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ABSTRACT

DO VARIOUS INNOVATION LINKAGES ENHANCE INNOVATION? INTERNATIONAL EVIDENCE

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Whereas various drivers of the international innovative activity have been studied in the literature, our understanding of the contributions of different innovation linkages to innovation deserves more attention. Are the different innovation linkages equally complementary to research inputs in fostering innovation? This paper addresses the contributions of different innovation linkages to innovation, across two different measures of innovation. We find that a broader index of innovation linkages shows positive and significant spillovers on innovation, while joint ventures and university-industry collaborations fail to exert a significant influence. These spillovers are reinforced by the positive and expected impacts of R&D spending. In other results, greater venture capital investments boost innovation in most cases, while more FDI boosts one type of innovation output. These findings are uniquely shown to be sensitive across least- and most innovative nations when a quantile regression is employed. Implications for technology policy are discussed.

Keywords: patents; innovation; innovation linkages; R&D; joint ventures; university-industry collaboration

JEL classification: O31; O33; O38

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1 Introduction

The continued importance of technological change globally to tackle microeconomic and macroeconomic issues has researchers and policymakers keenly interested in supporting and boosting innovation. As new challenges emerge with diseases, the environment, sustainability, space exploration, etc. new and better means are needed to meet them.

Whereas many initiatives, such as research subsidies, have shown to yield dividends, the differing innovation rates across nations (and even over time for a given nation) and the inability to find solutions to some lingering problems (e.g., a cure for the common cold) have underscored the need for continued attention to the process of research. It is in this respect that the current work attempts to add to the existing body of research. Specifically, we examine the spillovers from innovation linkages on innovation. Innovation linkages capture indirect (formal and informal) channels that impact innovation. These could be networks or other support mechanisms. They would complement the direct returns from R&D spending on innovation. For example, innovation linkages could emerge from geographic concentration of firms in certain clusters, which would lower the costs of formal and informal knowledge flows that facilitate innovation (see Chandrashekar and Bala Subrahmanya (2019)). Effective allocation of research resources is contingent upon a correct accounting of the costs and benefits of such endeavors.

Key questions addressed are:

- Are the different measures of innovation output equally affected by innovation linkages?
- Do least innovative and most innovative nations respond similarly to innovation linkages?

To address these questions, this paper uses data on a large sample of countries and addresses the contributions of different innovation linkages to innovation, across two different measures of innovation.

The measurement of science-technology linkages has been a challenge (see, for example, Fan et al. (2017), Meyer (2006)) and this research contributes in this regard. The key underlying reason is that the sources of knowledge and technology spillovers are many, ranging from spatial, formal and informal, etc., and all these vary by industry, technology, region, institutional setup, etc. Thus, it is nearly impossible for any single measure to capture the different dimensions.

This research can be seen fitting into the innovation spillovers literature, which has a substantial body of theoretical work (D'Aspremont and Jacquemin (1988), Griliches (1992)). A better understanding of innovation spillovers would result in a better accounting of the costs and benefits of research, both socially and privately (Antonelli (2006), Antonelli and Link (2015), de Groot et al. (2001), Döring and Schnellenbach (2006), Fischer and Varga (2003), Henderson (2007), Mowery et al. (2001), Sakakibara (2003), Singh (2005), Skare and Soriano (2021)). Broadly speaking, knowledge might diffuse via trade (impersonal or unintended diffusion) or via deliberative collaborative efforts (e.g., university-industry collaborations).

Overall, different empirical studies in the literature have captured specific dimensions of research spillovers in terms of their impacts on different performance dimensions. The underlying difficulty is that the channels of spillovers are varied, with some more readily prone to measurement than others, and that the spillovers diffuse differently over time. This paper adds to this body of work by comparing the relative innovation-productivity of different innovation linkages across a large sample of nations, while also accounting for how innovation may be differently captured. An evaluation of the

effectiveness of innovation linkages in promoting innovation can be useful in ascertaining the success of national or regional innovation systems (Lee and Park (2006), Li et al. (2021), Nelson (1993)).
The empirical results show that a broader index of innovation linkages shows positive and significant spillovers on innovation, while joint ventures and university-industry collaborations fail to exert a significant influence. These spillovers are reinforced by the positive and expected impacts of R&D spending. From a policy perspective, the findings will enable a better cost-benefit accounting of the process of innovation. At a broader level, the findings have implications for knowledge flows (see Antonelli and Link (2015)).
In other results, greater venture capital investments boost innovation in most cases, while more FDI boosts one type of innovation output. These findings are uniquely shown to be sensitive across least- and most innovative nations, which addresses the broader question of whether there are scale economies or increasing returns in the production of innovations. Implications for technology policy are discussed. The layout of the rest of the paper includes the background and the model in the next section, followed by data and estimation, results, and conclusions.

