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 between firms not just based on a firm sample, but on all firms that can be 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 “relevant” firms. Our empirical results indeed show that the measure performs better in an innovation model than the standard measure. We find – for a 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 localised as spillovers from geographically distant areas such as the USA and Japan matter, if at all, 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.

Key words: knowledge spillovers; innovation success; knowledge capital; patent citations; competition

JEL Classification: O31
1. 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 further extension to 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 effects 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 given 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. 1

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 data, 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

1 We are aware that 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.
country with a strongly internationalised 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 (EEE-PPAT) 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, no effect 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 localisation 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 analyse 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 of the study, the research hypotheses and the specification of the empirical model including econometric issues are presented. Section 3 describes the data that is used. In section 4 the results are presented. Section 5 summarizes and concludes.

2. Conceptual background

2.1 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., Spence 1984; Cohen and Levinthal 1989; Geroski 1995; and Aghion and Jaravel 2015).

A general though rather simplistic way to address this externality problem is to assume the diffusion of new private knowledge as 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 spillover capital as a (weighted) sum of the knowledge capital of a firm’s relevant economic environment (knowledge pool) is given by the following expression (see Griliches 1979, 1992):

\[
SO_i = \sum_{j \neq i} w_{ij}K_j
\]

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 Van Pottelbergh 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 (1) are a measure of scientific and technological “distance” among firms and industries (technological proximity; see, e.g., Jaffe 1986; Bloom et al. 2013) or of geographical distance (geographical proximity; see, e.g., Gust-Bardon 2012; Bloch 2013). 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:

\[ TECH_{ij} = \frac{T_i^j}{(T_i^j)^2} ; i \neq j \]  

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”:

\[ SPILL_{JAFFE_i} = \sum_j TECH_{ij}K_j ; i \neq j \]  

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 localised (see, e.g., Jaffe et al. 1993), in a globalised 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 $i=1,\ldots,n$ subsamples, where $n$ is the number of Swiss patenting firms in our sample. Each subsample contains $1 + n_{\text{cited},i}$ firms where $n_{\text{cited},i}$ is the number of firms cited by Swiss firm $i$. Each of these subsamples 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 $n_{\text{cited},i}$ firms in the subsample $i$. 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).

2.2 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) for two cross-sections in 1973 and 1979 comprising

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2 Actually, we calculated the Jaffe proximity measure for all firm pairings in each subsample, i.e. the focal firm $i$ and the $n_{\text{cited},i}$ cited firms in the subsample $i$ and we eliminated the interactions between the cited firms $n_{\text{cited},i}$ themselves, which we did not need for the construction of the spillover variable for focal firms.
American firms. Peri (2005) also reported a positive impact of a patent-based spillover variable on the number of patents of 147 US regions in the period 1975-1996. 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 1203 Italian firms over the period 1998-2003. 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 pooled data for 1022 manufacturing firms in Lower Saxony covering the period 1995 and 1997. 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.

### 2.3 Localised knowledge spillovers

The main idea is that geographical (spatial) proximity enhances the ability of firms to recognise 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., Feldman 1994). 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 localised.
However, only geographical proximity may not be sufficient for the existence of knowledge spillovers. As Feldman and Kogler (2010) emphasised, 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 put 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 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. Localisation 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 localisation hypothesis.

In a further paper, Jaffe and Trajtenberg (1999) found – based on citations of patents granted by the US patent office to inventors in the US, the UK, France, Germany, and Japan – 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 localisation tendency seems not only to occur in the US. The existence of localised spillovers has been challenged by Thomson and Fox-Kean (2005) not only substantially but also from a methodological point of view.³ In recent study, Murata et al. (2014) found based on a new distance-based test solid evidence supporting localisation.

Further studies that support the localisation hypothesis can be found in Peri (2005) based on patent citations for 113 European and North American regions over 22 years, Maurseth and Verspagen (2002) based on patent citations for European regions, and Fischer et al. (2009) based on high-tech patent citations in Europe.

For our study we formulate the following hypothesis:

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³ This has been the subject of the debate in the American Economic Review between Henderson et al. (2005) and Thomson and Fox-Kean (2005).
Hypothesis 2: Knowledge spillovers are stronger the smaller is the geographic distance among interacting firms, other things being equal.

