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Innovation catalysts

How multinationals reshape the global geography of innovation

Riccardo Crescenzi[1], **Arnaud Dyèvre**[2], **Frank Neffke**[3]

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Abstract: We study whether and when Research and Development (R&D) activities by foreign multinationals help in the formation and development of new innovation clusters. Combining information on nearly four decades worth of patents with socio-economic data for regions that cover virtually the entire globe, we use matched difference-in-differences estimation to show that R&D activities by foreign multinationals have a positive causal effect on local innovation rates. This effect is sizeable: foreign research activities help a region climb 14 percentiles in the global innovation ranks within five years. This effect materializes through a combination of knowledge spillovers to domestic firms and the attraction of new foreign firms to the region. However, not all multinationals generate equal benefits. In spite of their advanced technological capabilities, technology leaders generate fewer spillovers than technologically less advanced multinationals. A closer inspection reveals that technology leaders also engage in fewer technological alliances and exchange fewer workers in local labor markets abroad than less advanced firms. Moreover, technology leaders tend to set up their foreign R&D activities in regions with relatively low absorptive capacity. We attribute these differences to that fact that the trade-off between costs and benefits of local spillovers a multinational faces depends on the multinational's technological sophistication. This illustrates the importance of understanding corporate strategy when analyzing innovation clusters.

Keywords: Innovation, Regions, Foreign Direct Investment, Patenting, Cluster emergence

JEL Codes: O32, O33, R11, R12

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Introduction

Cross-border Research and Development (R&D) investments have expanded drastically in recent years. Between 2003 and 2017, the number of investment projects and the capital invested roughly doubled.[4] Cities and regions compete fiercely over such projects, in the hope that they will create high-quality jobs, accelerate the development of local innovation capabilities and put the region on the map as a recognized center of technological excellence. However, all too often this calculus overlooks that the multinational enterprises (MNEs) behind these investments may have few incentives to share their know-how with local firms. On the contrary, technologically advanced firms have much to lose, and little to gain, from local knowledge spillovers. It is therefore *a priori* unclear if, and under which conditions, attracting MNEs will help upgrade a location's technology base. In this paper, we therefore study whether and when research activities by foreign firms trigger the emergence of new centers of technological excellence.

We hypothesize that R&D facilities of foreign MNEs can create spillovers to the local economy that set in motion a process of collective learning (Athreye and Cantwell, 2007; Fu, 2007; Phelps, 2008; Ning et al., 2016; Blit, 2018). However, just because firms are willing to invest abroad to access knowledge assets outside their home regions (Phelps and Fuller, 2000; Belderbos et al., 2011; Crescenzi et al., 2014), they do not necessarily want to share their own knowledge assets with potential competitors. On the contrary, several authors (Shaver and Flyer, 2000; Cassiman and Veugelers, 2002; Alcacer and Chung, 2007) have argued that firms value inward spillovers to learn from others, but consider outward spillovers through which their own knowledge leaks to competitors to be costly. This cost-benefit tradeoff will depend on the knowledge gradient between firms. Although technology leaders may in principle *be able* to generate large knowledge spillovers, they have least to gain and most to lose from them. Therefore, technology leaders may try the hardest to prevent leaking their know-how to competitors. In contrast, for companies further down the technological ladder the balance may tilt in favor of engaging more fully in mutual local learning processes. Therefore, to understand how MNEs affect local learning, we need to consider the strategic tradeoffs these companies face.

We apply this conceptual framework to data from the United States Patent and Trademark Office (USPTO). We identify all inventors who file patents on behalf of firms headquartered in a foreign country. We take the emergence of such patents in a location to signal that a foreign firm has developed R&D activities there. We consider these events as 'treatments' to the local economy. We limit the analysis to treatments by foreign firms whose headquarters are located in the technologically advanced economies of the OECD to

[4] Own calculations based on fDi Markets data (Financial Times) for FDI Projects in the following 'innovation functions' (Crescenzi et al., 2014; Sturgeon, 2008): 'Design, Development & Testing'; 'Education & Training' and 'Research & Development'.

focus on knowledge diffusion from frontier to technologically less advanced economies. Next, we contrast regions with and without such treatments in a matched difference-in-differences estimation design to assess the causal impact of foreign firms on a region's innovation rate.

