Knowledge Spillovers and their Impact on Innovation Success - A New Approach Using Patent Backward Citations

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Abstract We propose a new patent-based measure of knowledge spillovers that calculates technological proximity based on firms that were identified via patent backward citations links. We argue that this measure has a couple of advantages as compared to the 'standard' measure proposed by Jaffe: First, it reflects spillovers from both domestic and foreign technologically 'relevant' firms, second, it is more precise because it only takes into account knowledge relations with technologically 'relevant' firms. Our empirical results indeed show that the measure performs better than the standard measure in an innovation model. We find - for a representative sample of Swiss firms - that knowledge spillovers measured in this way have a positive and significant impact on innovation success. However, the knowledge spillovers appear to be localized: Spillovers from geographically distant areas such as the USA and Japan matter less than spillovers from near destinations such as Europe and particularly Switzerland itself. Moreover, the spillover effect on innovation performance decreases with increasing number of competitors on the main product market so that this effect would appear only in niche markets or oligopolistic market structures. However, an additional effect of competition can only be detected for more radical innovation success.

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I Introduction

Since the two seminal papers by Jaffe (1986) and Jaffe et al. (1993) patent-based measures of knowledge spillovers have become the workhorse in micro-level studies. Although Bloom et al. (2013) substantially extended the original Jaffe measure and made an effort to include spillovers from product market, the original approach to measure knowledge spillovers as suggested by Jaffe has sustained its attractiveness. With the paper at hand we suggest a modified version of the Jaffe measure and show its qualities in the framework of a standard innovation model. Moreover, we show that competition has a significant impact on the effect of spillovers on innovation performance. In this paper, we also use the Jaffe approach to measure technological proximity between firms with the uncentered correlations between their underlying technological portfolios. A firm's technological portfolio is proxied by a firm's share of patent applications in technological fields according to the International Patent Classification (IPC). Annual patent flows are accumulated to patent stocks. The firms' patent stocks are then weighted with the patent-based Jaffe measure of technological proximity. For a focal firm the sum of these weighted patent stocks of the firms of the focal firm's technologically relevant environment is used as a proxy of potential knowledge spillovers in our innovation model.

However, we argue that the traditional Jaffe measure has two important drawbacks. First, it focuses on spillovers coming from firms belonging to a given sample. In most cases, such a sample is arbitrary and not representative of any relevant firm population. Furthermore, in most studies it is not possible to include spillovers from foreign firms although many patenting firms are acting globally and might benefit from knowledge generated elsewhere. Second, the traditional measure considers potential knowledge interactions with every firm in the sample, thus adding noise to the measure, even if many of these firms might not be technologically relevant for the focal firm.

Today's data availability and data processing capacities makes it possible to include much more firms that might be directly technologically relevant for a focal firm. For this exercise, the technological landscape of Switzerland is an ideal subject because Switzerland is a small country with a strongly internationalized economy. Therefore, we use a sample of firms with patent activities from the KOF Swiss Innovation Survey and search for links to other firms worldwide that are technologically relevant for the sample firms. Such technological links can be mapped with a focal firm's backward citations to another firm's patents. Thus, such backward links are used to identify technologically relevant firms worldwide. This is accomplished with the new names table in PATSTAT (the so-called ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table, EEE-PPAT table henceforth) that allows to identify cited firms. We then matched all patent applications that we found in PATSTAT with the cited firms, calculated their patent stocks and their patent shares in the underlying IPC classes.

We built N subsamples where N is the number of Swiss firms in our sample. Each subsample contains $1 + n_i$ firms where n_i is the number of firms cited by Swiss firm i. Based on this subsample we calculated the Jaffe measure for each Swiss firm in the usual way based on the proximity to cited firms' patent stocks worldwide.

The use of survey data combined with patent data has the advantage that we can measure a firm's innovation success with a variable measuring sales with innovative products, which is a better proxy for the commercial success of innovation activities than frequently used binary proxies or patent counts. In addition, we are able to control for important industry and firm-specific factors.

The new spillover measure is tested in the framework of an innovation equation in which we control, among other things, for absorptive capacity, appropriability, and competition conditions. The spillover proxy based on cited firms worldwide shows a positive and highly significant effect on innovation success. A statistically significant, positive effect is also found for a spillover variable that is based on citations of Swiss firms only. In contrast, only a relatively weak association with innovation success could be found for a spillover measure that is calculated for all Swiss applicants (irrespective of whether these firms are cited). The marginal effect of the new measure is not only larger, it also measures the relationship more precisely than the traditional measure. In addition, the spillover effect is stronger for sales stemming from new products as compared to modified products.

The results for regional spillovers show that cited firms' knowledge stocks both in Switzerland and in European countries matter for the commercial innovation success. For spillovers stemming from the USA or Japanese firms, we do not find an effect, which might be due to localization of spillovers as well as to differences between the countries with respect to their technological orientation.

A further contribution of this study is that we analyze interactions between knowledge spillovers and the degree of competition in the product market. Although the competition-innovation relationship has been investigated extensively, we are lacking studies looking at the impact of competition on knowledge spillovers empirically at firm level. We found that an increasing number of principal competitors in the main sales market worldwide of the focal firm reduces the spillover effect from cited firms. This result indicates that spillover effects on innovation performance are at largest for firms that operate in niche markets or in oligopolistic structures. However, this effect can be traced back solely to innovators with new products as compared to only modified products.

The paper is structured as follows: In section 2 the conceptual background, our 'new' spillover measure and the research hypotheses are presented. In section 3, the specification of the empirical model and econometric issues are described. Section 4 describes the data that is used and section 5 presents the results. Section 6 summarizes and concludes.

II Conceptual background

Knowledge spillovers: concept and measurement

Overview

A crucial aspect of innovative activity is the generation of knowledge, which to some extent has the character of a public good. This gives rise to externalities ('spillovers') that are a central theme in the literature on innovation in industrial economics (see, e.g., Aghion and Jaravel 2015; Cohen and Levinthal 1989; Geroski 1995; Griliches 1979; Spence 1984).

A general though rather simplistic way to address this externality problem is to assume the diffusion of new private knowledge leading to a 'spillover pool of knowledge' from which other economic actors can draw information useful for their own innovative activities. A general formulation for the spillovers as a (weighted) sum of the knowledge capital of a firm's relevant technological environment that gives rise to a knowledge pool is given by the following expression (see Griliches 1979, 1992):

$$SO_i = \sum_j w_{ij} K_j ; i \neq j \tag{II.1}$$

for focal firm i, where K_j is the patent-based knowledge capital of firm j belonging to the relevant economic environment of the focal firm i; w_{ij} is a weighting variable to be further specified.

On what should such a weighting variable be based? Broadly speaking, two distinct concepts of knowledge spillovers have been applied in literature (see De La Potterie (1997) for a review). According to the first one, spillover knowledge is related to flows of intermediate and/or capital goods and is assumed to be proportional to the value of the stream of goods between firms/industries (see, e.g., Wolff and Nadiri 1993). In the second concept, the weights in equation (II.1) are a measure of scientific and technological 'distance' among firms and industries (technological proximity; see, e.g., Bloom et al. (2013); Jaffe (1986)) or of geographical distance (geographical proximity; see, e.g., Bloch (2013); Gust-Bardon et al. (2012)). Here, we focus on measures of technological proximity.

