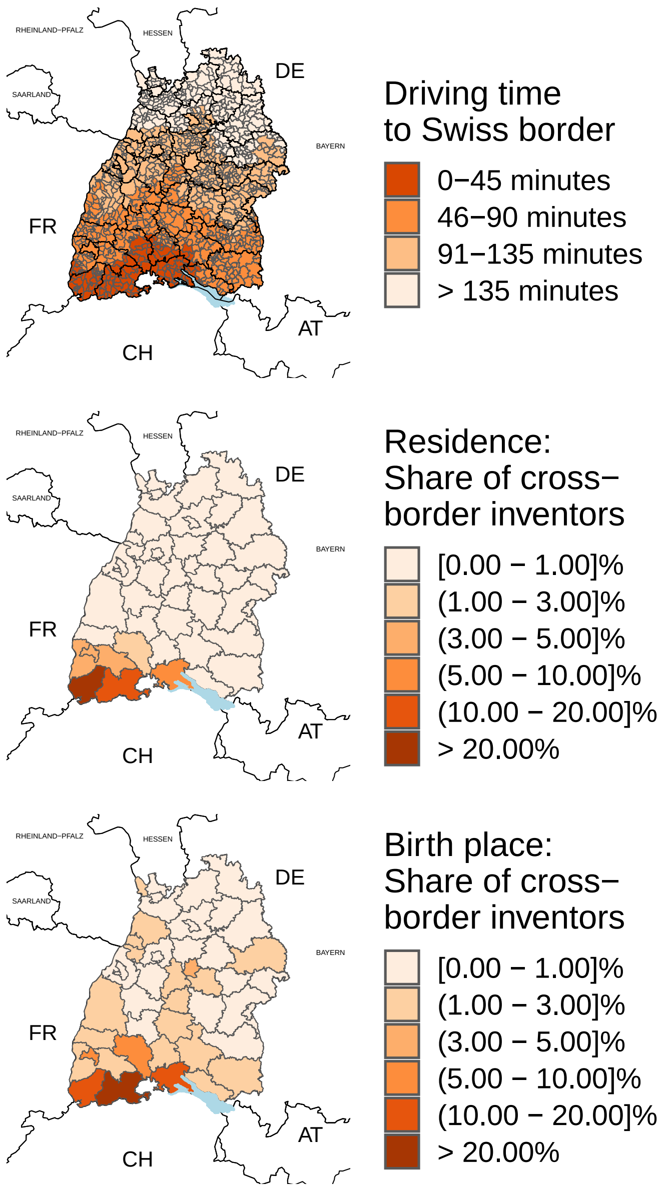
Watzinger, M., J. L. Krieger, and M. Schnitzer (2021): "Standing on the shoulders of science," *Harvard Business School Working Paper 21-128*.

Wernsdorf, K., M. Nagler, and M. Watzinger (2022): "ICT, collaboration, and innovation: Evidence from BITNET," *Journal of Public Economics*, 211, 104678.

Younge, K. A. and J. M. Kuhn (2016): "Patent-to-Patent Similarity: A Vector Space Model," *Mimeo*.

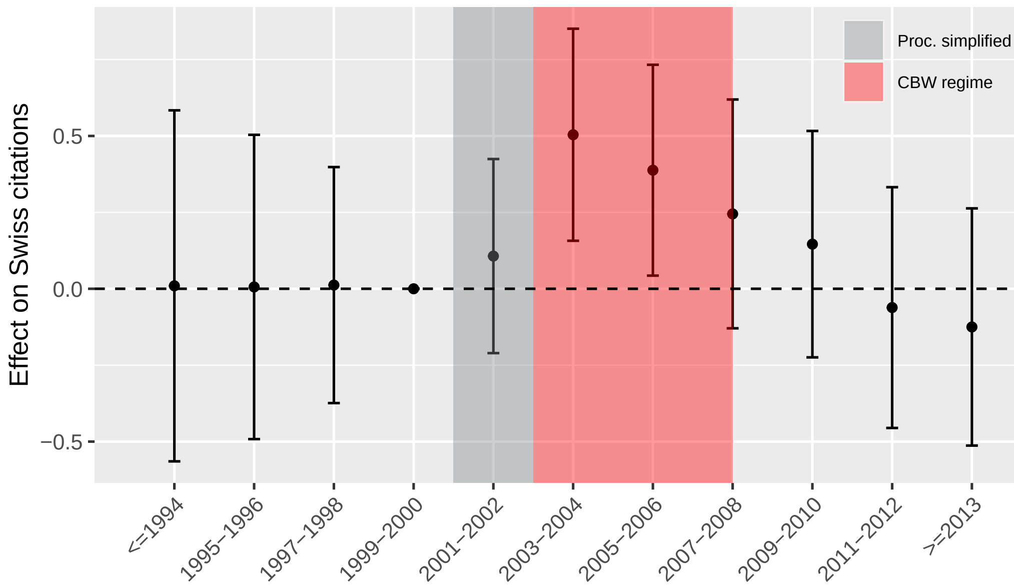
Figures

Figure 1: Driving distance to the Swiss-German border and the distribution of residences and place of birth for cross-border inventors in Baden-Württemberg



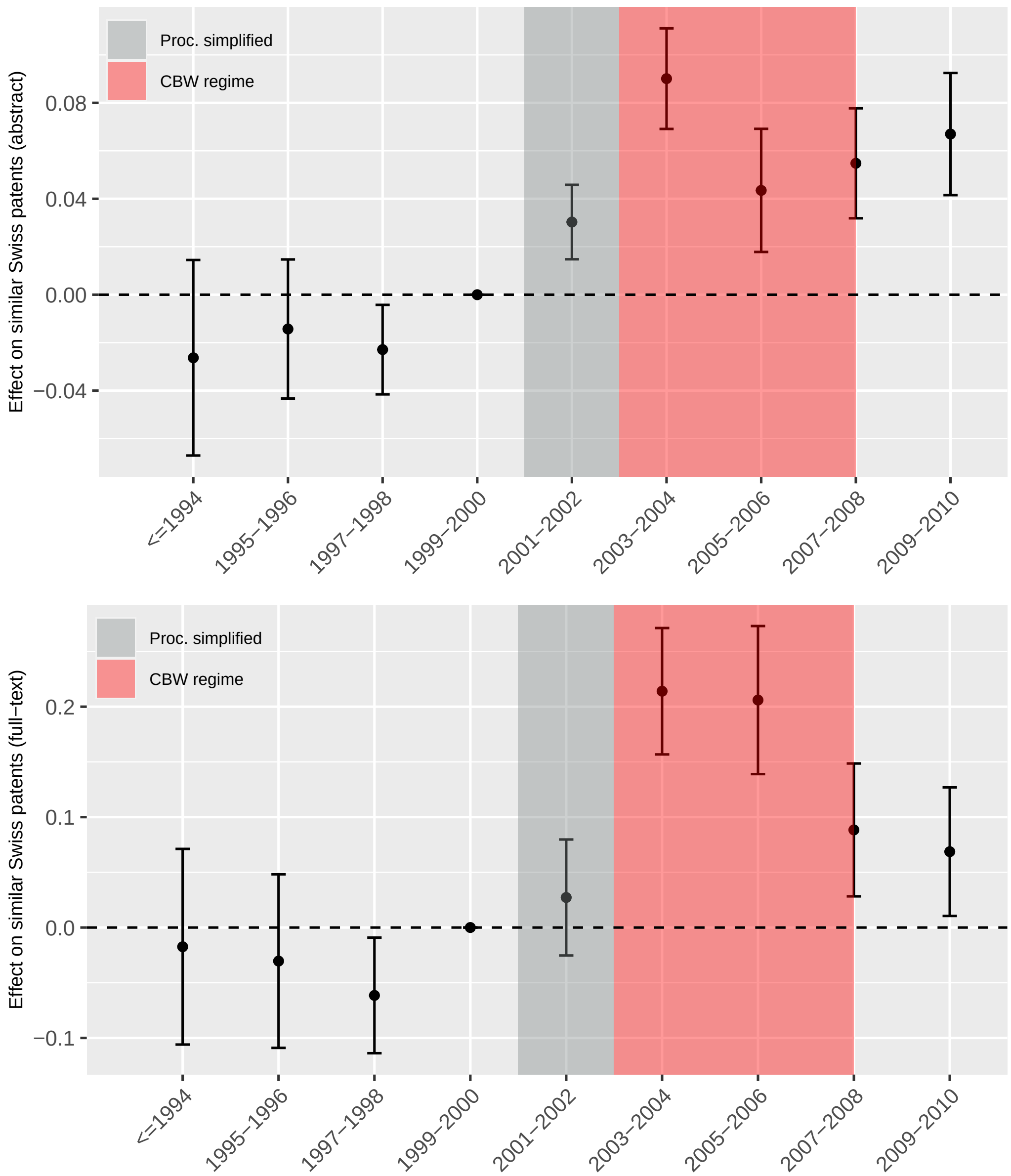
Notes: The top panel shows the driving time to the (nearest Swiss municipality on the) Swiss-German border for municipalities in Baden-Württemberg. Municipalities within 45 minutes are assigned to the border region in the main specification. The middle panel shows the Baden-Württemberg districts ("Landkreis") where cross-border inventors entering Switzerland reside. The bottom panel shows the districts where cross-border inventors have their declared place of birth. We show the district's share of all cross-border inventors. Data from the Central Migration Information System (ZEMIS) and EPO patent applications.