2 Background and the model

2.1 Background

This research can be seen as tying to the literature on impacts of R&D and to the effects of innovation linkages, especially external linkages.
Miguelez and Moreno (2018) focus on regional innovation and external linkages in Europe. A key question they ask is if the generation of new knowledge benefits from the combination of similar or dissimilar pieces of existing technologies – akin to whether there are scope economies in knowledge. They find that, at the local level, both related variety and unrelated variety influence regional innovation. An earlier study by Rothwell and Dodgson (1991) focused on firm size in this context, arguing that while small and medium-sized enterprises (SMEs) can enjoy a number of advantages in the innovation process, they can also suffer from a number of disadvantages, including the inability to establish the appropriate scientific networks. The importance of interpersonal networks in impacting knowledge diffusion was also found by Singh (2005). One specific dimension of collaboration, namely, university-industry collaboration, has received a fair bit of attention, especially following the passage of the Bayh-Dole Act (Mowery et al. (2001); also see Goel and Göktepe-Hultén (2013)). There is some evidence in the literature on the distinction between strong and weak spillover ties – Wang et al. (2017) provide evidence from the semiconductor industry.
A section of the literature has focused on the impacts of R&D on productivity. In this context, Coe and Helpman (1995) find that foreign R&D has beneficial effects on domestic productivity, and the estimated rates of return on R&D to be high, both in terms of domestic output and international spillovers (also see Engelbrecht (1997)).
Even beyond international borders, the geographic or spatial dimension of knowledge and technology spillovers is important domestically as well. The main premise is that knowledge spillovers are greater in the immediate vicinity and dissipate in more distant areas (Fischer and Varga (2003), Döring and Schnellenbach (2006), Henderson (2007)). Of course, the extent of spatial spillovers is subject to the nature of the industry, the type of technology, and institutional setup (e.g., the degree of intellectual

property protection). While we do not consider the spatial aspects directly in this paper, they are indirectly accounted for via the innovation linkage variables that span different jurisdictions.

In a dynamic sense, technology spillovers have longer-term payoffs as future technologies are based on current spillovers (Antonelli (2006)). How these spillovers depreciate over time is a key question in assessing the social returns from a given innovation (Henderson (2007)).

A broader overview of these issues is provided in an informative review by Feldman (1999). She identifies four separate strains in the empirical spillover literature: innovation production functions; the linkages between patent citations, knowledge spillovers via labor mobility; and knowledge spillovers embodied in traded goods (whereby knowledge is directly evident or possible through reverse engineering). She further notes that the spillovers are subject to knowledge agglomeration economies, the attributes of knowledge (e.g., basic or applied), and the characteristics of firms (both knowledge producers and recipients).

In the context of this brief literature overview, the contribution of this work lies in comparing the relative innovation-productivity of different innovation linkages across two patent measures for a large sample of nations.

2.2 The Model

Based on the above, we can formulate our main hypothesis:

H1: Greater innovation spillovers/linkages would lead to greater innovation, ceteris paribus.

Spillovers can be seen as boosting innovation by reducing the transaction costs of engaging in the pursuit of innovation.

Drawing on the above discussion and to test hypothesis H1, with the unit of observation being a country and year, the general form of the estimated equation is the following

Patenti = f(R&Dlag, Innovation linkagesj, GDP growth, Rule of Law, FDI,
Venture capital (VenCAP), Market size (POP), Ease of credit (CreditEASE)) (1)
i = Patent1, Patent2
j = UnivINDlag, JointVENlag, INNlink

The dependent variable is innovation output and we proxy this by the number of patents. While patents are the most readily available and frequently used measures of innovation output, they are imperfect, suffering from the inability to capture unpatented or unpatentable innovations as well as the inability to qualitatively distinguish across innovations. To somewhat get around this limitation, we use two alternative patenting measures. Patent1 is the number of resident patent applications per GDP filed at a given national or regional patent office, while Patent2 includes the number of Patent Cooperation Treaty (PCT) applications (per GDP). The Patent2 measure has a broader scope as it makes it possible for an applicant to seek patent protection for an invention simultaneously in a number of countries by filing a single international patent application. One could envision where small, first-time inventors in a nation might apply for Patent1, while large corporations, especially multi-national corporations, might more likely file Patent2 applications. The correlation between the two innovation measures, Patent1 and Patent2, is 0.7 (Table 2), implying that they are capturing somewhat different aspects of innovation output.

The main contribution of this work lies in considering the different dimensions of innovation linkages and their spillovers on innovation (across two different measures of patenting). Innovation linkages capture different aspects of (inward) innovation spillovers, and can alternately be viewed as indirect inputs in the innovation process (Antonelli (2006)). In practice, innovation spillovers are hard to capture, and, consequently, the related theoretical work (see D'Aspremont and Jacquemin (1988) for a seminal theoretical study has outpaced empirical work (see Antonelli and Link (2015) and Griliches (1992) for reviews of the literature). For instance, aspects of networking by scientists, including active and passive networking, are almost difficult to capture across nations, although such networks are crucial to research collaborations.[1]