The well-known Jaffe technological proximity measure between all firm pairings in a certain sample of enterprises takes the following form:

$$TECH_{ij} = \frac{T_i T_j'}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}}; i \neq j \tag{II.2}$$

where T_i and T_j are vectors containing the shares of patents of each firm in each technological field; $T_i = (T_{i1}, T_{i2}, , T_{iF})$ for F distinct technological fields. The pool of technology spillovers of the focal firm i in year t is proxied by what we call 'spillover measure':

$$SPILL\_JAFFE_i = \sum_j TECH_{ij} K_j; i \neq j \tag{II.3}$$

where K_j is the knowledge stock of firm j.

A major limitation of studies using this traditional measure is that they only focus on sample firms, i.e., firm i and firm j must be necessarily in the same sample. Because the firm datasets very often only comprise firms from one country (and in the most famous studies only firms from the US), it is not possible to account for spillovers that might come from firms outside the focal country. Although spillovers have been found to be localized (see, e.g., Jaffe et al. 1993), in a globalized world it is most likely that there are still spillovers from foreign countries that are not negligible.

A new spillover measure: technological relevance and foreign spillovers

In this paper, we both restrict and at the same time expand substantially the pool of firms from which a focal firm in our sample can receive spillovers. As a result, we obtain a new measure that might have advantages compared to the traditional Jaffe measure as it takes into account technological relevance and foreign spillovers. The last point is especially interesting in the case of Switzerland for which we have firm-level data. The position of Switzerland in the innovation global landscape is quite strong and firms are acting globally. As a consequence, they are also searching for knowledge globally. Especially for a small country, in-sample spillovers might neglect a substantial part of incoming knowledge from foreign countries and/or from firms that are not in the sample. 'Technologically relevant' firms worldwide are defined as those firms whose patents are cited in the focal Swiss firm's patents (backward citations). We identified all firms that are cited by Swiss firms in their patent applications to construct the sample of firms that build the technologically relevant environment of a focal firm. We consider backward citations to be a good proxy for the technological relevance of patents for the citing focal firm because it is likely that a firm cites patents (or examiners assign citations to its patents; see section 3.3) from firms that are active in similar industries, technological areas, etc.

Once we have identified the cited firms for each Swiss firm, we calculated the Jaffe proximity measures for $i = 1, ..., n$ sub-samples, where n is the number of Swiss patenting firms in our sample. Each sub-sample contains $1 + n_{cited\_i}$ firms where n_{cited_i} is the number of firms cited by Swiss firm i. Each of these sub-samples defines the technologically relevant environment for the respective focal firm. For the calculation of the spillover variable we use only the proximity measures between the focal firm and the n_{cited_i} firms in sub-sample i. As compared with the Jaffe measure the difference is that only those firms are taken into consideration for constructing the spillover variable whose patents (more precisely: at least 1 patent) have been cited in the patents of the focal firm (backward citations).[1]

[1] Actually, we calculated the Jaffe proximity measure for all firm pairings in each subsample, i.e., the focal firm i and the n_{cited_i} cited firms in subsample i, and we eliminated the interactions between the cited firms n_{cited_i} themselves as we did not need them for the construction of the spillover variable for the focal firms.

Knowledge spillovers and innovation performance

The relationship between knowledge spillovers and innovation performance is investigated in most extant studies in the framework of a patent equation which approximates a knowledge production function (see, e.g., Pakes and Griliches 1984) containing primarily R&D inputs and measures of knowledge spillovers based on patent or R&D stocks. The main idea is that knowledge spillovers may offer additional know-how to firms that are able to absorb such knowledge and combine it with in-house generated knowledge. Cohen and Levinthal (1989, 1990) demonstrated that knowledge spillovers can induce complementarities in R&D efforts and introduced the notion of absorptive capacity as the precondition for a firm to be able to exploit such spillovers. Hence, given a certain degree of absorptive capacity, the impact on innovation performance is expected to be positive in general, eventually mitigated by appropriability and/or competition factors (see below).

A positive effect of the R&D-based spillover variable on the number of patents has been already found in the seminal study of Jaffe (1986). Peri (2005) also reported a positive impact of a patent-based spillover variable on the number of patents from US regions. In a recent study, Bloom et al. (2013) investigated the relationship between two patent-based technological spillover variables and innovation output measured by the number of patents and found positive effects of spillovers on patents for a panel of US firms for the period 1981-2001.

Furthermore, two European studies, one based on data for Italian firms and the second on data for German firms, investigated the impact of R&D-based knowledge spillovers on measures of innovation output other than patents. Cardamone (2010) examined the impact of technological spillovers for a panel of Italian firms. The results showed that the probability of introducing a product or process innovation is negatively correlated with technological spillovers, contrary to the findings of most other studies. Jirjahn and Kraft (2011) examined the effects of spillovers as measured by a binary variable for 'firm taking innovation ideas from observing competitors' on innovation output based on firms in Lower Saxony. They found that spillovers have a positive impact on the probability of introducing 'incremental' innovations but no effect on the probability of 'drastic' innovations.

Based on the above discussion of extant literature, we formulate the following hypothesis:

Hypothesis 1: There is a positive relationship between knowledge spillovers and innovation performance.

Localization of knowledge spillovers

The main idea is that geographical (spatial) proximity enhances the ability of firms to recognize and absorb external knowledge that is relevant for this firm's innovation activities by reducing the inherent uncertainty of identification of relevant knowledge (see, e.g., Audretsch and Feldman 1996). Of course, in a world in which geographically dispersed activities can be linked electronically, the importance of geographic location as a factor of knowledge creation may seem irrelevant. Nevertheless, many empirical studies confirm that geographical distance still plays a significant role for the degree of knowledge diffusion. In particular, this is the case for the transfer of tacit knowledge components (see, e.g., Gertler 2003). Empirical evidence on spatial proximity is often based on patent citations by comparing the geographical location of patent citations with that of the cited patents. Feldman and Kogler (2010) surveyed the relevant literature and they found that most empirical studies confirm that knowledge spillovers are localized.

However, only geographical proximity may not be sufficient for the existence of knowledge spillovers. As Feldman and Kogler (2010) emphasized, cognitive distance, proxied, for example, by the Jaffe technological proximity measure, is a further important factor which could enhance knowledge diffusion if the technological profiles are close enough to enable absorption and implementation of external knowledge. However, if the technological profiles are too similar, the generated spillovers may be of minimal added value and consequently would not positively contribute to the innovation performance of the focal firm. As already stated in the seminal paper of Jaffe et al. (1993), the disentanglement of the two effects is not easy if the focus is on spatial proximity because "there are other sources of agglomeration effects that could explain the geographic concentration of technologically related activities without resort to localization of knowledge spillovers" (p. 579).

The main result of Jaffe et al. (1993) based on citations of patents that were granted by the US patent office was that citations to domestic patents are more likely to be domestic and even more likely to come from the same state as the cited patents. Localization fades over time but slowly. In contrast, Li (2014) found that distance effects increase over time for the same age of citations; otherwise, this study also supports the localization hypothesis.