Figure 2: The effect of the AFMP on knowledge diffusion: event study estimates using citations



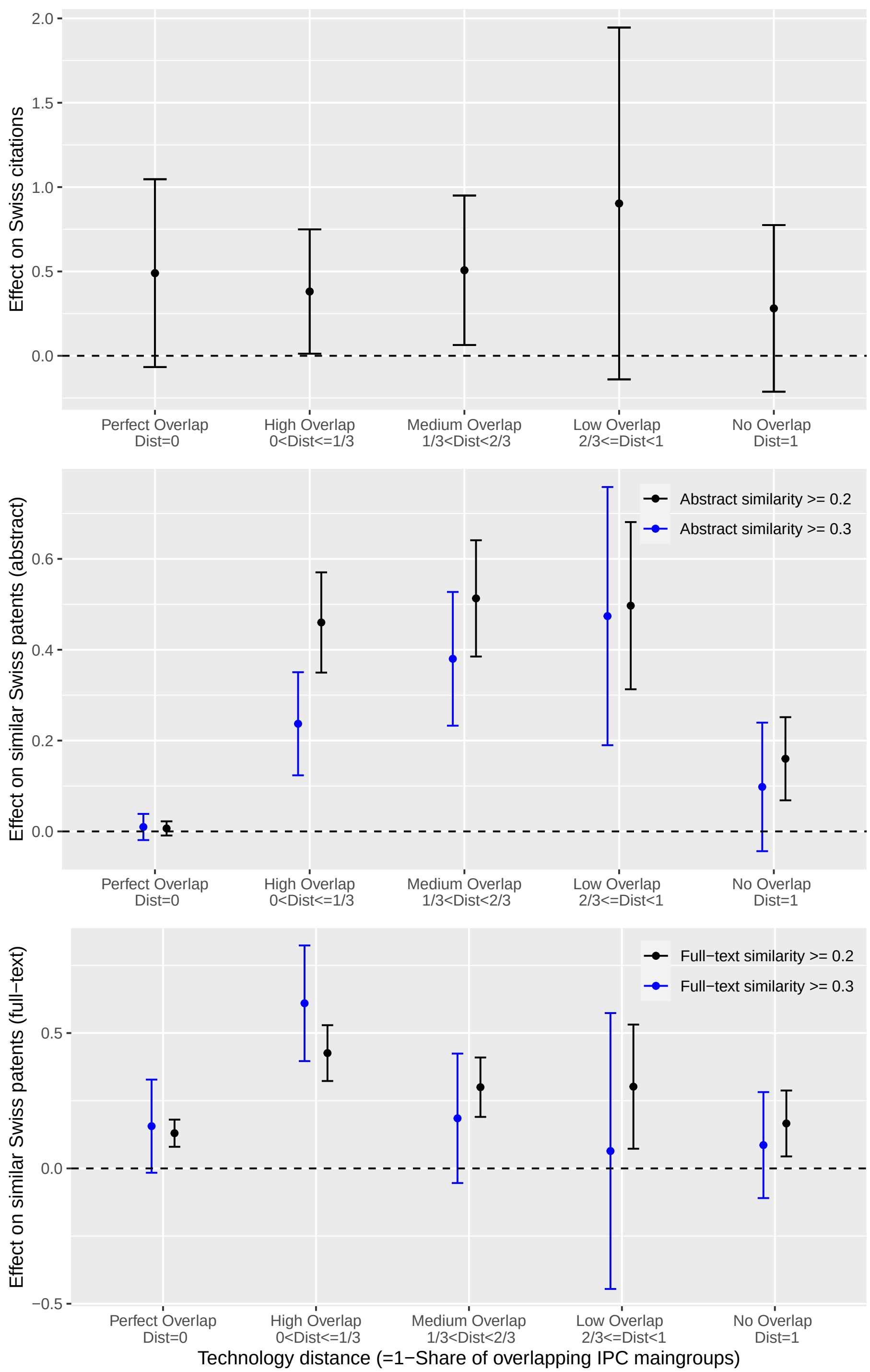
Notes: This figure shows the estimated treatment coefficients of model (1), where the dependent variable is the number of citations from patents filed in Switzerland received by Baden-Württemberg's patent i at time t. Treatment is defined as the share of inventors on patent i who reside (as of the time of filing) within 45 minutes of commute driving time of the Swiss-German border. Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000. Vertical bars represent 95% confidence intervals. The coefficient for the baseline period 1999-2000 is set to zero and shown without confidence interval. Robust standard errors are clustered at the patent level. Estimation by Poisson pseudo-maximum-likelihood (PML).

Figure 3: The effect of the AFMP on knowledge diffusion: event study estimates using textual similarity



Notes: This figure shows the estimated treatment coefficients of model (1), where the dependent variable is the number of textually similar patents to Baden-Württemberg's patent i and filed in Switzerland at time t. Treatment is defined as the share of inventors on patent i who reside (as of the time of filing) within 45 minutes of commute driving time of the Swiss-German border. In the upper panel, the similarity score is calculated using patents' abstracts; in the bottom panel, the similarity score is calculated using patents' full text. For both, the cosine similarity threshold is 0.2. Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000. Vertical bars represent 95% confidence intervals. The coefficient for the baseline period 1999-2000 is set to zero and shown without confidence interval. Robust standard errors are clustered at the patent level. Estimation by Poisson pseudo-maximum-likelihood (PML).

Figure 4: The effect of the AFMP on knowledge diffusion: difference-in-differences estimates by technological distance



Notes: This figure presents estimates derived from separate regressions (model 2), using as dependent variable the number of citations or textually similar patents at the specified technological distance from focal patent i. Vertical bars represent 95% confidence intervals. Technology distance between focal patent i and citing/textually similar patent j is calculated as one minus the share of j's IPC main groups that overlap with the IPC main groups of i. Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of citations from Swiss patents or textually similar Swiss patents tracked until 2007.