In the case of Switzerland, we thus expect that spillovers from firms in Switzerland would show a stronger association to 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.

2.4 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 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 Bond (1996) 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).4

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

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4 It has to be remarked that in this approach the appropriability aspect is not separated from the knowledge aspect.
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 performance.

2.5 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,5 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)6:

\[
LINNS_{it} = \alpha_0 + \alpha_1 LINNS_{it-1} + \alpha_2 LK_{it-1} + \alpha_3 LSPILL_{it-1} + \alpha_4 X_{it-1} + e_{it}
\]

where

\[
X_i = \{D_i; IPC_i; INPC_i; NCOMP_i; APPR_i; LEMPL_i; HQUAL_i; FOREIGN_i; industry dummies; year dummies\}; \text{ for firm } i, \text{ year } t
\]

5 We also use the sales share of new products (LINNS_N) and the sales share of significantly modified products (LINNS_M) as dependent variables separately.

6 The use of the lagged dependent variables LINNS_{it-1} (also LINNS_N_{it-1} and LINNS_M_{it-1}) as right-hand variable and of lagged covariates in (4) will be discussed and econometrically justified in the next subsection.
Thus, the total impact of knowledge on firm output is measured by \((\alpha_2 + \alpha_3)\), 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), degree of absorptive capacity (HQUAL), firm size (LEML), foreign ownership (FOREIGN), industry affiliation and reference year (see Table 1 for the exact definition of the variables). Controlling for appropriability and absorptive capacity is particularly relevant in our approach of perceiving spillovers that are based on patent citations as measures of technological linkages among firms.

Competition conditions are measured by two variables that capture behavioural aspects of competition (intensity of price competition IPC; intensity of on-price competition INPC) and one structural variable (number of main competitors in the relevant product market worldwide). In this way, we cover several aspects of the multi-faceted notion of market competition.

**Econometric issues**

We estimate the reduced form in (4) by generalized least squares (GLS). Standard errors are heteroscedasticity robust. The potential endogeneity of the spillover variable (LSPILL\(_{t-1}\)) is addressed by introducing the lagged dependent variable LINNS\(_{t-1}\). We assume that the unobserved heterogeneity \((q_{it})\) can be approximated by the lagged dependent variable. This means that:

\[
q_{it} = \beta_0 + \beta_1 \text{LINNS}_{it-1} + u_{it}
\]

We assume that \(u_{it}\) has zero mean and we are confident that \(u_{it}\) is not significantly correlated with the spillover variable (LSPILL\(_{it-1}\)) and the proxy for competition in equation (4), which are the main variables of interest. If this holds then \(\alpha_3\) and the coefficient of the competition variable (NCOMP\(_{t-1}\)) in equation (4) are unbiased and measure the effect of spillovers and competition on the innovation performance of firms (see Wooldridge 2010, p. 70 et seqq.). Why do we think that \(u\) is uncorrelated \([\text{Cov}(\text{LSPILL}, u) = 0 \text{ and Cov}(\text{NCOMP}, u) = 0]\)? Given our comprehensive control vector including the lagged dependent variable it is hard to think of lacking important information that is strongly correlated with spillovers and/or the number of principal competitors.

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7 The relationship we are interested in can be formulated by \(\text{LINNS}_{it} = \gamma_0 + \gamma_1 q_{it} + \gamma_2 K_{it-1} + \gamma_3 \text{LSPILL}_{it-1} + \gamma_4 X_{it-1} + \varepsilon_{it}\). After inserting (5), we get equation (4).
Reverse causality is not a concern in this setting, since all covariates are lagged by one period\(^8\). We are aware that the lagged dependent variable is endogenous, however, since we are not interested in the marginal effect of this variable, this is of no concern to our empirical estimation strategy.

3. Data

3.1 Swiss Innovation Panel

The data stems from 6 waves of the Swiss Innovation Survey\(^9\) conducted by the KOF in the years 1996, 1999, 2002, 2005, and 2008.\(^10\) 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 (see Table 2 for the composition by industry, firm size class and year of the sample used in the econometric estimations; Table A.1 for descriptive statistics; and Table A.2 for the correlations between the model variables).