In a further paper, Jaffe and Trajtenberg (1999) found with respect to spatial distance that patents whose inventors reside in the same country are 30% to 80% more likely to cite each other than inventors from other countries. Hence, the spillover localization tendency seems not only to occur in the US. The existence of localized spillovers has been challenged by Thompson and Fox-Kean (2005) substantially from a methodological point of view.[2] In a recent study, Murata et al. (2014) found based on a new distance-based test solid evidence supporting localization.

Further studies that support the localization hypothesis can be found in Peri (2005), Maurseth and Verspagen (2002), and Fischer et al. (2009).

For our study we formulate the following hypothesis:

Hypothesis 2: Knowledge spillovers are stronger the smaller the geographic distance among interacting firms is, other things being equal.

In the case of Switzerland, we thus expect that spillovers from firms in Switzerland will show a stronger association with innovation performance than those from firms from other countries and spillovers from firms in Europe a stronger association than those from firms from other more distant regions.

Knowledge spillovers and competition

Contrary to the extensive theoretical and empirical literature on the relationship between competition and innovation performance (see, e.g., the seminal paper of Aghion et al. (2005), research is silent about a possible moderating effect of competition on the innovation effect of spillovers. Under the assumption that the amount of spillovers is directly and positively related to the innovation performance of a firm, one could formulate the following hypothesis about the

[2] This has been the subject of the debate in the *American Economic Review* between Henderson et al. (2005) and Thompson and Fox-Kean (2005).

moderating performance effect of competition: if a competitive situation generates a large amount of spillovers then the expected performance effect is presumably high (positive) and if a competitive situation generates few spillovers the expected performance effect is low (negative). However, even in this respect the literature is not definite. In a survey of theoretical literature, De Bondt (1997) refers indirectly to this non-linearity concluding as follows: "In strategic investment [...] more spillovers typically lower effort, unless other factors such as a not too competitive oligopoly (high degree of product differentiation, small number of rivals) render the leakage effect small and then the opposite tendency may apply" (p. 13).[3]

There are some investigations about the amount of spillovers generated in specific competitive situations. Zirulia and Lacetera (2010) develop a model in which high knowledge spillovers lead firms to soften incentives [of scientists for R&D] in order not to benefit competitors, but only when product market competition is high; in contrast, high spillovers positively affect incentives when competition is low, yielding a non-linear relationship between the degree of spillovers and competition intensity.

With an agent-based simulation model, Wersching (2010) comes to the opposite results. He discusses the two views of Schumpeterian competition and their implications for innovation performance taking also knowledge spillovers into account. The simulation results show that a technological regime with many competitors in the product market is compatible with strong spillovers and in the case of only few competitors with weak spillovers.

Given that the theoretical discussion remains inconclusive, the issue of the influence of competition on the innovation effect of knowledge spillovers has to be settled empirically. Thus, we are agnostic and formulate the following three-part hypothesis:

Hypothesis 3a: Competition enhances the effect of knowledge spillovers on innovation performance.

Hypothesis 3b: Competition reduces the effect of knowledge spillovers on innovation performance.

Hypothesis 3c: Competition does not affect the effect of knowledge spillovers on innovation

[3] It has to be remarked that in this approach the appropriability aspect is not separated from the knowledge aspect.

performance.

III Model specification and econometric issues

Model specification

The usual framework to study the impact of technological knowledge and knowledge spillovers on innovation performance at the firm level is the knowledge production function which models the relationship between innovation input and innovation output (see for a standard model Crépon et al. (1998) and Cohen (2010) for a survey of this literature). We formulate this relationship as a function between the sales of innovative products (LINNS) (that includes sales with new and significantly modified products), i.e. a measure of innovation success, and the knowledge capital (LK) as well as knowledge spillovers (LSPILL) that contribute to this success (see Ramani et al. (2008) for a similar approach:

$$LINNS_{it} = \alpha_0 + \alpha_1 LK_{it-1} + \alpha_2 LSPILL_{it-1} + \alpha_3 X_{it-1} + e_{it} \tag{III.1}$$

where

$X_i = \{D_i; IPC_i; INPC_i; NCOMP_i; APPR_i; LEMPL_i; HQUAL_i; FOREIGN_i;$
industry dummies; year dummies$\}$;
for firm i, year t. Thus, the total impact of knowledge on firm output is measured by $(\alpha_1 + \alpha_2)$, the sum of the effects of a firm's own knowledge capital and the knowledge obtained by spillovers from enterprises of a firm's technologically relevant economic environment. We control for demand conditions (D), competition conditions (IPC; INPC; NCOMP), appropriability (APPR), the degree of absorptive capacity that is proxied with the share of highly qualified employees (HQUAL), firm size (LEMPL), foreign ownership (FOREIGN), industry affiliation and reference year (see Table III.1 for the exact definition of the variables). Controlling for appropriability and absorptive

capacity is particularly relevant in our approach of firms perceiving spillovers that are based on patent citations as measures of technological linkages among firms. Competition conditions are measured by one structural variable (number of main competitors in the relevant product market worldwide).

Econometric issues

We estimate the reduced form in (III.1) with Generalized Least Squares (GLS). Standard errors are heteroscedasticity robust. Reverse causality is not a concern in this setting since all covariates are lagged by one period.[4] Although we control for absorptive capacity and the existing knowledge stock, we are not able to include all firm-specific factors that are relevant to enable a firm to absorb spillovers from the technological environment, e.g., we do not observe management quality. In additional estimations that are detailed in V.1, the potential endogeneity of the spillover variable (LSPILL) is addressed by using additional lagged levels and differences of the focal variable as instruments. We have to note that in some of the empirical spillover literature, own knowledge capital rather than the spillover variable is assumed to be endogenous (e.g., in Lychagin et al. (2016)). We mainly follow Bloom et al. (2013) and focus on the spillover variable, but in Table V.5 we also present a specification where we treat both variables as endogenous.

[4]In fact, the covariates are lagged by three years. This is due to the survey data we use which is only available for each third year, see next section.