We consider three linkage measures: (i) joint venture and strategic alliance deals (JointVENlag);[2] (ii) university-industry research collaborations (UnivINDlag), (see Fischer and Varga (2003)); and (iii) a broader index of innovation linkages (INNlink) that includes (i) and (ii) as its components, and also includes GERD financed from abroad, state of cluster development, and patent families (see Table 1 for details). According to the source, GII, "The Innovation linkages sub-pillar draws on both qualitative and quantitative data regarding business/university collaboration on R&D, the prevalence of well-developed and deep clusters, the level of gross R&D expenditure financed by abroad, and the number of deals on joint ventures and strategic alliances", (https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2016-annex1.pdf, p.54). One would expect better/more innovation linkages to boost innovation, although there might be differences across specific channels. In our sample, innovation linkages were the highest in Israel (index value = 81.6), and the lowest in Niger (= 1.5). The index of innovation linkages would also aid in capturing cross-sectoral, in additional cross-national, connections that are often hard to capture (Dietzenbacher (2000)). Indeed, as noted by Engelbrecht (1997) and others, some innovation occurs outside the R&D sector. A broader index would capture some of these aspects. To account for the possibility of reverse feedbacks, we include a one-lag in these variables.

With respect to the innovation linkages, it is also likely that Patent1 and Patent2 would differently capture the spillovers from the different innovation linkages. If that is indeed the case, then that would be another contribution of this work.

Beyond innovation linkages that are the claimed novelty of this work, R&D input is the key input in innovation. In this context, there is the issue of the time lag between research spending being incurred and when the innovation materializes (Hall et al. (1986); also see Goel and Saunoris (2016)). Furthermore, there is the possibility of a bi-directional causality between the input and output of research. To address these aspects, we include a one-year lagged value of R&D (R&Dlag), which stood at about one percent of GDP in our sample.

Among the other control variables, GDP growth captures the strength of the economy and is associated with economic sentiments. In economies with high rates of economic growth, there is greater optimism, ceteris paribus, and this optimism is especially important for the pursuit of innovation. Given the year-to-year fluctuations in the GDP growth rates in many nations, we take the average 5-year GDP growth rate (per capita) from 2015-2019 (GDPgrAVG). The average growth in GDP per capita in our sample was around 2 percent.

Institutional quality is important in the smooth workings of the markets and in the ability of investors to protect intellectual property and reap related rewards. To this effect, we use the rule of law index (RuleLAW). Nations with a better/strengthened rule of law have better protection of property rights,

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[1] See Goel and Grimpe (2013) for a related study of German scientists.

[2] A subset of joint ventures could be research joint ventures – see Di Cagno et al. (2016), Kamien et al. (1992).

workings of the legal system, and the enforcement of contracts. These are all important factors in the pursuit of innovation.[3]

The consideration of venture capital (VenCAP) and FDI can be seen as capturing domestic versus external capital. Further, venture capital investments are generally seed capital investments in the initial stages, especially by nascent entrepreneurs, while FDI might be accompanied by some embedded technical know-how or process innovation (see Salim et al. (2017)). Related to this, the ease of obtaining credit (CreditEASE) is included to capture the costs of innovation. Greater ease of credit would lower the costs of innovation on the one hand, while making the status quo more desirable on the other hand. Finally, demand-pull innovation aspects are captured by including the market size, proxied by population. Other things being the sample, a large market would make some innovations more attractive by increasing their potential payoffs. In the following section, we discuss the data and the estimation techniques employed in our empirical analysis,

3 Data and estimation

3.1 Data

The main source of the data for this study is the Global Innovation Index (GII) 2020, https://www.wipo.int/global_innovation_index/en/2020/. This source provides comparable data on scores of nations on various dimensions of innovation input and output.[4] These data are supplemented with data from other international sources that are routinely used in the analysis.

Details about the variables used, including variable definitions, summary statistics, data sources are in Table 1, and Table 2 provides a correlation matrix between the key variables used in the analysis. The correlation between both the patent measures (Patent1 and Patent2) and the three innovation linkage measures (JointVENlag, UnivINDlag, INNlink) are positive, with Patent2 being relatively more highly correlated than Patent1. Interestingly, joint ventures are not correlated with Patent1, unlike with Patent2 (Table 2). We turn next to a discussion of the estimation strategy.

3.2 Estimation

To address different aspects of equation (1) and to test the validity of our results, we employ three different estimation strategies. First, Table 3 reports results from robust regression. Regression is less sensitive to outlying values compared to OLS estimation. The overall fit of the various models is quite decent, and the variance inflation factor (VIF) shows an absence of multicollinearity across the explanatory variables. Second, potential simultaneity issues are addressed in Table 4 through a 2SLS regression. Here R&D is instrumented by a dummy variable identifying island nations (ISLAND) and an index of a nation's infrastructure (INFRAst). The different diagnostic tests (reported at the bottom of the table) generally support our instrument choice. Finally, quantile regression (see Koenker and

[3] Some studies have used a narrower index of patent protection to account for some related aspects (Goel and Saunoris (2016)).