3.2 Patent data

Annual information about patent applications comes from PATSTAT (EPO 2013) and the Derwent World Patent Index (WPI) by Thomson Reuters.\(^11\) Based on the number of patent

\(^8\) 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.

\(^9\) The questionnaire of the survey, which resemble closely the “Community Innovation Survey”, is available at www.kof.ethz.ch in German, Italian, and French.

\(^10\) In the estimations, we use 3-year lags for all variables except for the dependent variable that comes from the 2011 survey.

\(^11\) 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 (OECD 2009; Martinez 2010).
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):
\[ K_{it} = (1 - d)K_{it-1} + R_{it} \]  \hspace{5cm} (6)

where \( K_{it} \) is the patent capital of firm \( i \) in \( t \), \( d \) the depreciation rate, and \( R_{it} \) new patent
applications in \( t \). The initial value is calculated as follows:
\[ K_{i0} = \frac{R_{i0}}{(d + g)} \]  \hspace{5cm} (7)

The growth rate \( g \) is calculated from the 10-year average growth rate at 2-digit industry level
for patent applications before 1990.\(^{12}\) Table 3 shows the calculated average patent capital by
industry, firm size class and year. Chemicals, machinery and electronics/instruments are the
industries with the largest patent stocks reflecting their high level of patenting activities.

The patent data also entails information about the technological fields (IPC code) on 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 (2) and (3) in section 2).

3.3 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\(^{13}\). First, we searched for patent applications that are cited by patents
assigned to a Swiss applicant.\(^{14}\) 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

\(^{12}\) The reason for using industry-level information is that we did not match older patent applications. The sector
assignment of patent applications necessitated the use of concordance tables, in our case that by Lybbert and Zolas
(2014).

\(^{13}\) See du Plessis et al. (2009), Peeters et al. (2009) and Magermann et al. (2009) for a description of the
harmonisation routines.

\(^{14}\) 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 very well indicate knowledge flows. 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 would 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 used
to identify the technologically relevant firms. 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
change the elasticity of the spillover variable for all regions (0.079 versus 0.080, see Table A.3 and the discussion
in section 4.4). 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.
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.\(^\text{15}\) We also assigned technological fields on subclass level to each patent application starting from the year 1995. We ended up with \(N\) datasets for the \(N\) subsamples described above. For each subsample, we calculated the firms’ share of patents in the underlying subclasses (pooled over all years). Each dataset has \(F \cdot (1 + n_{\text{cited},i})\) 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.

### 3.4 Spillover variables for different regions

Based on formula (2), we first calculated the spillover measure that takes into account all backward citation links (see Table 4 for the average number of backward citations of Swiss firms by industry and by firm size class; chemicals, machinery, electrical machinery and electronics/instruments, which are the most innovative industries, show the highest number of citations). 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 \(i=1,...,n\) subsamples with \(1 + n_{\text{cited},i,r}\) firms where \(n_{\text{cited},i,r}\) is the number of firms in region \(r\) cited by Swiss firm \(i\) (see Table 3 for the calculated average patent capital of the cited firms by regions).

\[^{15}\] As we can directly query the EEE-PPAT IDs in PATSTAT, we were able to retrieve patent applications up to 1971.
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 (3) in section 2).\textsuperscript{16}

3.5 Self-citations

From formulas (1) to (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 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.\textsuperscript{17} The number of backward links then drops to 122,629.

3.6 Potential biases

Our results might be confronted with some 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.\textsuperscript{18} 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

\textsuperscript{16} 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.
\textsuperscript{17} This might apply to some foreign subsidiaries.
\textsuperscript{18} In fact, we use families for both “cited” and “citing” patents.
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 (EPO) even if the applicant is from the US.19 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.20

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 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.21

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19 A large number of the cited firms are US firms, namely 39,437, compared with 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.

20 In Table A.3, columns 3 and 6, we show estimates when the spillover measure is additionally weighted with the share of backward citations.