Over a 5-year period, patenting rates in treated regions increase by roughly 0.13 log-points more than in untreated regions. As a consequence, treated regions climb, on average, 14 percentiles in the global innovation ranks. This increase is in part attributable to local knowledge spillovers: the entry of a foreign MNE causes an increase in patenting by domestic firms. Another part is due to signaling effects: the fact that the MNE is able to produce patentable inventions in a region proves to other foreign firms that the region is capable of supporting high-tech R&D activities, attracting further foreign R&D activities.

However, not all foreign firms increase local innovation rates equally. Contrary to expectations raised in existing scholarly work (e.g. Harris and Robinson, 2003; Haskel et al., 2007) and in parts of the mainstream policy discourse on Foreign Direct Investment (FDI) (What Works Centre, 2019), technology leaders are not the main drivers of technology diffusion. On the contrary, the arrival of technology leaders generates fewer spillovers to a local economy than the arrival of MNEs that rank lower in their technology field's patenting distribution. A closer inspection of some of the channels through which knowledge spillovers materialize corroborates this conclusion. Foreign technology leaders engage in fewer local alliances and exchange fewer workers with local firms than lower-ranking MNEs. Instead, they rely more on their headquarters as a source of labor and see their patents cited less frequently by local firms. Finally, technology leaders locate disproportionally in regions with comparatively limited absorptive capacity (Cohen and Levinthal, 1990).

These results highlight that understanding the evolution of innovation clusters requires an account of the heterogeneous incentives of key actors in such clusters. The strategic motivations behind MNEs' sub-national location decisions have been studied extensively in economic geography, international economics and international business. However, insights from these streams of research have not been fully absorbed into the literature on innovation clusters. Conversely, international economics and business scholars traditionally focus more on FDI and MNEs themselves than on how they impact regions and clusters. By drawing insights from across these strands of the literature, we contribute to a number of existing debates. First, our study adds to our understanding of cluster emergence and evolution (Feldman and Braunerhjelm, 2006; Menzel & Fornahl, 2010). Second, our findings relate to the discussion on knowledge spillovers in local economies (Glaeser et al., 1992; Henderson, 1995; Jaffe et al., 1993). Third, these findings are related to the work on how knowledge diffuses through the mobility of firms and people (Fosfuri et al., 2001; Saxenian, 2007; Javorcick, 2004; Breschi and Lissoni, 2009; McCann and Acs, 2011; Crescenzi et al., 2015; Bahar and Rapoport, 2018). In this sense, our work is closely related to Blit (2018), who shows that firms located in the countries of an MNE's R&D satellites disproportionally cite patents filed at the MNE's headquarter location. Fourth, by highlighting the importance of firms' strategic motivations, our study links the work on actors of change in economic geography (Isaksen et al., 2018; Neffke et al., 2018) to the literature on location choice. Fifth, our analyses complement the literature on spillovers from FDI, as surveyed in, for instance, Keller (2004). However, unlike most of this literature, we focus on effects on innovation, not productivity. Finally, our work informs policy debates on (regional) middle-income traps (Aghion and Bircan, 2016), suggesting that certain types of FDI can remedy such traps.

Stylized facts and conceptual framework

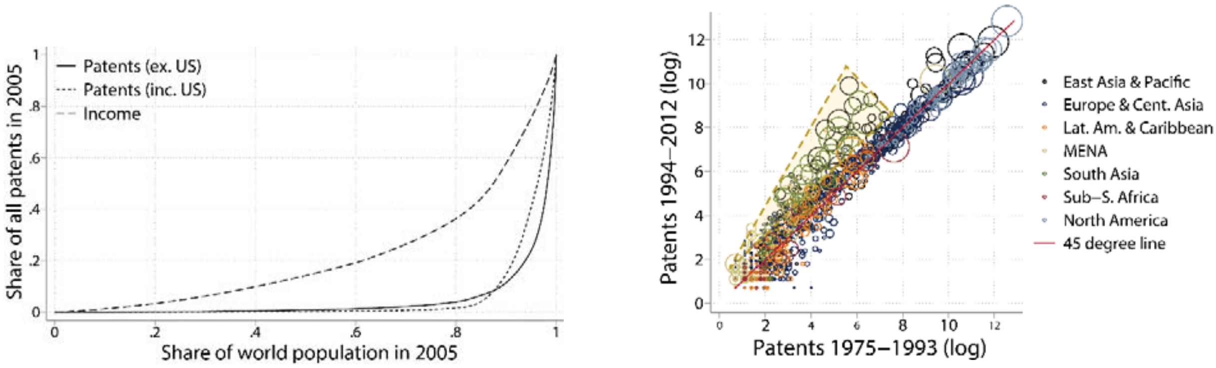
Stylized facts on the global geography of innovation

Participation in the global innovation contest is a privilege reserved for only a handful of regions. Figure 1 (left) shows population-weighted spatial Lorenz curves for income (dashed curve) and patenting in 2005. The dotted curve depicts total patenting output, the solid curve excludes patents by US inventors. The already high spatial concentration of global income pales against the concentration of innovative activity: in 2012, the ten most innovative regions in the world together accounted for 39% of all patents and for 45% of patents filed by inventors outside the US.