[4] While the GII is available for a few more years, the coverage of nations (and in some case of the variables included) varies somewhat from year to year. We employ a cross-section analysis from the 2020 GII report, in part to maximize coverage and because the index and institutional variables in the analysis do not change much from year to year.

Hallock (2001)) are reported to see how the effects of innovation linkages vary across the distribution (at the median, 25th quantile, and 75th quantile) of the respective dependent variables. The results section follows.

4 Results

4.1 Baseline models

The baseline, using robust regression, are presented in Table 3, with four models for each dependent variable, respectively.

As expected, the effect of lagged R&D on innovation is positive and statistically significant. This finding holds across both measures of innovation - Patent1 and Patent2. R&D is the key input in the production of innovation and our results bear this out. In terms of the magnitude of the effects, the elasticity of Patent1 with respect to R&Dlag is 0.57 (Model 3a.4), while the corresponding elasticity with respect to Patent2 in Model 3b.4 is 0.62. Thus, the productivity of R&D in generating patents (keeping in mind that not all output of research is patented or is patentable) is similar across the two measures of innovation.

Turning to the impacts of innovation linkages that form the main contribution of this work, we see that the coefficients on both UnivINDlag and JointVENlag are positive but statistically insignificant. It could be the case that the effects of university-industry collaborations and joint ventures on innovation occur with a longer time lag than one year or the manner in which the underlying variables are measured is unable to uncover some important channels of influence.[5] The story is stronger when a broader measure of innovation linkages, INNlink, is considered. In this case, the resulting coefficient is positive and statistically significant and this true for both dependent variables. The broader measure is able to capture a wider set of potential spillovers on innovation, including spillovers from and within the various channels. Quantitatively, the elasticity of Patent1 with respect to INNlink in Model 3a.4 is 0.53, while the elasticity of Patent2 with regard to INNlink in Model 3b.4 is 0.57, implying that the spillovers from innovation linkages are of a similar order of magnitude across both measures of innovation.

Interesting results also emerge with respect to FDI - it is positive and statistically significant in most cases when Patent2 is the dependent variable, but not in Models 3a.1-3a.4. FDI contributes to broader innovation, but not to narrower innovation. A part of this effect is likely due to the fact that larger, multi-national, corporations are more likely to file for Patent2 type of patents (also see Liao and Yu (2013) for some evidence from Taiwanese firms).

Finally, the effects of GDP growth and the rule of law were statistically insignificant. This was also the case for population (POP) and CreditEASE in most cases - the positive sign on POP is consistent with demand-pull effects, and the negative sign on CreditEASE with status quo discussed above. The following sections test the robustness of these findings.

[5] For example, the university-industry collaboration variable, UnivIND, is based perceptions of survey respondents - see Table 1 for details. Goel and Göktepe-Hultén (2013) considered more direct measures of academic-industry collaborations in Germany and found that both industry cooperation and consultancy increased the likelihood of patenting, with the impact of industrial cooperation being more robust (also see Lee and Park (2006), Slavova and Jong (2021)).

4.2 Addressing potential simultaneity between R&D and innovation

Although Table 3 uses the lagged values of R&D to address simultaneity between the input and output of innovation (see Henderson (2007)), we also employ 2SLS estimation in Table 4 to address causality issues. ISLAND and INFRAst are employed as instruments for R&D, with the two models, respectively using the two dependent variables from Table 3. The geographic isolation of island nations provides different incentives to invest in R&D, and the prevalence/strength of infrastructure in a nation affects R&D (via related transaction costs). The overall fit of both models is decent and instrument choice is generally supported by the two chosen instruments.

Regarding the main variable of interest, R&D, we find the effect of R&D to be positive and significant (at the 10% level). This is true for both patent measures and supports the earlier findings in Table 3.

With respect to the other results, larger nations (POP) have greater innovation when Patent1 is the dependent variable (Model 4.a), and more venture capital deals facilitate Patent2. Further, in the case of Patent2, the coefficient on CreditEASE is negative and marginally significant. This was also true in Model 3b.3 in Table 3. The other controls lack significance, which is generally supportive of earlier findings.

4.3 Effects of innovation linkages across the distribution of innovation

Table 5 provides some additional insights into the effects of innovation linkages across the distribution of innovation. Using quantile regression, this enables us to address the second question posed in the Introduction: Do the least innovative and most innovative nations respond similarly to innovation linkages?

The two panels in Table 5 alternate report results from the two dependent variables, considering the quantiles q25 (less innovation), q50 (median), and q75 (more innovative). The number of nations included varies somewhat across the two panels, with the overall fit of Patent2 regressions relatively better than those with Patent1.