21 In the regressions, we control for firm size that is strongly correlated with the number of backward citations and the number of patents.
4. Results

4.1 Basic model and comparison of spillover measures

Columns 2 and 5 in Table 5 show the estimates for the basic model for LINNS based on the spillover variables LSPILL and LSPILL_CH according to equation (3) in section 2. 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 0.098% of the sales of innovative products. The respective elasticity for the spillover variable is 0.084 (0.080 for LSPILL). Thus, the joint effect of own and spillover patent capital amounts to 0.182 (0.186 for LSPILL), i.e. a change of 1% of the joint knowledge capital is related to a change of 0.182% of innovative sales.\(^{22}\) 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 5, column 1), irrespective of whether they are cited or not. The coefficient of the spillover variable is 0.029, i.e. much smaller than that for the new measure and it is statistically insignificant 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 measured by the backward citations reflecting 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 level 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.

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

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\(^{22}\) 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.
spillover-related patent capital is significantly more important for modified products than for new products. The elasticity is 0.096 as compared to 0.056 for spillovers from cited Swiss firms and 0.093 versus 0.053 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 might be 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.23

4.2 Basic model and competition effects

Table 6, columns 1 to 3 shows the estimates of the basic model expanded by the interaction term between the overall spillover variable LSPILL and the competition variable NCOMP that measures the number of principal competitors on the main product market. The coefficient of NCOMP becomes significantly positive in the estimates for LINNS and LINNS_N and remains insignificant for LINNS_M. 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 new products (see column 2) and can be interpreted as a hint in favor 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.

In columns 4 to 6, we specify the competition effect in an alternative way by interacting the spillover variable with a dummy variable that takes the value 1 if the number of competitors is larger than 15, this being the cut-off value from where on competition matters (see the significantly positive coefficient of the dummy variable NCOMP>15 in columns 4 and 6). The negative and statistically significant coefficient of the interaction term confirms the previous results and yields the additional insight that increasing the number of competitors above 15

23 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.
decreases the spillover effect on innovation performance. Again, this result can be primarily traced back to innovation success with new products.

As already mentioned, our interpretation of this finding is 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. In polypolistic markets, firms lack the financial means for comprehensive investments in R&D and consequently, 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 knowledge stocks are likely to be higher, hence, more spillovers are generated and their effect on innovation performance is expected to be larger. This supports Hypothesis 3b with respect to the number of competitors as a measure of market concentration. 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.

4.3 Regional effects

As already described, we calculated separately spillover variables based on backward citations from Swiss firms only (LSPILL_CH), from 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 7, column 1). In a further step, we inserted the four regional spillover variables separately in the innovation equation and estimated four different models (Table 7, 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 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 significantly smaller extent than Swiss firms (0.045; column 3). The coefficients

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24 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.
of the spillovers from US and Japanese firms are negative and statistically insignificant. 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. This can be explained by the large technological distance between Swiss firms and firms from USA and Japan. Hence, the regional effect is strengthened by the technological proximity effect.

4.4 Robustness tests

We conducted three robustness tests with respect to the effects of the spillover variable and the competition effects. The three 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. Tables A.3 (columns 1 and 4) 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. In columns 2 and 5, 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 and 6, the spillover measure is weighted with the share of backward citation links (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 4 and 5) but not in (c) (column 6).

25 A distinction between new and modified products did not yield any further insights. Therefore, results are not shown here.
26 See also footnote 12.
27 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.
5. Summary and conclusions

In this paper, we contribute to the 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 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 localised 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 profit from spillovers, while firms in markets with few competitors (less than 15) profit more from spillovers, but only with respect to firms that innovate with new products. This result indicates that spillovers are 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 and Hollenstein 1996; Arvanitis 1997). 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.
A limitation of the study 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.
References