Tables

Table 1: Descriptive statistics

	Mean	Std. dev.	p10	p25	p50	p75	p90
EPO+DPMA patents (N=65,787)							
share of inventors within 45 min. of border	0.0730	0.2517	0	0	0	0	0
# swiss_cites	0.0089	0.1177	0	0	0	0	0
EPO patents (N=30,255)							
share of inventors within 45 min. of border	0.0781	0.2570	0	0	0	0	0
# citations from Swiss patents	0.0137	0.1506	0	0	0	0	0
# similar Swiss patents:							
abstr. simil. ≥ 0.1	85.0380	55.4469	25	45	75	113	158
abstr. simil. ≥ 0.2	13.3550	12.1858	2	5	10	19	29
abstr. simil. ≥ 0.3	2.8246	3.9429	0	0	1	4	8
abstr. simil. ≥ 0.4	0.6221	1.4241	0	0	0	1	2
full-text simil. ≥ 0.1	1.6663	2.0768	0	0	1	2	4
full-text simil. ≥ 0.2	1.0479	1.6891	0	0	0	1	3
full-text simil. ≥ 0.3	0.1607	0.5707	0	0	0	0	1
full-text simil. ≥ 0.4	0.0180	0.1627	0	0	0	0	0

Notes: Sample of patents filed in in Baden-Württemberg between 1990-2000, with diffusion outcomes tracked in each year between 1990-2010.

Table 2: The effect of the AFMP on knowledge diffusion: difference-in-differences estimates using citations

Dependent Variable	No. of citations from Swiss patents	
Outcome period	Until 2007	Until 2015
	(1)	(2)
$AFMP_t \times BorderBW_i$	0.430***	0.225**
	(0.121)	(0.107)
Patent FE	✓	✓
Cohort × Year FE	✓	✓
Observations	57,783	126,575
Patents	4,520	6,185

Notes: Estimates from the patent-level model $E[y_{i,t}|X_{i,t}] = \exp[\alpha_i + \beta(AFMP_t \times BorderBW_i) + \delta_{t^*(i),t}]$, where $BorderBW_i$ is the share of inventors on patent i that reside (as of the time of filing) within 45 minutes of commute driving time of the Swiss-German border and $AFMP_t$ captures the timing of the reform. The percent-increase in the dependent variable due to the reform is given by $\exp(\beta) - 1$. Estimates are based on the sample of patents filed in Baden-Württemberg between 1990-2000, with forward citations from Swiss patents tracked until 2007 or 2015. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood (PML). Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table 3: The effect of the AFMP on knowledge diffusion: difference-in-differences estimates using textual similarity

Dependent Variable	No. of similar Swiss patents							
Panel A	Abstract simil. ≥ 0.1		Abstract simil. ≥ 0.2		Abstract simil. ≥ 0.3		Abstract simil. ≥ 0.4	
Outcome Period	Until 2007	Until 2010	Until 2007	Until 2010	Until 2007	Until 2010	Until 2007	Until 2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AFMP_t \times BorderBW_i$	0.0339***	0.0319***	0.0731***	0.0766***	0.0585***	0.0666***	0.02150	0.0151
	(0.0056)	(0.0056)	(0.0113)	(0.0114)	(0.0159)	(0.0164)	(0.0248)	(0.0237)
Observations	366,610	456,991	366,024	456,340	351,225	441,845	256,276	337,896
Patents	30,127	30,127	30,076	30,082	28,845	29,127	21,056	22,314
Panel B	Full-text simil. ≥ 0.1		Full-text simil. ≥ 0.2		Full-text simil. ≥ 0.3		Full-text simil. ≥ 0.4	
Outcome Period	Until 2007	Until 2010	Until 2007	Until 2010	Until 2007	Until 2010	Until 2007	Until 2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$AFMP_t \times BorderBW_i$	0.135***	0.102***	0.204***	0.177***	0.229***	0.202***	0.145	0.0837
	(0.0195)	(0.0181)	(0.0243)	(0.0225)	(0.0554)	(0.0513)	(0.151)	(0.136)
Observations	360,905	452,075	334,774	423,489	165,764	222,242	37,382	52,301
Patents	29,582	29,763	27,316	27,803	13,410	14,520	3,074	3,466

Notes: Estimates from the patent-level model $E[y_{i,t}|X_{i,t}] = \exp[\alpha_i + \beta(AFMP_t \times BorderBW_i) + \delta_{t^*(i),t}]$, where $BorderBW_i$ is the share of inventors on patent i that reside (as of the time of filing) within 45 minutes of commute driving time of the Swiss-German border and $AFMP_t$ captures the timing of the reform. The percent-increase in the dependent variable due to the reform is given by $\exp(\beta) - 1$. Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents tracked until 2007 or 2010. All regressions include patent FE and Cohort $\times$ Year FE. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table 4: The effect of the AFMP on knowledge diffusion across technical fields by relative distance to the knowledge frontier

Dependent Variable	No. of citations from Swiss patents		No. of similar Swiss patents Abstract simil. ≥ 0.2		No. of similar Swiss patents Full-text simil. ≥ 0.2	
Techn. fields of patents	Restricted	All	Restricted	All	Restricted	All
	(1)	(2)	(3)	(4)	(5)	(6)
$AFMP_t \times BorderBW_i$	-0.207	-0.0451	-0.0746**	0.0315**	-0.09758	-0.0451
	(0.300)	(0.151)	(0.0346)	(0.0124)	(0.0724)	(0.0278)
$AFMP_t \times BorderBW_i$	0.519		0.110***		0.225***	
$\times\{0 < RLS_{f(i)} \leq 1.7pp\}$	(0.362)		(0.0370)		(0.0844)	
$AFMP_t \times BorderBW_i$	0.898***		0.128***		0.482***	
$\times\{RLS_{f(i)} > 1.7pp\}$	(0.337)		(0.0365)		(0.0800)	
$AFMP_t \times BorderBW_i$		1.535***		0.230***		0.994***
$\times RLS_{f(i)}$		(0.390)		(0.0412)		(0.0852)
Patent FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
Observations	42,141	57,783	241,058	366,010	224,438	334,774
Patents	3,297	4,520	19,799	30,075	18,334	27,316

Notes: $RLS_{f(i)}$ is the average difference in citation lag to science in field f (which patent i belongs to) between patents filed in Switzerland and patents filed in Baden-Württemberg. Positive values indicate that Switzerland is closer to the knowledge frontier in field f, whereas negative values indicate that Baden-Württemberg is closer to the knowledge frontier. Fields such that $\{RLS_f(i) < 0\}$ (base category): organic fine chemistry, metallurgy, handling, surface technology/coating, telecommunications, IT methods. Fields such that $\{0 < RLS_f(i) \leq 1.7pp\}$ (Switzerland moderately ahead): textiles/paper machines, thermal processes/apparatus, environmental technology, measurement, civil engineering, mechanical elements, control, other consumer goods. Fields such that $\{0 < RLS_f(i) > 1.7pp\}$ (Switzerland decisively ahead): biological materials, basic materials chemistry, chemical engineering, medical technology, engines/pumps/turbines, electrical machinery/apparatus/energy, biotechnology, other special machines. Columns 1,3 and 5 restrict to fields where the relative ranking of Switzerland and Baden-Württemberg is unambiguous (see Section 6.2). Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents tracked until 2007. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Appendix - For Online Publication Only

“Cross-Border Commuters and Knowledge Diffusion”