The results provide some interesting and informative insights. First, whereas lagged R&D positively affects Patent2 across the distribution, its effect on Patent1 is significant at the median (and at 10% level of significance). Second, the positive influences of lagged R&D are relatively the highest for most innovative nations. These nations seem to translate R&D inputs more efficiently into innovative outputs. Third, the innovation spillovers from overall innovation linkages (INNlink) are significant for least innovation nations in Panel 5B. Such nations are able to effectively able to use innovation linkages as complementary to other innovation inputs. Fourth, greater ease of obtaining credit makes innovation less attractive for least innovative nations with Patent2 as the dependent variable (Panel 5B). In other words, easier availability of credit makes the status quo (no innovation) more desirable. The adverse spillovers of credit easing on innovation do not seem to be widely recognized. Fifth, the effect of FDI, unlike Table 3, on Patent2 seems more diffused and lacks statistical significance. Finally, nations with larger markets, as denoted by population (POP), increase Patent1 in most innovative nations. Such nations are better able to respond to demand-pull innovation, and resident patents (Patent1) measure (Patent1) picks that up (over the broader, more international, Patent2 measure).

Overall, the quantile regression results show the sensitivity of the results in Table 3, and underscore the importance of paying attention to the underlying measure of the innovation output before making resulting technology policy decisions. The concluding section follows.

5 Conclusions

Whereas various drivers of the international innovative activity have been studied in the literature, our understanding of the contributions of different innovation linkages to innovation deserves more attention (Antonelli and Link (2015), Feldman (1999), Guckenbiehl et al. (2021), Griliches (1992)). This paper addresses the contributions of different innovation linkages to innovation, across two different measures of innovation. The use of multiple spillover channels also ties to addressing the payoffs from embodied and disembodied technical change (Krammer (2014)). The large sample of nations considered is an additional contribution of this work.

Considering three aspects of innovation linkages in terms of their impact on innovation, we find that a broader index of innovation linkages shows positive and significant spillovers on innovation, while joint ventures and university-industry collaborations fail to exert a significant influence. These results support Hypothesis H1, with the qualification that specific channels of spillovers might not have a significant impact. These spillovers are reinforced by the positive and expected impacts of R&D spending. In other results, greater venture capital investments boost innovation in most cases, while more FDI boosts one type of innovation output.

These findings are uniquely shown to be sensitive across least- and most innovative nations when a quantile regression is employed.

Turning to the questions posed in the Introduction, we are able to provide the following answers:

- Are the different measures of innovation output equally affected by innovation linkages? The two measures of innovation considered seem to benefit similarly from innovation linkages. A ten percent increase in the broad index of innovation linkages (INNlink) tends to increase innovation (patent applications) by about 5-6 percent (Table 3). Thus, some channels of spillover transmissions have stronger ties to innovation than others (Wang et al. (2017)).
- Do least innovative and most innovative nations respond similarly to innovation linkages? No. Table 5 shows that it is the least innovative nations that benefit from innovation linkages (using broad innovation linkage index). On the other hand, the most innovative nations do not seem to benefit significantly from innovation linkages.

A number of implications for technology policy emerge from the analysis. First, given the complementarity between R&D spending and innovating linkages, nations with resources constraints in supporting R&D directly might look to complementary channels to boost innovation. Second, sound technology policies would benefit from the use of multiple measures of innovation output, since our analysis shows that some factors driving innovation change in magnitude and significance whether Patent1 or Patent2 is used as a measure of innovation output. The broader Patent2 measure might be more relevant when regional technology policies are being framed (see Liao and Yu (2013), Yang et al. (2021)). Third, the sensitivity of some drivers of innovation to the prevalence of innovation (Table 5), suggests that technology policies be tailored to nations with different innovation rates – one size does not fit all when it comes to technology policy. At a broader level, these findings can prove useful in the design and updates of national innovation systems (see Nelson (1993)). Finally, the role of inward FDI is complementary to domestic VC funding in that both boost innovation. Relatively speaking, VC investments are generally more forward-looking and frequently are in new technologies (or even unproven) technologies. FDI can also be a channel of technology spillovers (Salim et al. (2017)).

In closing, we point out some limitations of this work. One, we have been unable to account for all channels of knowledge transmission. For example, the role of networking through professional conferences and associations is important (Goel and Grimpe (2013)), but not captured in the measures employed. Two, the qualitative distinction across patents (e.g., design versus utility patents), and across industry/product types are likely crucial in determining the extent and the speed of spillovers. Incorporation of these aspects must await the availability of data at a finer level of detail.

REFERENCES

Antonelli, C. (2006). Diffusion as a process of creative adoption. *Journal of Technology Transfer* 31(2): 211–226.

Antonelli, C., and A. N. Link (Eds.) (2015). Routledge Handbook of the Economics of Knowledge. Oxon: Routledge.

Chandrashekar, D., and M. H. Bala Subrahmanya (2019). Exploring the factors of cluster linkages that influence innovation performance of firms in a cluster. *Economics of Innovation and New Technology* 28(1): 1–22.

Coe, D.T., and E. Helpman (1995). International R&D spillovers. *European Economic Review* 39(5): 859–887.

D'Aspremont, C., and A. Jacquemin (1988). Cooperative and noncooperative R&D in duopoly with spillovers. *American Economic Review* 78(5): 1133–1137.

de Groot, H.L.F., P. Nijkamp, and Z. Acs (2001). Knowledge spill-overs, innovation and regional development. *Papers in Regional Science* 80(3): 249–253.