TABLE III.1

Description of variables

Variables	Definition
LINNS	Sales of innovative (new + significantly modified) products; natural logarithm
LINNS_N	Sales of innovative products that are new; natural logarithm
LINNS_M	Sales of innovative products that are significantly modified; natural logarithm
D	Expected demand at the product market; five-level ordinal variable (1: very weak demand development; 5: very strong demand development)
NCOMP	Number of competitors at the main product market; five-level ordinal variable (1: up to 5 competitors; 2: 6 to 10; 3: 11-15; 4: 16-50; 5: > 50)
APPR	Easiness of copying innovations; five-level ordinal variable (-1: very weak copy easiness; -5: very strong easiness)
LEMPL	Number of employees in full time equivalents; natural logarithm
HQUAL	Share of employees with tertiary level education
FOREIGN	Foreign-owned; binary variable: 1: yes; 0: no
LK	Knowledge capital based on patents; natural logarithm
LSPILL_ALL	Knowledge spillover based on interaction with all Swiss applicants that have at least 1 patent (see section 2); natural logarithm
LSPILL	Knowledge spillover based on interaction with all applicants whose patents have been cited by the focus firms (backward citations); natural logarithm
LSPILL*NCOMP	Interaction term of LSPILL with NCOMP
LSPILL_CH	LSPILL based on backward citations only of Swiss applicants; natural logarithm
LSPILL_EU	LSPILL based on backward citations only of European applicants; natural logarithm
LSPILL_US	LSPILL based on backward citations only of US applicants; natural logarithm
LSPILL_JP	LSPILL based on backward citations only of Japanese applicants; natural logarithm
LSPILL_APP	LSPILL based on backward citations filed by the applicant (excluding those added by examiners); natural logarithm
LSPILL_FIRMS	LSPILL based on backward citations only of applicants that are private corporations; natural logarithm
LSPILL_BACK	LSPILL based on backward citations, weighted with the share of backward links cited by a firm; natural logarithm

IV Data

Swiss innovation panel

The data stems from 6 waves of the Swiss Innovation Survey conducted by the KOF in the years 1996, 1999, 2002, 2005, and 2008.[5] The surveys are based on a disproportionately stratified random sample of firms with more than 5 employees (in full time equivalents) covering the industries of the manufacturing, construction and (commercial) service sector. The sample stratification refers to 2-digit industries and within each industry to three industry-specific firm size classes. The investigation at hand only uses data for manufacturing firms with patent applications with 264, 316, 328, 332, and 304 observations for the years 1996, 1999, 2002, 2005 and 2008 respectively. The resulting panel dataset is highly unbalanced. Due to missing values for model variables we end up with 640 observations in the pooled version.

Patent data

Annual information about patent applications comes from PATSTAT (EPO 2013) and the Derwent World Patent Index (WPI) by Thomson Reuters.[6] Based on the number of patent applications, we calculated patent stocks as proxies for knowledge stocks for each firm and year using the perpetual inventory method and a depreciation rate of 15% (see Hall et al. 2010):

$$K_{it} = (1 - d)K_{it-1} + R_{it} \tag{IV.1}$$

where K_{it} is the patent capital of firm i in t, d the depreciation rate, and R_{it} new patent applications

[5] The questionnaire of the survey, which resembles closely the "Community Innovation Survey", is available at www.kof.ethz.ch in German, Italian, and French. In the estimations, we use three-year lags for all variables except for the dependent variable that comes from the 2011 survey.

[6] We conducted several rounds of names matching: First, we used all patent applicants from Swiss applicants from WPI between 1990 and 2010, cleaned the applicants' names and firm names, and matched the cleaned applicants' names with firm names from the Innovation Survey automatically with a matching software. Afterwards, we checked the results manually. We also searched each firm name from the panel in ESPACENET and PATSTAT to get as many as possible patent applications. At the end, all matched patent applications we found were compiled in one dataset and checked once again. For the analysis here, we use patent families rather than single applications. Families comprise multiple applications of the same invention in different countries. Thus, they better reflect inventions than single patent applications (Martínez 2011; OECD 2009).

in t. The initial value is calculated as follows:

$$K_{i0} = R_{i0}/(d + g) \tag{IV.2}$$

The growth rate g is calculated from the 10-year average growth rate at 2-digit industry level for patent applications before 1990.[7]

The patent data also entails information about the technological fields (IPC code) at different levels of aggregation. We use the subclass level with four digits (for further explanations, see WIPO (2014)) yielding 617 subclasses for the calculation of the Jaffe measure of technological proximity (see equations (II.2) and (II.3) in section 2).

The EEE-PPAT tables with names of applicants

We identified all cited firms with the EEE-PPAT table that contains cleaned and harmonized names of applicants.[8] First, we searched for patent applications that are cited by patents assigned to a Swiss applicant. These patent applications were matched with the 'person' table from PATSTAT and then matched with names and IDs from the EEE-PPAT table. In sum, we found 125,449 distinct firms that are cited by Swiss firms from our sample (including self-citations). The distribution of the number of cited firms is quite skew. In fact, 10% of the firms account for about 75% of all backward links. 50% of the firms have less than 31 backward links, whereas 1% of the firms have more than 2,460 links.

In the next step, we collected all patent applications for each cited firm in PATSTAT. This enabled us to calculate the patent stocks of cited firms in the same way we did it for the Swiss firms using the perpetual inventory method.[9] We also assigned technological fields at subclass level to each patent application starting from the year 1995. We ended up with N datasets for the N sub-samples described above. For each sub-sample, we calculated the firms' share of patents in the underlying

[7] The reason for using industry-level information is that we did not match older patent applications before 1990. The sector assignment of patent applications necessitated the use of concordance tables, in our case that by Lybbert and Zolas (2014).

[8] See Du Plessis et al. (2009); Magerman et al. (2009); Peeters et al. (2009) for a description of the harmonization routines.

[9] As we can directly query the EEE-PPAT IDs in PATSTAT, we were able to retrieve patent applications up to 1971.

subclasses (pooled over all years). Each dataset has $F \times (1 + n_{cited\_i})$ observations. Finally, we calculated the spillover measures using a programming loop over all datasets. The final measures for the Swiss firms were then assigned to the firm IDs in the innovation survey.

Spillover variables for different regions

Based on formula (II.2), we first calculated the spillover measure that takes into account all backward citation links. In a further step, we looked at different geographical areas separately, i.e., we calculated the measure only based on cited firms that belong to certain regions as identified by the person country codes of the patent applicants. As main regions of interest, we chose Switzerland (as home-base), 'Europe' (i.e., all European countries except for Switzerland), the United States and Japan. The United States and Japan are chosen because of their economic and technological importance and because of their importance as patentees that makes them a potential technological source. For each region r, we get $i = 1, ..., n$ sub-samples with $1 + n_{cited\_i\_r}$ firms where $n_{cited\_i\_r}$ is the number of firms in region r cited by Swiss firm i.

For comparison, we also calculated the spillover measure in the usual way where we only take into account Swiss applicants irrespective of whether they are cited or not (formula (II.3)).[10]

Self-citations

From formulas (II.1) to (II.3), it is immediately clear that backward links that are based on self-citations must be excluded. Otherwise, our measure would not measure incoming external knowledge spillovers properly. More severely, the knowledge capital of a focal firm would enter the right-hand side of the regressions twice: First, as a focal firm's knowledge stock and, second, as weighted external knowledge stock through the spillover measure.

Excluding self-citations is involved because we have to deal with datasets with different firm identifiers: The survey data uses other identifiers than the EEE-PPAT table. Therefore, we cannot simply match the two data sources based on firm IDs. However, we can identify 'matching' firms in the respective datasets based on the patent applications they have in common. Concretely, we

[10] However, in contrast to the 'traditional approach', we take into account all Swiss applicants and not solely Swiss applicants that are part of the sample.

used all backward citations we could find for the Swiss firms (citing firms) and matched both the cited and citing patent applications with IDs from the EEE-PPAT table. Afterwards, we deleted all backward links where the cited patent applicant and the citing patent applicant have the same firm from the EEE-PPAT table in common in order to eliminate systematically all links between entities that might belong to the same company or are in any kind of judicial relationship.[11] The number of backward links then drops to 122,629.