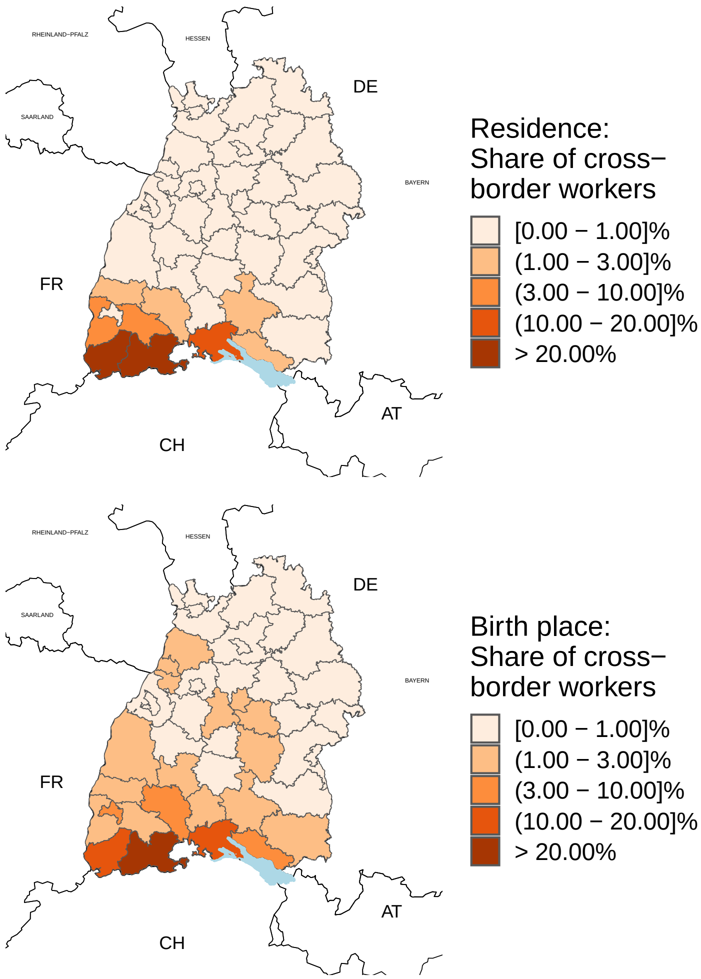
by Gabriele Cristelli and Rainer Widmann

October 2023

Contents

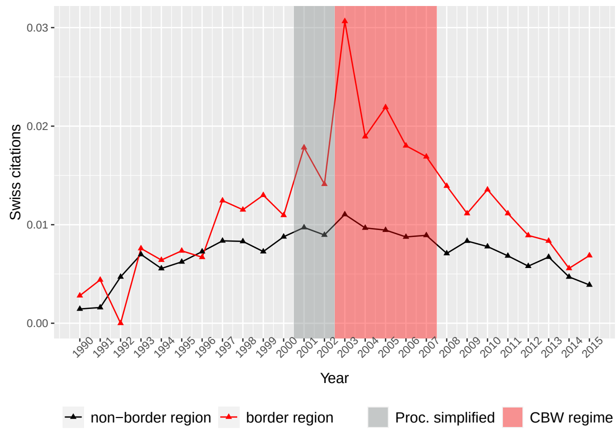
A. Additional Figures

Figure A1: Spatial distribution of cross-border workers by residence and place of birth



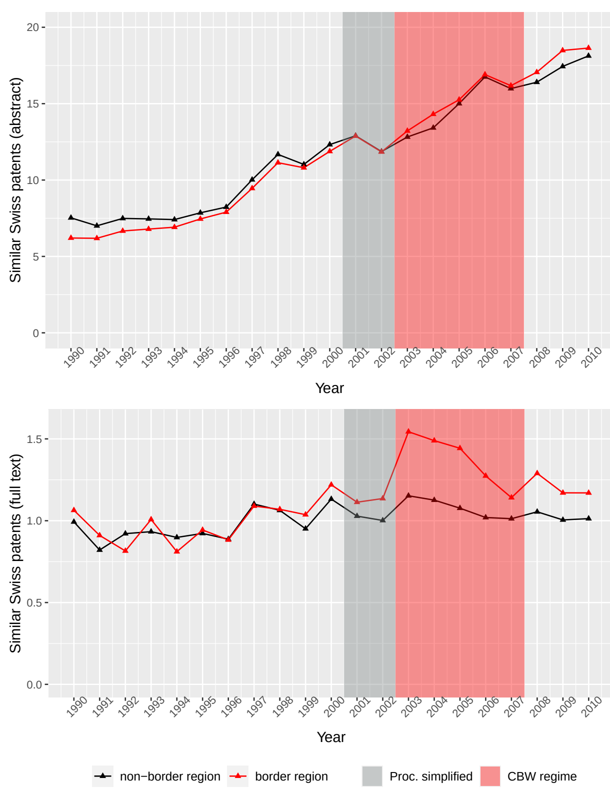
Notes: The top panel shows the Baden-Württemberg districts ("Landkreis") where cross-border workers entering Switzerland reside. The bottom panel shows the districts where cross-border workers have their declared place of birth. We show the district's share of all cross-border workers. 93.5% of cross-border workers reside in districts that are within a 45-minute drive of the Swiss border (using the minimum driving distance across municipalities in the district). 71.0% reside in the three closest districts (Lörrach, Waldshut, Konstanz). 81.4% of cross-border workers were born in districts that are within a 45-minute drive of the Swiss border, while 54.8% were born in the three closest districts. Data from the Central Migration Information System (ZEMIS).

Figure A2: Average yearly citations from Switzerland



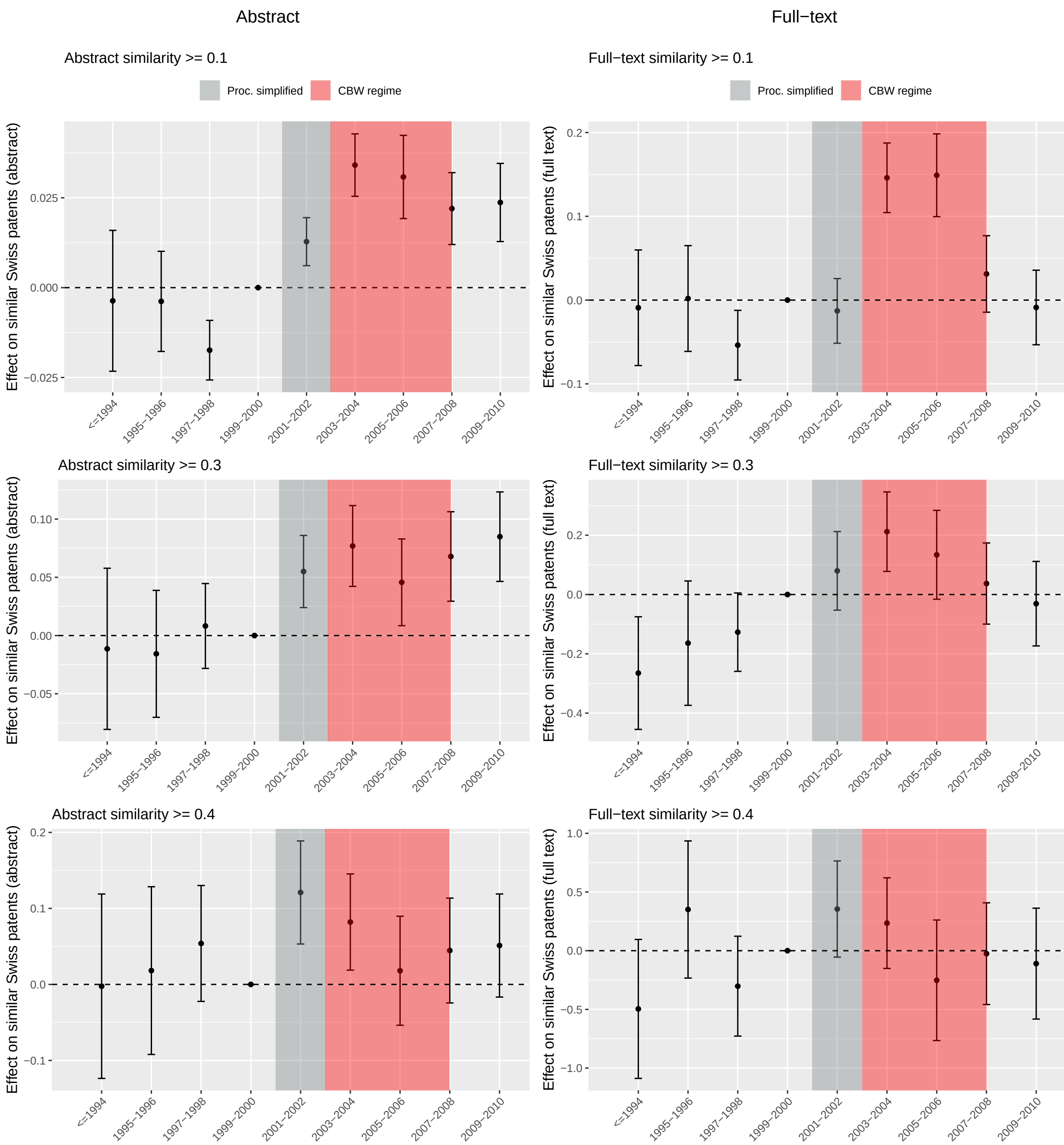
Notes: Sample is patents filed in Baden-Württemberg between 1990-2000. Patents from Baden-Württemberg are assigned to the border region if at least one inventor resides within 45 minutes of driving time to the Swiss-German border.