Di Cagno, D., A. Fabrizi, V. Meliciani, and I. Wanzenböck (2016). The impact of relational spillovers from joint research projects on knowledge creation across European regions. *Technological Forecasting and Social Change* 108: 83–94.

Dietzenbacher, E. (2000). Spillovers of innovation effects. *Journal of Policy Modeling* 22(1): 27–42.

Döring, T., and J. Schnellenbach (2006). What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature. *Regional Studies* 40(3): 375–395.

Engelbrecht, H.-J. (1997). International R&D spillovers, human capital and productivity in OECD economies: An empirical investigation. *European Economic Review* 41(8): 1479–1488.

Fan, X., W. Liu, and G. Zhu (2017). Scientific linkage and technological innovation capabilities: International comparisons of patenting in the solar energy industry. *Scientometrics* 111: 117–138.

Feldman, M.P. (1999). The new economics of innovation, spillovers and agglomeration: A review of empirical studies. *Economics of Innovation and New Technology* 8(1-2): 5–25.

Fischer, M., and A. Varga (2003). Spatial knowledge spillovers and university research: Evidence from Austria. *Annals of Regional Science* 37: 303–322. <https://doi.org/10.1007/s001680200115>

Goel, R.K., and D. Göktepe-Hultén (2013). Industrial interactions and academic patenting: evidence from German scientists. *Economics of Innovation and New Technology* 22(6): 551–565.

Goel, R.K., and C. Grimpe (2013). Active versus passive academic networking: Evidence from micro-level data. *Journal of Technology Transfer* 38(2): 116–134.

Goel, R.K., and J. W. Saunoris (2016). Institutional path dependence and international research intensity. *Economic Modelling* 52(PB): 851–858.

Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics* 94(supplement): 29–47.

Guckenbiehl, P., G. C. de Zubielqui, and N. Lindsay (2021). Knowledge and innovation in start-up ventures: A systematic literature review and research agenda. *Technological Forecasting and Social Change* 172: 121026.

Hall, B.H., Z. Griliches, and J. A. Hausman (1986). Patents and R and D: Is there a lag? *International Economic Review* 27(2): 265–283.

Henderson, J.V. (2007). Understanding knowledge spillovers. *Regional Science and Urban Economics* 37(4): 497–508.

Kamien, M.I., E. Muller, and I. Zang (1992). Research joint ventures and R&D cartels. *American Economic Review* 82(5): 1293–1306.

Koenker, R., and K. F. Hallock (2001). Quantile regression. *Journal of Economic Perspectives* 15(4): 143–156.

Krammer, S.M.S. (2014). Assessing the relative importance of multiple channels for embodied and disembodied technological spillovers. *Technological Forecasting and Social Change* 61: 272–286.

Lee, J.-d., and C. Park (2006). Research and development linkages in a national innovation system: Factors affecting success and failure in Korea. *Technovation* 26(9): 1045–1054.

Li, Y., Y.Wei, Y. Li, Z. Lei, and A. Ceriani (2021). Connecting emerging industry and regional innovation system: Linkages, effect and paradigm in China. *Technovation*, 102388, in press.

Liao, T.-J., and C.-M. J. Yu (2013). The impact of local linkages, international linkages, and absorptive capacity on innovation for foreign firms operating in an emerging economy. *Journal of Technology Transfer* 38: 809–827.

Meyer, M. (2006). Measuring science-technology interaction in the knowledge-driven economy: The case of a small economy. *Scientometrics* 66: 425–439.

Miguelez, E., and R. Moreno (2018). Relatedness, external linkages and regional innovation in Europe. *Regional Studies* 52(5): 688–701.

Mowery, D.C., R.R. Nelson, B.N. Sampat, and A. A. Ziedonis (2001). The growth of patenting and licensing by U.S. universities: An assessment of the effects of the Bayh–Dole Act of 1980. *Research Policy* 30(1): 99–119.

Nelson, R.R. (ed.) (1993) National Innovation Systems: A Comparative Analysis. Oxford: Oxford University Press.

Rothwell, R., and M. Dodgson (1991). External linkages and innovation in small and medium-sized enterprises. *R&D Management* 21(2): 125–138.

Salim, A., M. R. Razavi, and A. Afshari-Mofrad (2017). Foreign direct investment and technology spillover in Iran: The role of technological capabilities of subsidiaries. *Technological Forecasting and Social Change* 122: 207–214.

Sakakibara, M. (2003). Knowledge sharing in cooperative research and development. *Managerial and Decision Economics* 24(2-3): 117–132.

Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science* 51(5): 756–770.

Skare, M., and D. R. Soriano (2021). Technological and knowledge diffusion link: An international perspective 1870–2019. *Technology in Society* 66: 101652.

Slavova K., and S. Jong (2021). University alliances and firm exploratory innovation: Evidence from therapeutic product development. *Technovation* 107: 102310.