Potential biases and problems with patent data

In the European patent system, most of the citations are added by patent examiners rather than by applicants or inventors (see Criscuolo and Verspagen 2008). Nevertheless, many authors use citation counts as – perhaps noisy – proxies for knowledge flows. Schoenmakers and Duysters (2010) argue that inventors might not bother to include a citation and that they might simply forget to include a citation, or even deliberately not include a citation for strategic reasons. Overall, they conclude that particularly with respect to the European Patent Office also non-inventor citations might indicate knowledge flows very well. Duguet and MacGarvie (2005) analyzed to what extent survey responses to the French innovation survey on R&D outsourcing, external R&D, cooperative R&D and other technology sources can predict backward and forward citations. They found support for the claim that patent citations are associated with technology flows as identified from the survey questions for some, but not all, channels. Roach and Cohen (2013) did a similar exercise for knowledge flows from US research institutes to firms and found that citations reflect knowledge flows through channels of 'open science', but not through contract-based relationships.

In this paper, we assume that examiners add citations that reflect their expert opinion covering existing patented knowledge on the topic in question. We do not see any reason why applicants should not also have perceived the same knowledge as examiners, even if they have not reported it in their applications. Consequently, we assume that citations (including examiners' additional citations) can be at least used to identify firms that are relevant for a focal firm from a technological point of view.[12] In additional estimates, we investigated the influence of examiner citations on the robustness of our results. Using only citations that were added by applicants does not considerably

[11] This might apply to some foreign subsidiaries.
[12] We do not attempt to capture knowledge flows with backward citations in this paper.

change the elasticity of the spillover variable for all regions (0.099 versus 0.093, see the discussion in section V.1). Thus, our estimates are quite robust with respect to the distinction between citations that were added by the examiner or the applicant or solely by the applicant.

Our results might be confronted with some other potential biases that arise from different aspects of the underlying data and the patent system. The latter are discussed in De Rassenfosse et al. (2013) and Bacchiocchi and Montobbio (2010). First, results might be subject to an institutional bias when patents are used that are from countries with different patent systems. However, this problem can be mitigated by using patent families as we did.[13] Second, there might be a geographic bias as applicants tend to file in their home patent offices and examiners tend to cite patents from their home offices. However, we reduce the possibility of this bias by avoiding looking at single patent offices. De Rassenfosse et al. (2013) found that small countries such as Belgium, the Netherlands, and Switzerland first file their patents at the European Patent Office. Thus, this kind of bias can be avoided in case of European cited firms. Problems might arise, if, for example, a US firm only applies in the US but not in Europe and the respective patent is not cited by a Swiss firm only because it is not applied for in Europe. We assume that 'technologically relevant' patents are mostly filed also at the European Patent Office (as the most important patent offices beneath the USPTO and the JPO) even if the applicant is from the US.[14] Moreover, patent families that comprise a large number of patents that have been applied for internationally are more valuable (Harhoff et al. 2003). Therefore, relevant patent families should comprise patent applications in multiple geographical jurisdictions. A final argument against a geographical bias is that we only look at backward citation links and not at the number of backward citations. Once a foreign firm has received one backward citation, it is taken into account in our analysis.[15]

A further bias might arise from including backward citations to patents that were applied for or granted a long time ago. However, we argue that we are not interested in the cited invention per se, but rather in the general technological relevance of the cited firm. If a patent cites an invention that was made a long time ago, the cited invention or at least the firm behind it should still possess

[13] In fact, we use families for both 'cited' and 'citing' patents.

[14] A large number of the cited firms are US firms, namely 39,437 compared 32,778 European firms. We also want to emphasize that a home bias with respect to USPTO citations (the citation practices are different from the European patent system) does not matter as we only look at citations Swiss firms made rather than citations US firms made.

[15] In Table V.4, column 3, we show estimates when the spillover measure is additionally weighted with the share of backward citations.

technological characteristics that could make it a potential spillover source otherwise it would not have been cited by the focus firm.

There might be also concerns that our results are driven by firm size and the Chemical and Pharmaceutical industry (the largest firms with the largest number of patent applications can be found here). However, inclusion of these firms is essential as they might be important spillover sources for smaller firms in Switzerland and their knowledge capital might affect the innovation performance of other firms through our spillover measure.[16]

V Results

Basic model and comparison of spillover measures

Columns 2 and 5 in Table V.1 show the estimates for the basic model for LINNS based on the spillover variables LSPILL and LSPILL_CH according to equation (II.3). LSPILL is based on all backward links, whereas LSPILL_CH only refers to cited Swiss firms. Both the elasticity of the knowledge capital and the spillover variables are positive and statistically significant (columns 2 and 5). For SPILL_CH, an increase by 1% of a firm's knowledge capital is associated with an increase by 0.123% of the sales of innovative products. The respective elasticity for the spillover variable is 0.099 (0.094 for LSPILL). Thus, the joint effect of own and spillover patent capital amounts to 0.222 (0.223 for LSPILL), i.e. a change of 1% of the joint knowledge capital is related to a change of 0.222% of innovative sales.[17] The positive sign of the spillover variable confirms hypothesis 1.

We compare the estimates for the new citation-based measure referring to cited Swiss firms (LSPILL_CH) with the estimates for a standard Jaffe spillover variable based on patent stocks of all Swiss firms with patents (LSPILL_ALL; Table V.1, column 1), irrespective of whether they

[16] In the regressions, we control for firm size that is strongly correlated with the number of backward citations and the number of patents.

[17] In a recent study based on data for several OECD countries for the period 1974-2002, Acharya (2015) estimated an average elasticity of intra-industry R&D spillovers (with respect to labor productivity) of 0.071, which is of the same magnitude as our estimates at firm level.

TABLE V.1

Basic Model: Comparison of Two Different Measures of Knowledge Spillovers, GLS Random Effects Estimates