Figure A3: Average number of textually similar patents from Switzerland



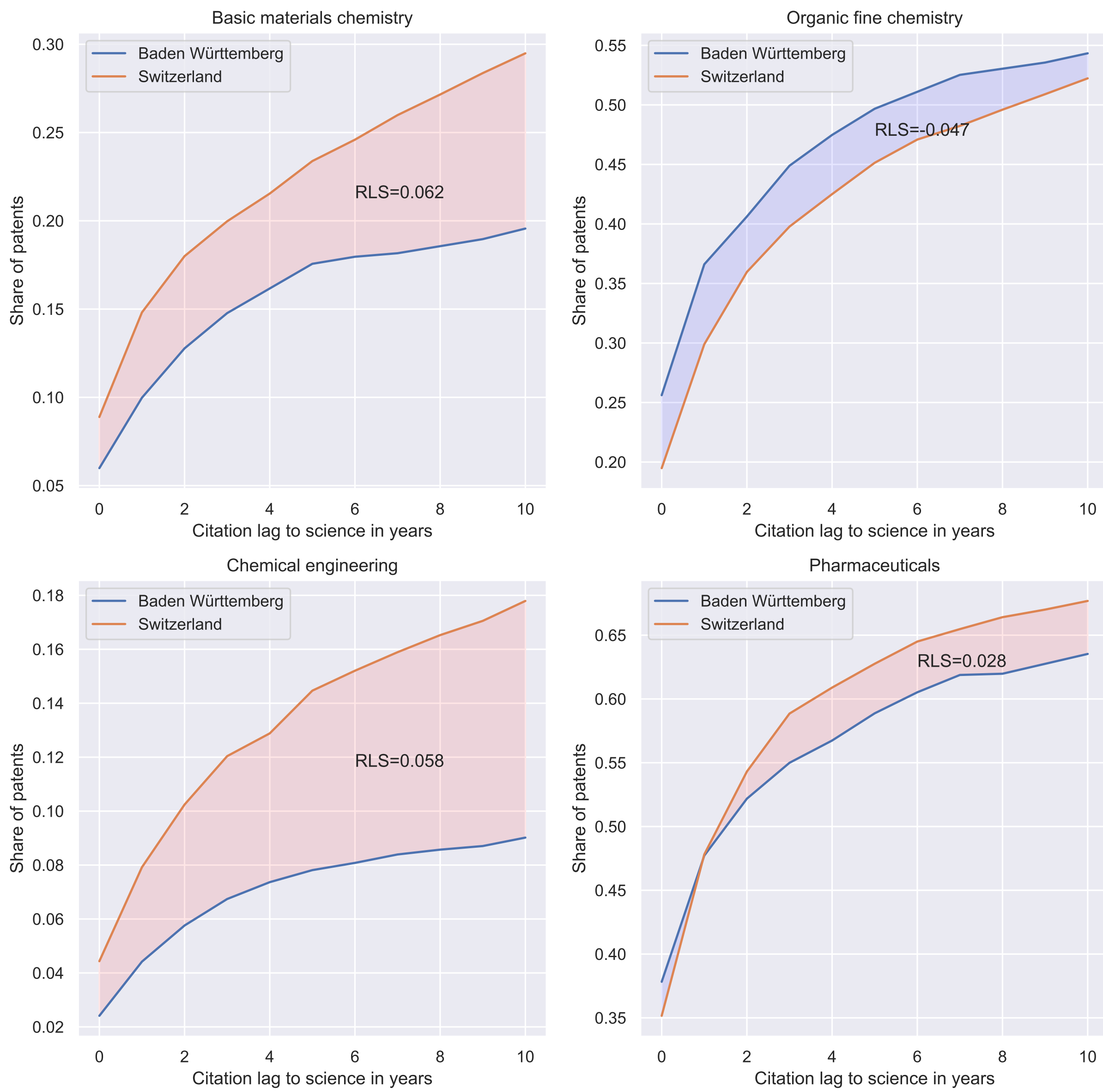
Notes: Sample is patents filed in Baden-Württemberg between 1990-2000. Patents from Baden-Württemberg are assigned to the border region if at least one inventor resides within 45 minutes of driving time to the Swiss-German border.

Figure A4: The effect of the AFMP on knowledge diffusion: event study estimates using textual similarity by different cosine similarity thresholds



Notes: The dependent variable is the number textually similar patents to Baden-Württemberg's patent i and filed in Switzerland at time t. Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000. Vertical bars represent 95% confidence intervals. The coefficient for the baseline period 1999-2000 is set to zero and shown without confidence interval. Robust standard errors are clustered at the patent level. Estimation by Poisson pseudo-maximum-likelihood (PML).

Figure A5: Science-citation lag for different technical fields



Notes: Graphs shows the cumulative share of patents filed at the EPO between 1990-2000 by applicants from Switzerland and Baden-Württemberg that cite at least one scientific article that was published within t years before the patent's filing year. Data on citations to scientific articles is from Poege et al. 2019.

B. Additional Tables

Table A1: The effect of the AFMP on knowledge diffusion: difference-in-differences estimates using textual similarity intervals

Dependent variable	No. of similar Swiss patents			
Panel A	Abstract similarity in interval			
	$0.1 \leq$ sim. < 0.2	$0.2 \leq$ sim. < 0.3	$0.3 \leq$ sim. < 0.4	$0.4 \leq$ sim. ≤ 1
Outcome Period	Until 2007	Until 2007	Until 2007	Until 2007
	(A1)	(A2)	(A3)	(A4)
$AFMP_t \times BorderBW_i$	0.0267***	0.0769***	0.0685***	0.0215
	(0.0051)	(0.0115)	(0.0171)	(0.0248)
Observations	361,389	452,688	180,756	231,581
Patents	29,624	29,806	16,937	16,938
Panel B	Full-text similarity in interval			
	$0.1 \leq$ sim. < 0.2	$0.2 \leq$ sim. < 0.3	$0.3 \leq$ sim. < 0.4	$0.4 \leq$ sim. ≤ 1
Outcome Period	Until 2007	Until 2007	Until 2007	Until 2007
	(B1)	(B2)	(B3)	(B4)
$AFMP_t \times BorderBW_i$	0.0174	0.199***	0.236***	0.145
	(0.0273)	(0.0251)	(0.0551)	(0.151)
Observations	188,753	319,316	161,675	37,382
Patents	15,414	25,928	13,059	3,074

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents tracked until 2007. All regressions include patent FE and Cohort × Year FE. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Robustness checks for the effect of the AFMP on knowledge diffusion