Wang, C.-C., H.-Y. Sung, D.-Z. Chen, and M.-H. Huang (2017). Strong ties and weak ties of the knowledge spillover network in the semiconductor industry. *Technological Forecasting and Social Change* 118: 114–127.

Yang, R., T. Che, and F. Lai (2021). The Impacts of production linkages on cross-regional collaborative innovations: The role of inter-regional network capital. *Technological Forecasting and Social Change* 170: 120905.

Table 1: **Variable definitions, summary statistics, and data sources**

Variable	Definition (mean; std. dev.)	Source
Patent1	Number of resident patent applications filed at a given national or regional patent office (per billion PPP$ GDP), (3.525; 9.16)	GII
Patent2	Number of Patent Cooperation Treaty (PCT) applications (per billion PPP$ GDP). A PCT application refers to an international patent applications filed through the WIPO-administered Patent Cooperation Treaty (PCT). The PCT system makes it possible to seek patent protection for an invention simultaneously in a number of countries by filing a single international patent application, (0.929; 1.86)	
R&D	Gross expenditure on R&D, % of GDP, (0.944; 0.99)	
R&Dlag	One-year lag of R&D, (0.938; 0.99)	
JointVENlag	Joint venture - strategic alliance deals; number of deals, fractional counting, per billion PPP$ GDP, lagged one year, (0.032; 0.07)	
UnivINDlag	University-industry research collaboration; index based on the average answer to the survey question: In your country, to what extent do businesses and universities collaborate on research and development (R&D)? [1 = do not collaborate at all; 7 = collaborate extensively]; higher values, greater collaboration, lagged one year, (45.179; 14.55)	
INNlink	Index of innovation linkages, including university-industry research collaboration, state of cluster development, GERD financed from abroad, joint venture/strategic alliance deals, patent families filed in two offices. Higher values, better outcomes, (26.507; 15.89)	
GDPgrAVG	GDP per capita growth; %, 5-year average 2015-2019, (1.998; 2.32)	WDI
RuleLAW	Rule of law index. Index reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Higher values, better outcomes, (50.528; 24.21)	GII
POP	Population, in million, (55.034; 176.55)	
FDI	Foreign direct investment (FDI), net inflows (% of GDP, three-year average), (4.076; 6.61)	
CreditEASE	Ease of getting credit; higher values, better outcomes, (62.664; 20.53)	
VenCAP	Venture capital deals per investment location: Number of deals (per billion PPP$ GDP), (0.111; 0.21)	
INFRAst	Index of infrastructure, including information and communication technologies (ICTs), general infrastructure, and ecological sustainability. Higher values, better outcomes, (41.184; 12.71)	
ISLAND	Dummy variable (=1) identifying an island nation (0.15; 0.35)	

Note: All data are annual for 2019 (or the year reported in GII 2020) by country, unless otherwise indicated.
GII: Global Innovation Index 2020, https://www.wipo.int/global_innovation_index/en/2020/
(The original source of the UnivIND variable listed in GII is World Economic Forum, Executive Opinion Survey).
WDI: World Development Indicators, https://datacatalog.worldbank.org/dataset/world-development-indicators

Table 2: **Correlation matrix of key variables**

	Patent1	Patent2	R&D	R&Dlag	JointVENlag	UnivINDlag	INNlink
Patent1	1.00						
Patent2	0.69	1.00					
R&D	0.62	0.85	1.00				
R&Dlag	0.62	0.86	0.99	1.00			
JointVENlag	0.02	0.34	0.30	0.32	1.00		
UnivINDlag	0.34	0.66	0.71	0.72	0.44	1.00	
INNlink	0.35	0.79	0.81	0.82	0.60	0.82	1.00

Observations = 89

Table 3: **Innovation linkages and innovation: Baseline models**

Dependent variable→	Patent1				Patent2			
Model→	3a.1	3a.2	3a.3	3a.4	3b.1	3b.2	3b.3	3b.4
R&Dlag	3.53**	3.29**	3.55**	2.15**	0.95**	0.88**	0.98**	0.61**
	(9.1)	(7.4)	(9.9)	(4.6)	(11.8)	(11.0)	(11.5)	(7.2)
UnivINDlag		0.01				0.001		
		(0.3)				(0.1)		
JointVENlag			1.19				0.27	
			(0.2)				(0.2)	
INNlink				0.07**				0.02**
				(2.4)				(3.2)
RuleLAW	-0.02	-0.01	-0.02	-0.02	0.002	-0.001	0.001	0.002
	(0.9)	(0.5)	(0.9)	(1.4)	(0.4)	(0.2)	(0.3)	(0.7)
GDPgrAVG	-0.07	-0.06	-0.06	0.02	-0.02	-0.02	-0.01	-0.005
	(0.5)	(0.4)	(0.5)	(0.2)	(0.5)	(0.5)	(0.4)	(0.2)
POP	0.006	0.006	0.006	0.0002	0.0002	0.0002	0.0002	0.0004*
	(1.3)	(1.2)	(1.3)	(0.1)	(0.9)	(0.8)	(0.8)	(1.7)
FDI	0.03	0.03	0.02	-0.02	0.02**	0.02**	0.02**	0.01
	(0.8)	(0.7)	(0.6)	(0.5)	(2.3)	(2.4)	(2.0)	(1.4)
VenCAP	3.44**	3.33**	3.41**	1.93	1.43**	2.92**	1.29*	0.41
	(2.3)	(2.2)	(2.3)	(1.4)	(2.3)	(8.1)	(1.9)	(0.8)
CreditEASE	-0.01	-0.01	-0.01	-0.02	-0.01	-0.01**	-0.01	-0.01
	(0.7)	(0.5)	(0.6)	(1.5)	(1.5)	(2.1)	(1.5)	(1.4)
N	73	72	74	74	69	69	69	69
F-value	27.9**	23.1**	27.0**	23.2**	60.0**	69.9**	50.7**	59.8**
R^2	0.53	0.56	0.54	0.58	0.77	0.77	0.77	0.78
VIF	1.53	1.79	1.70	2.24	1.57	1.83	1.74	2.30