	(1) $LINNS_t$	(2) $LINNS_t$	(3) $LINNS\_N_t$	(4) $LINNS\_M_t$	(5) $LINNS_t$	(6) $LINNS\_N_t$	(7) $LINNS\_M_t$
D_{t-1}	0.064	0.056	0.126**	0.061	0.058	0.127**	0.063
	(0.046)	(0.047)	(0.052)	(0.045)	(0.047)	(0.052)	(0.045)
$NCOMP_{t-1}$	-0.010	-0.012	0.019	-0.003	-0.011	0.020	-0.003
	(0.030)	(0.030)	(0.032)	(0.032)	(0.030)	(0.032)	(0.031)
$LEMPL_{t-1}$	0.964***	0.911***	0.889***	0.061	0.903***	0.881***	0.920***
	(0.039)	(0.042)	(0.045)	(0.045)	(0.042)	(0.046)	(0.050)
$HQUAL_{t-1}$	0.010***	0.009***	0.006*	0.009***	0.009***	0.006*	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$FOREIGN_{t-1}$	0.188**	0.184**	0.223**	0.258***	0.200**	0.232**	0.271***
	(0.093)	(0.093)	(0.100)	(0.095)	(0.091)	(0.099)	(0.096)
$APPR_{t-1}$	0.022	0.018	0.065*	-0.019	0.018	0.065*	-0.018
	(0.032)	(0.032)	(0.035)	(0.036)	(0.032)	(0.035)	(0.036)
LK_{t-1}	0.128***	0.123***	0.182***	0.069	0.129***	0.184***	0.080
	(0.037)	(0.048)	(0.053)	(0.051)	(0.046)	(0.051)	(0.049)
$LSPILL\_ALL_{t-1}$	0.053*						
	(0.030)						
$LSPILL\_CH_{t-1}$		0.099***	0.071**	0.113***			
		(0.028)	(0.031)	(0.029)			
$LSPILL_{t-1}$					0.094***	0.073***	0.098***
					(0.028)	(0.028)	(0.029)
Industry dummies (15)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies (4)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Const.	10.448***	10.855***	10.364***	9.904***	10.752***	10.286***	9.765***
	(0.376)	(0.375)	(0.363)	(0.387)	(0.362)	(0.355)	(0.372)
N	701	696	653	628	696	653	628
Wald chi2	1495.97***	1555.93***	1314.47***	1318.99***	1562.36***	1286.87***	1300.46***
R2 overall	0.72	0.73	0.69	0.73	0.73	0.69	0.72
R2 between	0.75	0.75	0.72	0.75	0.75	0.72	0.75
R2 within	0.05	0.05	0.06	0.03	0.05	0.06	0.03
Rho	0.44	0.42	0.46	0.34	0.42	0.46	0.35

*,** and *** denote significance on the levels 10%, 5% and 1%, respectively.

are cited or not. The coefficient of the spillover variable is 0.053, i.e., much smaller than that for the new measure, and statistically significant at the 10% test level. We interpret this result as evidence that the new spillover variable identifies more relevant external knowledge as shown by a substantial larger contribution (larger elasticity) of spillovers to a firm's innovation success. Hence, the better performance of the new measure is presumably due to the identification of firms that are really technologically relevant for the focal firm as identified with backward citation links reflecting links to external knowledge that the focal firm anticipated when generating its inventions.

Further variables that show as expected positive and statistically significant coefficients at the usual test levels are the measure for absorptive capacity (HQUAL) and the measure for firm size (LEMPL). The coefficient of the appropriability variable (APPR), a further relevant control variable, is positive but not significant for LINNS.

In columns 3 and 4 and 6 and 7, respectively, we investigate the new spillover variables for the sales with 'new' (LINNS_N) and 'significantly modified' (LINNS_M) products separately. This distinction captures more radical vs. more incremental innovations. The results show that spillover-related patent capital is significantly more important for modified products than for new products. The elasticity is 0.113 for LINNS_M as compared to 0.056 for LINNS_N for spillovers from cited Swiss firms and 0.098 versus 0.073 for spillovers from all cited firms worldwide. Moreover, own patent capital is insignificant for modified products, but highly significant for new products. This indicates that incremental innovation success is more dependent on external knowledge ('open innovation'), whereas radical innovation success is more related to exploitation of own knowledge resources. Indeed, APPR shows a positive and significant coefficient for the sales with new products, thus supporting this presumption.[18]

V.1 Basic model and competition effects

Table V.2, columns 1 to 3 shows the estimates of the basic model expanded by the interaction term between the overall spillover variable LSPILL and a dummy variable that takes on value 1 if the number of competitors on the main product market is larger than 15, this being the cut-off

[18] Our results are in line with Jirjahn and Kraft (2011) who have found that spillovers do not stimulate drastic innovations, although they solely rely on survey data and the dependent variable and spillover variable are therefore specified differently.

TABLE V.2

GLS Random Effects Estimates; Competition Effects

	(1) $LINNS_t$	(2) $LINNS\_N_t$	(3) $LINNS\_M_t$
D_{t-1}	0.049	0.117**	0.062
	(0.047)	(0.052)	(0.045)
$LEMPL_{t-1}$	0.906***	0.883***	0.924***
	(0.042)	(0.046)	(0.050)
$HQUAL_{t-1}$	0.009***	0.006**	0.010***
	(0.003)	(0.003)	(0.003)
$FOREIGN_{t-1}$	0.224**	0.254**	0.286***
	(0.091)	(0.099)	(0.096)
$APPR_{t-1}$	0.023	0.068*	-0.014
	(0.032)	(0.035)	(0.035)
LK_{t-1}	0.133***	0.185***	0.087*
	(0.045)	(0.049)	(0.048)
$LSPILL_{t-1}$	0.102***	0.082***	0.098***
	(0.028)	(0.029)	(0.030)
$NCOMP > 15_{t-1}$	0.217	0.355*	0.174
	(0.168)	(0.190)	(0.193)
$LSPILL \times NCOMP > 15_{t-1}$	-0.075*	-0.098**	-0.053
	(0.041)	(0.040)	(0.049)
Industry dummies (15)	Yes	Yes	Yes
Year dummies (4)	Yes	Yes	Yes
Const.	10.788***	10.399***	9.775***
	(0.353)	(0.346)	(0.361)
N	702	659	632
Wald chi2	1588.58***	1297.93***	1284.20***
R2 overall	0.73	0.69	0.72
R2 between	0.75	0.71	0.75
R2 within	0.06	0.07	0.03
Rho	0.40	0.45	0.35

value from where on competition matters (see the significantly positive coefficient of the dummy variable NCOMP>15 in columns 1 and 3). The coefficient of the interaction term is negative and statistically significant at the usual test level. This means that the effect of spillovers on the commercial success of innovations is significantly lower in markets with a larger number of competitors. This negative effect can be traced back primarily to sales with new products (see column 2) and is a hint in support of Hypothesis 3b. Obviously, more competition on the product market increases the need to innovate more radically, but reduces the contribution of spillovers to innovation success with new products. In face of stronger competition, radical innovators might also be careful that own knowledge does not leak out to rivals; this explains the positive sign of the appropriability variable in the estimates for LINNS_N.

There are two possible interpretations of the finding that the effect of spillovers is weakened when firms are operating in markets with many competitors (polypolistic markets). One possible explanation for this result refers to the size of the knowledge capital stock of the cited firms.[19] In polypolistic markets, firms lack the financial means for comprehensive investments in R&D and con-

[19]However, the spillover measure also includes the technological proximity measure, which is multiplied with the size of the knowledge capital stock. The proposed explanation only refers to the knowledge capital stock. More in-depth analysis would be necessary to include the proximity measure into the explanation of the observed facts.