Dependent Variable	No. of citations from Swiss patents/ No. of similar Swiss patents					
Robustness check	Applicant loc.	Inventor loc. with alternative treatment			Train commute	OLS
Treatment definition	Share applts	Share invts	Share invts	Share invts	Share invts	Share invts
	≤45 min	≤30 min†	≤45 min†	≤60 min	≤45 min	≤45 min
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Citations						
$AFMP_t \times BorderBW_i$	0.576***	0.167	0.427***	0.256***	0.347***	0.00522***
	(0.111)	(0.170)	(0.122)	(0.0956)	(0.116)	(0.0011)
Observations	57,783	50,115	53,296	57,783	57,783	799,554
Patents	4,520	3917	4167	4,520	4,520	65,787
Panel B: Abstract similarity ≥ 0.2						
$AFMP_t \times BorderBW_i$	0.0764***	0.115***	0.0743***	0.0445***	0.0749***	0.0427***
	(0.0104)	(0.0196)	(0.0114)	(0.00706)	(0.0107)	(0.0101)
Observations	366,024	320,394	337,538	366,024	366,024	368,106
Patents	30,076	26,366	27,723	30,076	30,076	30,255
Panel C: Full-text similarity ≥ 0.2						
$AFMP_t \times BorderBW_i$	0.212***	0.185***	0.206***	0.132***	0.195***	0.0622***
	(0.0226)	(0.0325)	(0.0244)	(0.0179)	(0.0235)	(0.0110)
Observations	334,774	294,152	309,514	334,774	334,774	368,106
Patents	27,316	24,042	25,247	27,316	27,316	30,255

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents tracked until 2007. All regressions include patent FE and Cohort × Year FE. In column 6, we transform the dependent variable by the inverse hyperbolic sine. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood in columns 1-5, Ordinary Least Squares in column 6. The implied semi-elasticities in columns 1-5 may be computed as $\exp(\hat{\beta}) - 1$ and in column 6 as $\sinh(\sinh^{-1}(\bar{y}) + \hat{\beta})/\bar{y}$-1, where $\hat{\beta}$ is the estimated coefficient and $\bar{y}$ is the mean of the dependent variable. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A3: The effect of the AFMP by distance of Swiss applicants to the border

Dependent Variable	No. of citations from Swiss patents		No. of similar Swiss patents Abstract simil. ≥ 0.2		No. of similar Swiss patents Full-text simil. ≥ 0.2	
Distance Swiss applts to border	$\leq$45 min	>45 min	$\leq$45 min	>45 min	$\leq$45 min	>45 min
Outcome Period	Until 2007	Until 2007	Until 2007	Until 2007	Until 2007	Until 2007
	(1)	(2)	(3)	(4)	(5)	(6)
$AFMP_t \times BorderBW_i$	0.494***	0.0823	0.175***	-0.0028	0.344***	0.108***
	(0.172)	(0.182)	(0.0196)	(0.0096)	(0.0406)	(0.0322)
Patent FE	✓	✓	✓	✓	✓	✓
Cohort $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	22,429	28,948	364,388	365,058	290,424	309,286
Patents	1,777	2,275	29,938	29,997	23,532	25,120

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents tracked until 2007. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Knowledge diffusion across Swiss applicants (within 45 minutes of driving time to the border) by presence of German cross-border inventor on the citing/similar patent

Dependent Variable	No. of citations from Swiss patents		No. of similar Swiss patents Abstract simil. ≥ 0.2		No. of similar Swiss patents Full-text simil. ≥ 0.2	
Inventor team composition on the citing/similar patent	includes German CBI	not include German CBI	includes German CBI	not include German CBI	includes German CBI	not include German CBI
	(1)	(2)	(3)	(4)	(5)	(6)
$AFMP_t \times BorderBW_i$	1.155***	0.408**	0.644***	0.143***	0.376***	0.358***
	(0.399)	(0.193)	(0.0751)	(0.0167)	(0.0775)	(0.0438)
Patent FE	✓	✓	✓	✓	✓	✓
Cohort $\times$ Year FE	✓	✓	✓	✓	✓	✓
Observations	2,711	19,303	196,434	364,169	105,983	282,173
Patents	269	1,531	15,893	29,920	8,309	22,830

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents by Swiss applicants within 45 minutes of driving time to the border tracked until 2007. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Knowledge diffusion across Swiss applicants (within 45 minutes of driving time to the border) by employment of German cross-border inventors

Dependent Variable	No. of citations from Swiss patents		No. of similar Swiss patents Abstract simil. ≥ 0.2		No. of similar Swiss patents Full-text simil. ≥ 0.2	
Share of cross-border inventors in all inventors at Swiss applicant 2002-2007	$\geq 5\%$	$< 5\%$	$\geq 5\%$	$< 5\%$	$\geq 5\%$	$< 5\%$
	(1)	(2)	(3)	(4)	(5)	(6)
$AFMP_t \times BorderBW_i$	2.765*	0.628	0.409***	0.0495	0.683**	0.646***
	(1.608)	(0.813)	(0.0893)	(0.0414)	(0.268)	(0.140)
Patent FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
Observations	1,422	5,202	152,130	177,822	50,376	105,876
Patents	242	867	25,355	29,637	8,396	17,646

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents by Swiss applicants within 45 minutes of driving time to the border tracked until 2007. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Knowledge diffusion across Swiss municipalities (within 45 minutes of driving time to the border) by employment of German cross-border inventors

Dependent Variable	No. of citations from Swiss patents			No. of similar Swiss patents Abstract simil. ≥ 0.2			No. of similar Swiss patents Full-text simil. ≥ 0.2		
Share of cross-border inventors in all inventors in Swiss municipality 2002-2007	$\geq$ 5%	1-5%	< 1%	$\geq$ 5%	1-5%	< 1%	$\geq$ 5%	1-5%	< 1%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$AFMP_t \times BorderBW_i$	1.256***	-0.0463	-0.0069	0.208***	0.212***	0.0347	0.435***	0.230***	-0.0079
	(0.312)	(0.252)	(0.483)	(0.0218)	(0.0294)	(0.0171)	(0.0763)	(0.0568)	(0.0609)
Patent FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,567	12,278	3,693	347,652	360,942	347,538	177,636	220,717	169,058
Patents	477	993	345	28,541	29,650	28,503	14,286	17,719	13,340

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents by Swiss applicants within 45 minutes of driving time to the border tracked until 2007. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Additional results for the effect of the AFMP by channel of diffusion

Dependent Variable	No. of citations from Swiss patents/ No. of similar Swiss patents					
	Within corp. groups	Between corp. groups	DE/CH co-applicants	CH applts. only	Inventor self-cite	No inventor self-cite
Outcome period	Until 2007	Until 2007	Until 2007	Until 2007	Until 2007	Until 2007
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Citations						
$AFMP_t \times BorderBW_i$	1.692**	0.486***	-0.138	0.450***	0.2118	0.436***
	(0.815)	(0.123)	(0.748)	(0.122)	(0.576)	(0.125)
Observations	1,711	56,551	1,603	56,485	2,313	56,064
Patents	172	4,418	187	4,415	229	4,385
Panel B: Abstract similarity ≥ 0.2						
$AFMP_t \times BorderBW_i$	0.161	0.0732***	0.0197	0.0732***		
	(0.115)	(0.0114)	(0.137)	(0.0113)		
Observations	29,287	366,010	36,669	366,024		
Patents	2,329	30,075	3,721	30,076		
Panel C: Full-text similarity ≥ 0.2						
$AFMP_t \times BorderBW_i$	0.359	0.215***	-0.293*	0.212***		
	(0.230)	(0.0243)	(0.168)	(0.0245)		
Observations	15,572	333,967	37,390	334,374		
Patents	1,305	27,247	2,972	27,280		