Notes: Notes: See Table 1 for variable definitions. The reported estimates are based on robust regression and all models included a constant term.

The reported R2s and VIF values are based on corresponding OLS regressions and the numbers in parentheses are (absolute) t-statistics, with * and **, respectively, signifying statistical significance at the 10% and 5% (or better) levels.

Table 4: **Innovation linkages and innovation: 2SLS regressions**

Dependent variable→	Patent1	Patent2
Model→	4.a	4.b
R&D	6.65*	1.03*
	(1.8)	(1.9)
RuleLAW	-0.04	0.02
	(0.3)	(1.1)
GDPgrAVG	0.09	-0.04
	(0.2)	(0.5)
POP	0.02**	0.0004
	(3.2)	(0.6)
FDI	0.04	0.01
	(0.3)	(0.2)
VenCAP	-1.59	1.72*
	(0.3)	(1.9)
CreditEASE	-0.07	-0.02*
	(1.3)	(1.8)
N	76	70
F-value	5.49**	15.21**
R2 (centered)	0.52	0.73
Underidentification test	8.3**	7.4**
[p-value]	[0.02]	[0.02]
Weak identification test	4.1	3.6
Overidentification test	2.5	0.31
[p-value]	[0.11]	[0.58]

Notes: See Table 1 for variable definitions. The reported estimates are based on 2SLS, with ISLAND and INFRAst used as instruments for R&D, and all models included a constant term.

The underidentification test is Anderson canon. corr. LM statistic, the weak identification test is Cragg-Donald Wald F statistic, and the overidentification test is the Sargan statistic.

The numbers in parentheses are (absolute) z-statistics, with * and **, respectively, signifying statistical significance at the 10% and 5% (or better) levels.

Table 5: **Innovation linkages and innovation: Quantile regressions**

	q25	q50	q75
Panel 5A: Dependent variable = Patent1			
R&Dlag	1.22 (0.9)	3.24* (1.8)	5.32 (1.2)
INNlink	0.04 (0.9)	0.02 (0.3)	-0.02 (0.1)
RuleLAW	-0.002 (0.1)	-0.02 (0.5)	-0.02 (0.3)
GDPgrAVG	0.08 (0.6)	-0.06 (0.3)	-0.23 (0.8)
POP	0.001 (0.1)	0.005 (0.3)	0.03** (2.2)
FDI	-0.02 (0.3)	0.02 (0.3)	0.14 (0.9)
VenCAP	-0.35 (0.1)	4.28 (1.1)	2.18 (0.3)
CreditEASE	-0.01 (0.6)	-0.02 (0.7)	-0.03 (0.7)
N		76	
Pseudo R2	0.20	0.27	0.43
Panel 5B: Dependent variable = Patent2			
R&Dlag	0.85** (3.8)	0.87** (2.8)	1.24** (2.9)
INNlink	0.03** (2.5)	0.02 (0.8)	0.05 (1.6)
RuleLAW	-0.001 (1.1)	-0.002 (0.2)	-0.01 (1.0)
GDPgrAVG	-0.01 (0.2)	-0.002 (0.1)	-0.04 (0.6)
POP	0.0002 (0.3)	0.0002 (0.2)	-0.0003 (0.2)
FDI	0.02 (0.6)	0.02 (0.6)	-0.003 (0.1)
VenCAP	0.92 (0.7)	2.55 (1.5)	1.89 (0.8)
CreditEASE	-0.01** (2.2)	-0.01 (1.6)	-0.001 (0.1)
N		70	
Pseudo R2	0.43	0.53	0.62

Notes: See Table 1 for variable definitions. q25, q50, and q75 represent different quantiles in these quantile regressions, with q50 denoting the median regression. The numbers in parentheses are (absolute) t-statistics based on 200 bootstrap replications, and * and **, respectively, denote statistical significance at the 10% and 5% (or better) levels.