TABLE V.3

GLS Random Effects Estimates; Regional Effects

	(1) $LINNS_t$	(2) $LINNS_t$	(3) $LINNS_t$	(4) $LINNS_t$	(5) $LINNS_t$
D_{t-1}	0.057	0.056	0.058	0.062	0.063
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
$NCOMP_{t-1}$	-0.010	-0.012	-0.010	-0.010	-0.010
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
$LEMPL_{t-1}$	0.916***	0.911***	0.933***	0.951***	0.960***
	(0.043)	(0.042)	(0.042)	(0.043)	(0.041)
$HQUAL_{t-1}$	0.008***	0.009***	0.009***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$FOREIGN_{t-1}$	0.171*	0.184**	0.171*	0.195**	0.195**
	(0.093)	(0.093)	(0.093)	(0.094)	(0.094)
$APPR_{t-1}$	0.021	0.018	0.021	0.019	0.021
	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)
LK_{t-1}	0.126**	0.123***	0.129***	0.178***	0.192***
	(0.053)	(0.048)	(0.049)	(0.047)	(0.049)
$LSPILL\_CH_{t-1}$	0.088***	0.099***			
	(0.031)	(0.028)			
$LSPILL\_EU_{t-1}$	0.028		0.063***		
	(0.025)		(0.024)		
$LSPILL\_US_{t-1}$	-0.018			0.016	
	(0.027)			(0.026)	
$LSPILL\_JP_{t-1}$	-0.021				-0.006
	(0.030)				(0.027)
Industry dummies (15)	Yes	Yes	Yes	Yes	Yes
Year dummies (4)	Yes	Yes	Yes	Yes	Yes
Const.	10.835***	10.855***	10.771***	10.588***	10.524***
	(0.388)	(0.375)	(0.387)	(0.392)	(0.377)
N	696	696	696	696	696
Wald chi2	1584.50***	1555.93***	1515.15***	1531.74***	1571.40***
R2 overall	0.73	0.73	0.73	0.73	0.73
R2 between	0.75	0.75	0.75	0.75	0.75
R2 within	0.05	0.05	0.05	0.05	0.05
Rho	0.42	0.42	0.43	0.43	0.43

sequently, knowledge advancements are weaker and the average knowledge capital stock is likely to be lower than in markets with less competitors. Hence, fewer spillovers are generated and their effect on innovation performance is lower. In markets with few R&D active competitors, the firms knowledge stocks are likely to be higher on average, hence, more spillovers are generated and their effect on innovation performance is expected to be larger. The second interpretation refers to a kind of 'business-stealing effect' as described in Bloom et al. (2013) and is more related to the total knowledge stock in a market – that is increased by a larger number of R&D active firms – rather than the average knowledge stock: Firms benefit from competition on the technological market if the social benefits arising from R&D spillovers exceed the costs of knowledge leakage, but they suffer from competition on the product market at the same time so that the compound effect of competition and spillovers on performance measures is negative.

On the whole, it appears that knowledge spillovers contribute disproportionately stronger to innovation success in more concentrated markets for a given level of appropriability and absorptive capacity. This is particularly the case when innovating firms pursue strategies of high degree of innovativeness.

Regional effects

As already described, we calculated separate spillover variables based on backward citation links to Swiss firms only (LSPILL_CH), to European firms (LSPILL_EU), US firms (LSPILL_US) and Japanese firms (LSPILL_JP), respectively. We inserted all four regional spillover variables in the LINNS equation and estimated the model once again (Table V.3, column 1). In a further step, we inserted the four regional spillover variables separately in the innovation equation and estimated four different models (columns 2 to 5). The estimates with all four spillover variables show that only the coefficient of the spillover variable from other Swiss firms is positive and statistically significant. Thus, the overall spillover effect can be traced back mainly to spillovers from other Swiss firms, the geographically nearest economic environment of a Swiss enterprise. The separate estimates for each regional variable confirm this finding and yield the additional insight that European firms also contribute to knowledge spillovers of Swiss firms, but to a smaller extent than Swiss firms (0.063; column 3). The coefficients of the spillovers from US and Japanese firms are negative and statistically insignificant.[20] These results support Hypothesis 2 and they are in accordance with the findings of recent studies for the US (Li (2014); based on citations for the period 1980-1997) and six large industrial countries for the period 1980-2000 (Malerba et al. 2013). Although American and Japanese firms possess of quite large patent stocks on average, spillovers from these stocks result in smaller effects than the much smaller stocks of Swiss and European firms. A possible explanation is a large technological distance between Swiss firms and firms from USA and Japan. Hence, the regional effect might be strengthened by the technological proximity effect.

Robustness tests and further estimations

Robustness of the spillover effect

We conducted three robustness tests with respect to the effects of the spillover variable and the competition effects. The tests refer to (a) the exclusion of examiner citations, (b) the exclusion of non-profit organisations, and (c) the consideration of weights for the backward citations. Table

[20] A distinction between new and modified products did not yield any further insights. Therefore, results are not shown here.

V.4 (column 1) shows results where we only include links based on citations made by applicants and exclude citations added by examiners. The results are robust. The EEE-PPAT table contains sector affiliations of the patent applicants. It has to be mentioned that not all patent applicants are private firms although they are by far the majority.[21] In column 2, we consider only spillovers from profit-oriented firms (other institutions were excluded before calculating the proximity measures). Again, the results are robust.

In column 3, the spillover measure is weighted with the share of backward citations (i.e., the number of backward citations that occur between a Swiss firm and a cited firm relative to the total number of backward citations a Swiss firm made). Obviously, the relative number of backward citations has an influence on the magnitude of the effect of spillovers (as measured in this study) on innovation performance. The elasticity of the spillover measure becomes larger, but remains in the same range of magnitude. Thus, our findings without weighting are rather conservative, the elasticities of the spillover measures displaying a kind of lower bound. With respect to the competition effect, the interaction effect with competition is supported in the case of (a) and (b) (see column 2 and 4) but not in (c) (column 6).

Robustness of the econometric specification

In further estimations, we check the robustness of our results with respect to different econometric models and the possible endogeneity of model variables. Wooldridge (2010, pp. 70) considers simple proxy variable solutions in order to eliminate omitted variable bias. He uses the lagged dependent variable in order to proxy for unobserved heterogeneity. However, this procedure is only valid in the cross-section (provided that that one lag of the dependent variable is available). We therefore estimate Ordinary Least Squares. Although the spillover effect decreases by about 21% (results not shown), it is still highly significant and the results are robust even when accounting for unobserved heterogeneity in this simple way.

In addition, Table V.5 shows Blundell-Bond estimates that are panel-consistent dynamic GMM estimates also including the lagged dependent variable as regressor (Arenallo and Bover 1995;

[21] We can detect 118,373 private firms, 5,551 non-profit organizations, and 1,598 universities that were cited by Swiss applicants. Individuals can also apply for patents, but they were excluded from the analysis from the beginning.