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents or citations from Swiss patents tracked until 2007. All regressions include patent FE and Cohort × Year FE. In column 1, only textually similar patents or citations by Swiss applicants with the same Global Ultimate Owner as the German applicant of the original patent in the Orbis Ownership Snapshot of 2007 are counted. Column 2 excludes such textually similar patents or citations by Swiss applicants. In column 3, only textually similar patents or citations by Swiss-German co-applicants are counted, while column 4 excludes them. Column 5 restricts to citations by Swiss applicants with at least one inventor that also appears on the original patent (identified by name). Column 6 excludes such citations. Robust standard errors clustered at the patent level are given in parentheses. Estimations by Poisson pseudo-maximum-likelihood. Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

Table A8: The effect of the AFMP on knowledge diffusion by technological distance

	Dependent variable: No. of similar Swiss patents by Technological Distance (= 1− Share of overlapping IPC main groups)				
	$Dist = 0$	$0 < Dist \leq 1/3$	$1/3 \leq Dist < 2/3$	$2/3 \leq Dist < 1$	$Dist = 1$
Outcome Period	Until 2007	Until 2007	Until 2007	Until 2007	Until 2007
	(1)	(2)	(3)	(4)	(5)
Panel A: Abstract similarity ≥ 0.2					
$AFMP_t \times BorderBW_i$	0.00659	0.460***	0.513***	0.497***	0.160***
	(0.00797)	(0.0563)	(0.0653)	(0.0939)	(0.0467)
Observations	365,003	274,916	212,646	58,109	173,400
Patents	29,990	22,491	17,264	4,853	13,940
Panel B: Abstract similarity ≥ 0.3					
$AFMP_t \times BorderBW_i$	0.00975	0.237***	0.380***	0.474***	0.0980
	(0.0147)	(0.0579)	(0.0751)	(0.145)	(0.0722)
Observations	344,416	176,811	123,313	30,225	95,800
Patents	28,278	14,477	10,005	2,563	7,698
Panel C: Full-text similarity ≥ 0.2					
$AFMP_t \times BorderBW_i$	0.130***	0.426***	0.300***	0.302***	0.166***
	(0.0256)	(0.0526)	(0.0560)	(0.117)	(0.0621)
Observations	305,096	206,564	158,499	42,010	135051
Patents	24,756	16,699	12,677	3,438	10,775
Panel D: Full-text similarity ≥ 0.3					
$AFMP_t \times BorderBW_i$	0.156*	0.610***	0.185	0.0642	0.0861
	(0.0878)	(0.109)	(0.122)	(0.260)	(0.100)
Observations	108,928	67,775	58,144	14,517	57,929
Patents	8,758	5,511	4,692	1,214	4,645

Notes: Estimates based on the sample of patents filed in Baden-Württemberg between 1990-2000, with the number of textually similar Swiss patents tracked until 2007. Robust standard errors are clustered at the patent level. Estimation by Poisson pseudo-maximum-likelihood (PML). Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

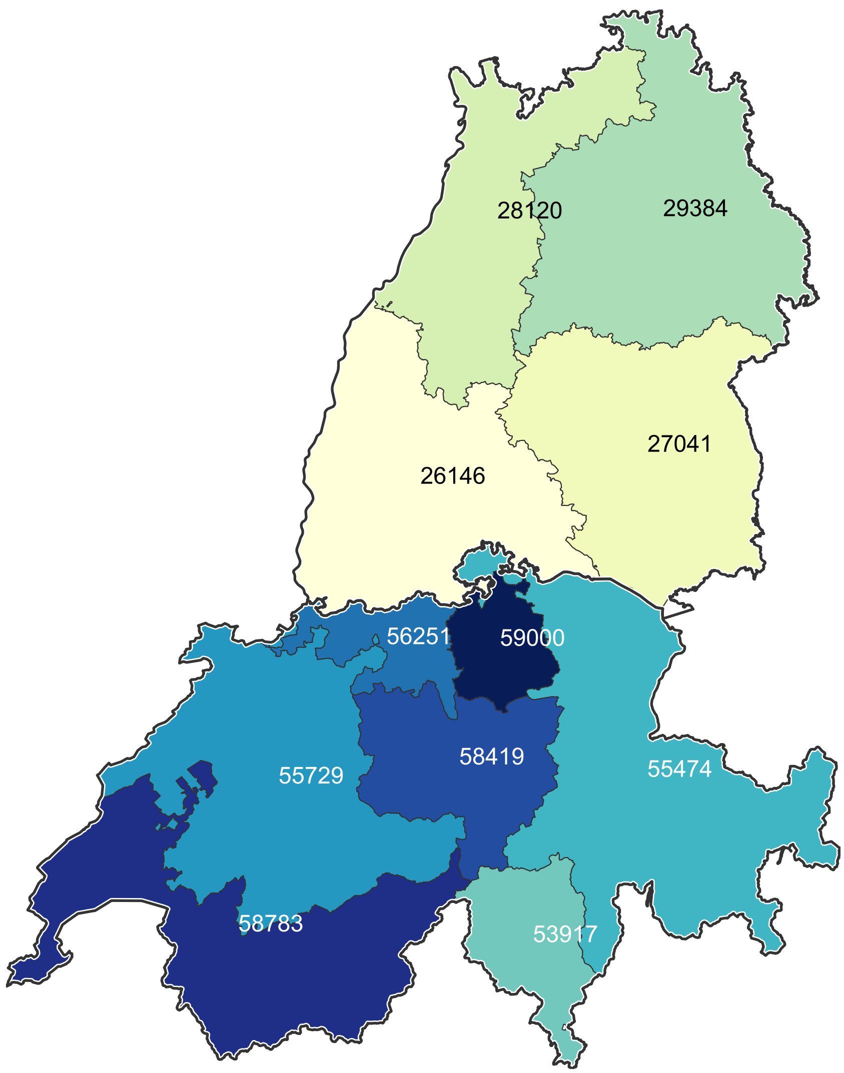
Table A9: The effect of the AFMP on reverse knowledge flows

Dependent Variable	No. of citations from BW patents		No. of similar BW patents Full-text simil. ≥ 0.2		No. of similar BW patents Full-text simil. ≥ 0.3	
Outcome Period	Until 2007	Until 2015	Until 2007	Until 2010	Until 2007	Until 2010
	(1)	(2)	(3)	(4)	(5)	(6)
$AFMP_t \times BorderCH_i$	-0.143	-0.0728	-0.0385**	-0.0270	-0.116***	-0.119***
	(0.0939)	(0.0837)	(0.0166)	(0.0176)	(0.0410)	(0.0452)
Patent FE	✓	✓	✓	✓	✓	✓
Cohort × Year FE	✓	✓	✓	✓	✓	✓
Observations	37,580	52,291	180,352	226,716	96,579	127,575
Patents	2,906	3,307	14,286	14,533	7,598	8,152

Notes: Estimates based on the sample of patents filed in Switzerland between 1990-2000, with the number of textually similar patents from Baden-Württemberg or citations from patents from Baden-Württemberg tracked until 2007, 2010 or 2015. $BorderCH_i$ is the share of inventors on patent i that reside (as of the time of filing) within 45 minutes of commute driving time on the Swiss side of the Swiss-German border. Robust standard errors are clustered at the patent level. Estimation by Poisson pseudo-maximum-likelihood (PML). Reported significance levels are *** p<0.01, ** p<0.05, * p<0.1.