## TABLES

Table 1: Definition of the variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>LINNS</td>
<td>Sales of innovative (new + significantly modified) products; natural logarithm</td>
</tr>
<tr>
<td>LINNS_N</td>
<td>Sales of innovative products that are <em>new</em>; natural logarithm</td>
</tr>
<tr>
<td>LINNS_M</td>
<td>Sales of innovative products that are <em>significantly modified</em>; natural logarithm</td>
</tr>
<tr>
<td>D</td>
<td>Expected demand at the product market; five-level ordinal variable (1: very weak demand development; 5: very strong demand development)</td>
</tr>
<tr>
<td>NCOMP</td>
<td>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: &gt; 50)</td>
</tr>
<tr>
<td>APPR</td>
<td>Easiness of copying innovations; five-level ordinal variable (-1: very weak copy easiness; -5: very strong easiness)</td>
</tr>
<tr>
<td>LEMPL</td>
<td>Number of employees in full time equivalents; natural logarithm</td>
</tr>
<tr>
<td>HQUAL</td>
<td>Share of employees with tertiary level education</td>
</tr>
<tr>
<td>FOREIGN</td>
<td>Foreign-owned; binary variable: 1: yes; 0: no</td>
</tr>
<tr>
<td>LK</td>
<td>Knowledge capital based on patents; natural logarithm</td>
</tr>
<tr>
<td>LSPILL_ALL</td>
<td>Knowledge spillover based on interaction with all Swiss applicants that have at least 1 patent (see section 2)</td>
</tr>
<tr>
<td>LSPILL</td>
<td>Knowledge spillover based on interaction with all applicants whose patents have been cited by the focus firms (backward citations) (see section 2)</td>
</tr>
<tr>
<td>LSPILL*NCOMP</td>
<td>Interaction term of LSPILL with NCOMP</td>
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<td>LSPILL_CH</td>
<td>LSPILL based on backward citations only of <em>Swiss</em> applicants</td>
</tr>
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<td>LSPILL based on backward citations only of <em>European</em> applicants</td>
</tr>
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<td>LSPILL based on backward citations only of <em>US</em> applicants</td>
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<td>LSPILL based on backward citations filed by the applicant (excluding those added by examiners)</td>
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<td>LSPILL based on backward citations only of applicants that are <em>private corporations</em></td>
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<tr>
<td>LSPILL_BACK</td>
<td>LSPILL based on backward citations, weighted with the share of backward links cited by a firm</td>
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Table 2: Composition of the dataset by industry, firm size class and year (number of firms)

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Table 3: Patent capital per firm by industry and firm size class

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Table 4: Number of backward citations per firm of Swiss firms by industry and firm size class

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Table 5: Basic model; comparison of two different measures of knowledge spillovers; GLS random effects estimates

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Note: *, **, *** denote statistical significance at the 10%, 5% and 1% test level, resp.
Table 6: GLS random effects estimates; competition effects

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Note: *, **, *** denote statistical significance at the 10%, 5% and 1% test level, resp.
Table 7: GLS random effects estimates; regional effects

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Note: *, **, *** denote statistical significance at the 10%, 5% and 1% test level, resp.
## APPENDIX

Table A.1: Descriptive statistics (N=640)

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Table A.2: Correlation matrix of the model variables

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Table A.3: GLS random effects estimates for LINNS$_t$

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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year dummies (4)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Const.</td>
<td>7.771***</td>
<td>7.731***</td>
<td>7.463***</td>
<td>7.600***</td>
<td>7.578***</td>
<td>7.383***</td>
</tr>
<tr>
<td></td>
<td>(0.650)</td>
<td>(0.652)</td>
<td>(0.642)</td>
<td>(0.634)</td>
<td>(0.636)</td>
<td>(0.629)</td>
</tr>
<tr>
<td>N</td>
<td>640</td>
<td>640</td>
<td>640</td>
<td>640</td>
<td>640</td>
<td>640</td>
</tr>
<tr>
<td>Wald chi2</td>
<td>2314.362***</td>
<td>2273.518***</td>
<td>2254.558***</td>
<td>2331.842***</td>
<td>2291.964***</td>
<td>2295.475***</td>
</tr>
<tr>
<td>R$^2$ overall</td>
<td>0.770</td>
<td>0.769</td>
<td>0.768</td>
<td>0.772</td>
<td>0.771</td>
<td>0.769</td>
</tr>
<tr>
<td>R$^2$ between</td>
<td>0.809</td>
<td>0.808</td>
<td>0.810</td>
<td>0.812</td>
<td>0.811</td>
<td>0.811</td>
</tr>
<tr>
<td>R$^2$ within</td>
<td>0.006</td>
<td>0.006</td>
<td>0.006</td>
<td>0.008</td>
<td>0.007</td>
<td>0.006</td>
</tr>
<tr>
<td>rho</td>
<td>0.280</td>
<td>0.281</td>
<td>0.278</td>
<td>0.272</td>
<td>0.274</td>
<td>0.274</td>
</tr>
</tbody>
</table>

Note: *, **, *** denote statistical significance at the 10%, 5% and 1% test level, resp.