TABLE V.4

GLS Random Effects

	(1) $LINNS_t$	(2) $LINNS_t$	(3) $LINNS_t$
D_{t-1}	0.055	0.056	0.065
	(0.047)	(0.047)	(0.047)
$NCOMP_{t-1}$	-0.012	-0.010	-0.011
	(0.030)	(0.030)	(0.030)
$LEMPL_{t-1}$	0.902***	0.935***	0.932***
	(0.042)	(0.040)	(0.040)
$HQUAL_{t-1}$	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
$FOREIGN_{t-1}$	0.195**	0.191**	0.201**
	(0.092)	(0.094)	(0.092)
$APPR_{t-1}$	0.018	0.015	0.020
	(0.032)	(0.032)	(0.032)
LK_{t-1}	0.129***	0.130***	0.180***
	(0.046)	(0.050)	(0.045)
$LSPILL\_APP_{t-1}$	0.093***		
	(0.027)		
$LSPILL\_FIRMS_{t-1}$		0.107**	
		(0.044)	
$LSPILL\_BACK_{t-1}$			0.141***
			(0.054)
Industry dummies (15)	Yes	Yes	Yes
Year dummies (4)	Yes	Yes	Yes
Const.	10.811***	10.778***	10.582***
	(0.368)	(0.388)	(0.363)
N	696	696	696
Wald chi2	1564.275***	1546.643***	1538.597***
R2 overall	0.731	0.728	0.728
R2 between	0.752	0.748	0.751
R2 within	0.048	0.050	0.047
Rho	0.426	0.430	0.425

TABLE V.5

Blundell-Bond estimates

	(1) $LINNS_t$	(2) $LINNS_t$	(3) $LINNS_t$
$LINNS_{t-1}$	-0.014	0.020	-0.022
	(0.127)	(0.115)	(0.110)
D_t	0.089	0.084	0.099
	(0.060)	(0.067)	(0.063)
$NCOMP_t$	-0.046	-0.067	-0.040
	(0.061)	(0.064)	(0.059)
$LEMPL_t$	0.928***	0.804***	0.882***
	(0.200)	(0.201)	(0.159)
$HQUAL_t$	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)
$FOREIGN_t$	-0.008	0.036	0.019
	(0.168)	(0.183)	(0.147)
$APPR_t$	0.019	0.022	0.017
	(0.044)	(0.047)	(0.047)
LK_t	-0.020	-0.023	0.086
	(0.161)	(0.163)	(0.119)
$LSPILL_t$	0.056**	0.065***	0.059***
	(0.024)	(0.025)	(0.022)
Const.	11.678***	11.752***	11.730***
	(2.404)	(2.142)	(1.626)
N	721	721	721
Wald chi2	37.008***	40.783***	162.102***
N instruments	23	30	40
Sargan test (chi2)	16.76	24.56	30
Sargan test (p-value)	0.080	0.219	0.451
AR(1) p-value	0.003	0.002	0.004
AR(2) p-value	0.771	0.818	0.718

Blundell and Bond 1998).[22] The estimator uses further lags and lagged differences of $LINNS_{i,t-1}$ as instruments in a differenced equation and in a level equation, respectively. Additionally, we account for potential endogeneity of LSPILL by introducing the lagged difference and the lags $LSPILL_{i,t-2}$ and $LSPILL_{i,t-3}$ as instruments in the system estimation (column 2). In column 3, we also include instruments for LK in the same way.[23] At the bottom of the table, we report the Sargan test statistics and tests on zero autocorrelation. The Sargan test on valid overidentifying restrictions cannot be rejected for the specifications in column (2) and (3). The tests on zero autocorrelation show that the errors are serially uncorrelated as we cannot reject at order 2. Although prior innovation success does not show any statistically significant association with current innovation success once we account for endogeneity of prior innovation success, the spillover effect remains highly significant which supports our baseline results.

Interestingly, in the additional estimations we provide in Table V.5, the coefficient of patent capital is most often insignificant - quite in contrast to our baseline results. Lychagin et al. (2016) also get insignificant coefficients for own knowledge capital in some specifications when accounting for spillovers.

VI Summary and conclusions

In this paper, we contribute to literature in three ways: First, we examine the impact of knowledge spillovers as measured by a patent-based proximity measure on innovation success. Second, we propose a new measure that extends the traditional Jaffe spillover measure; it uses backward citation links to identify the firms to which a focal firm is technologically exposed. Third, we investigate the performance effects of spillovers in markets with different degrees of competition.

Based on a comprehensive data set comprising firm-level survey information for a representative panel of Swiss firms and patent information for all firms worldwide with patents that have been cited by Swiss firms, we found that (a) the proposed new spillover measure shows a positive and

[22] The Blundell-Bond estimates turn out to be more efficient in our case than the Arenallo-Bond estimates (Arellano and Bond 1991; Blundell and Bond 1998). The method is similar to the one applied in Lychagin et al. (2016) (see Table VI in their paper) although they treat only own knowledge capital and lagged productivity (their lagged dependent variable) as endogenous.

[23] We do not lag the independent variables that we include in the regressions from the outset as in the baseline models. The reason is that the estimator uses lags and lagged differences for the endogenous variables and that we have to reject the test on joint significance of regressors when using lagged regressors from the outset in this model.

significant effect of knowledge spillovers on innovation success as measured by the sales share of innovative products; (b) spillovers are more important for innovation success with modified products (incremental innovations) as compared to new products (radical innovations), while a firm's own patent capital is more important for success with new products than with modified products; (c) the knowledge spillovers are localized and concentrated primarily in Switzerland and to a smaller extent in Europe; and (d) market competition is important for the innovation effects of spillovers, but only with respect to radical innovation success.

With respect to competition, we found that firms in markets with many competitors do not benefit from spillovers, while firms in markets with few competitors (less than 15) benefit more from spillovers, but only with respect to firms that innovate with new products. This result indicates that spillovers are more important for Swiss firms that operate in niche markets (e.g., measuring instruments) or in typical R&D intensive, oligopolistic markets (e.g., pharmaceuticals). It reflects exactly the innovation strategy of many Swiss firms as it is investigated and discussed in previous studies (see, e.g., Arvanitis 1997; Arvanitis and Hollenstein 1996). However, with respect to the direct spillover effect, firms with a higher level of innovativeness draw on own accumulated knowledge to a larger extent than on external knowledge from spillovers and try to prevent knowledge leakage to rivals.

From a theoretical point of view, a possible mechanism for explaining our finding is as follows: intensive competition as indicated by the presence of many principal competitors might reduce the financial opportunities to invest in R&D. As internal R&D contributes to the absorptive capacity that is needed for the exploitation of external knowledge, the lack of R&D investments tends to reduce the performance effects of spillovers.

It is a limitation of this study that we only consider spillovers from patenting firms. If firms do not patent their inventions, they might chose other means of knowledge protection, such as secrecy, first-mover advantages, etc. It is likely that, for example, 'secrecy' leads to lower knowledge externalities, but the extent of spillovers from other strategic appropriability mechanisms is unknown. Cohen et al. (2002) suggest that R&D spillovers are significantly greater in industries and countries where appropriability is low, notwithstanding the relative effectiveness of particular mechanisms. Future investigations could shed light on the spillover effects of different appropriability mechanisms, but they are not subject of the present study. A further limitation is that it refers to one country only. The matching of firm survey data with patent data for several countries with different technological profiles would enable researchers to test the citation-based spillover measure on a wider basis and gain additional insights with respect to the role of knowledge spillovers in the innovation process.

With respect to the interaction effect that we find for spillovers and competition, a theoretical model would clearly help to understand the mechanisms from a conceptual point of view. This paper is a first attempt to understand the mechanisms between competition, spillovers, own existing knowledge and innovation success from an empirical point of view. Further progress in this area might depend on finding suitable instruments for spillovers and on further disentangling the relationships between the focal variables applying appropriate econometric methods.

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