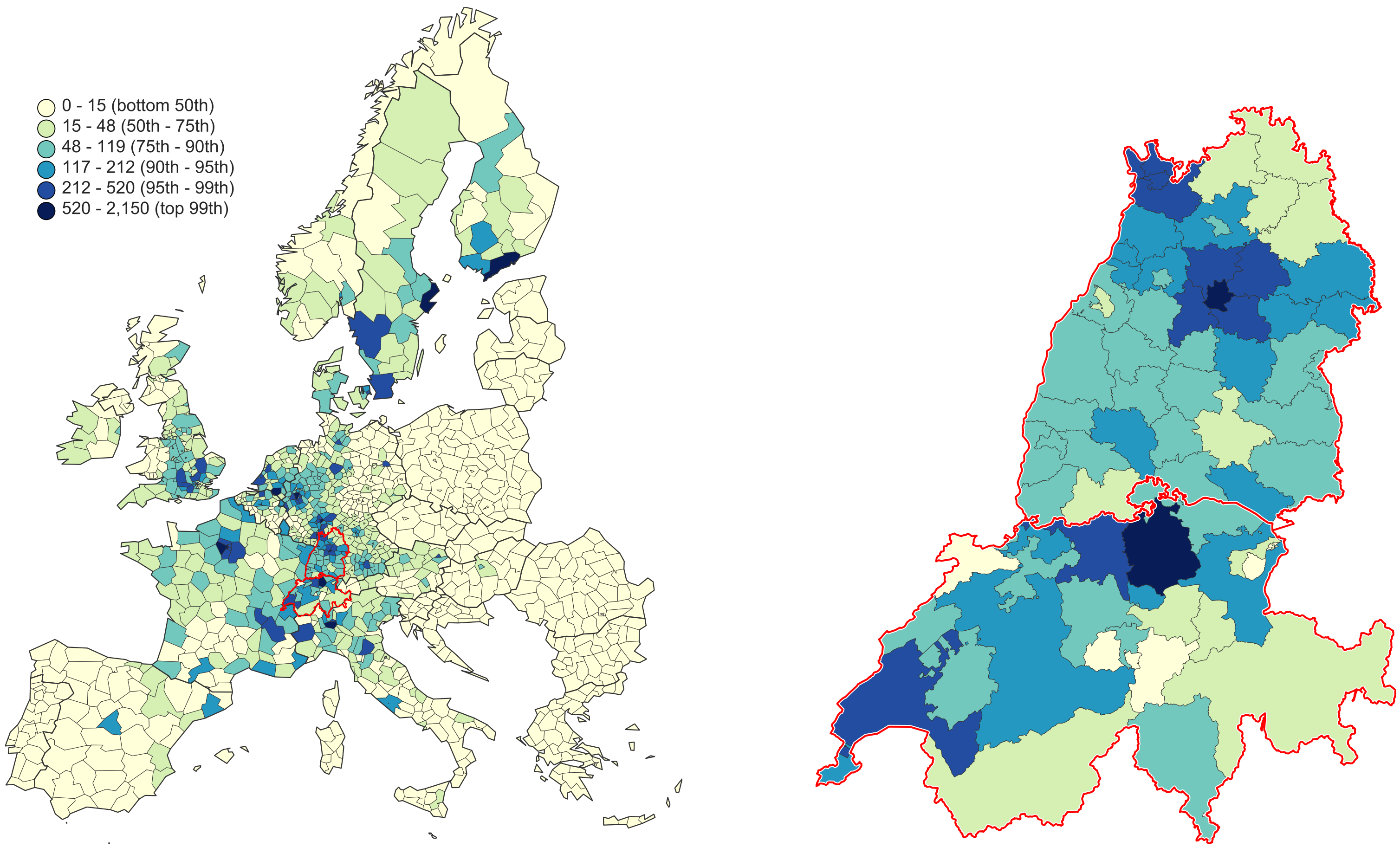
C. Background Information on Baden-Württemberg and Switzerland

Figure A6: Average Gross Yearly Salary in Baden-Württemberg and Switzerland by NUTS-2 areas in 2002 (Euros)



Notes: Nominal gross yearly salaries. Data for Baden-Württemberg are obtained from the *"Employee remuneration, gross wages and salaries in the federal states of the Federal Republic of Germany"* database, maintained by the German Federal Statistical Office in association with the statistical offices of each federal state. Data for Switzerland are obtained from the *"Swiss Earnings Structure Survey"*, maintained by the Swiss Federal Statistical Office. Both German and Swiss gross salaries are reported in Euros, the latter converted from Swiss francs at 2002 exchange rates.

Figure A7: Average Yearly EPO Filings in Europe by Nuts-3 areas, 1990-1999

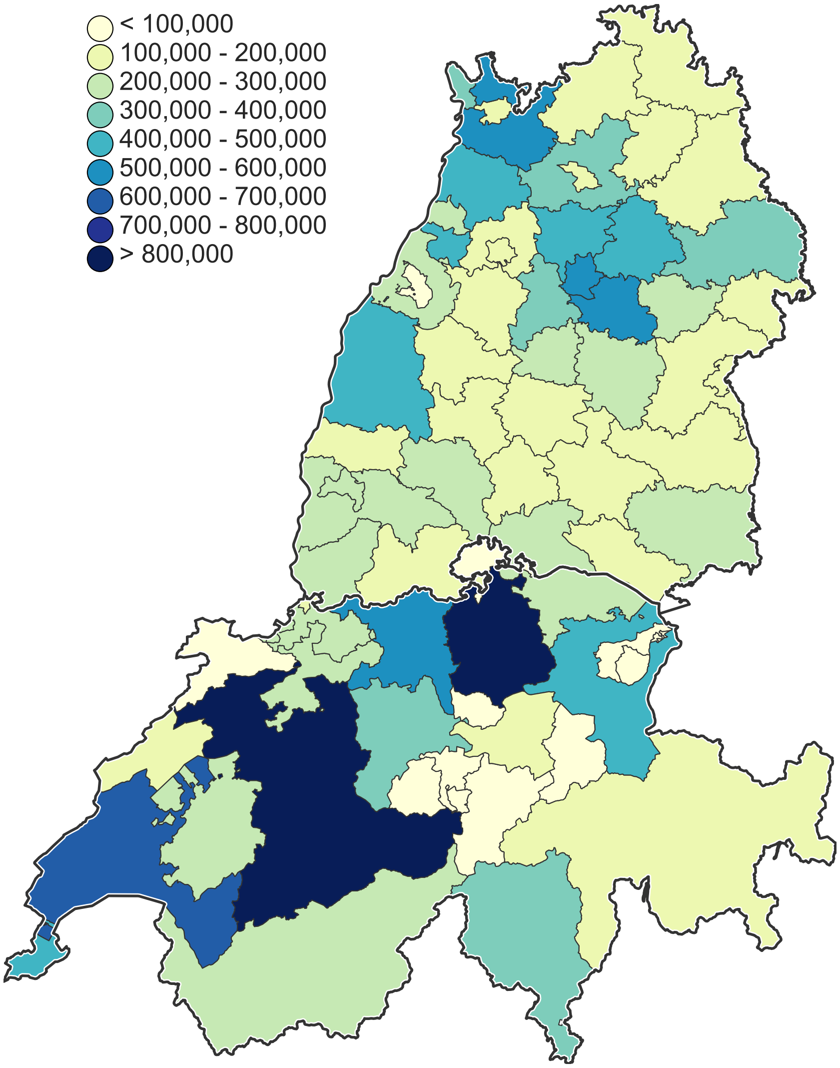


(a) Europe

(b) Baden-Wüerttemberg and Switzerland

Notes: Nuts-3 areas in the EU (excluding Cyprus), plus Norway, Switzerland, and the UK. Nuts-3 areas are colored according to the average number of EPO patents filed between 1990-1999 (DOCDB family level). Patent filings assigned to a location according to the inventors' addresses. If a patent lists inventors located in different NUTS-3 regions, it is counted more than once. In order to avoid the erroneous assignment of cross-border inventors' patents to their residence, patent counts for Baden-Wüerttemberg exclude all filings by applicants with a Swiss address, while patent counts for Switzerland exclude all filings by applicants with a German address. Data obtained from Patstat version 2019b.

Figure A8: Population in Baden-Württemberg and Switzerland by NUTS-3 areas, 2000



Notes: Population (no. of inhabitants) data for Baden-Württemberg are obtained from the German Federal Statistical Office, while for Switzerland are obtained from the Swiss Federal Statistical Office.