The distribution of innovative activity is not only skewed, it also hardly changes over time. Figure 1 (right) shows regions' patenting output in the period 1994-2012 against the period 1975-1993. Most regions are on or close to the 45-degree line, implying that few regions manage to forge ahead or fall behind. However, some positive exceptions exist, highlighted by the triangular overlay. These regions accelerated their patent production and rose in the world's innovation ranks. Conceptually, they form the motivation for our study.

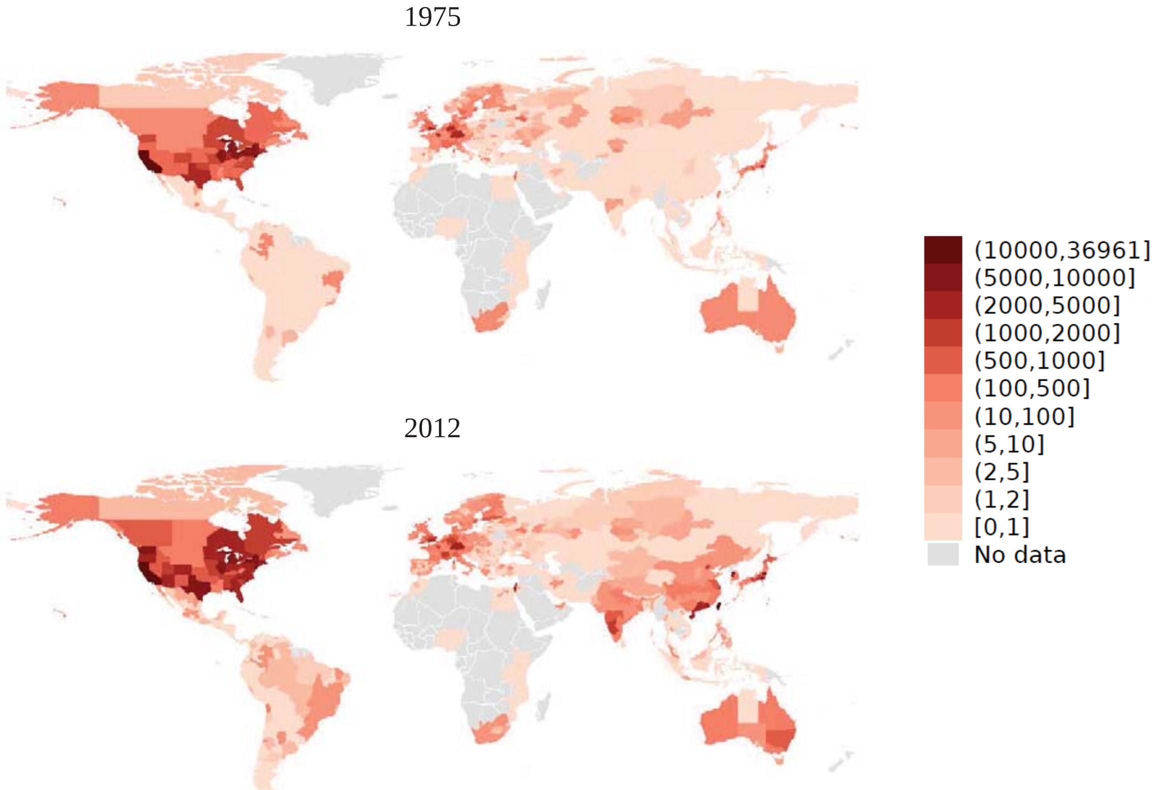
Figure 2 shows where such new centers of technological excellence have emerged. It displays the global geography of innovation as expressed in USPTO patents in 1975 and 2012. Patenting rates have most prominently accelerated in Korea, Taiwan, India and China, and to a lesser extent in Eastern Europe, Canada and Israel.

Figure 1: Inter-regional inequality of income and innovation and stability of regional innovation ranks



Notes: *Left*: Population weighted spatial Lorenz curves of patent and income shares for the year 2005. Shares of patents are unweighted counts of USPTO patents assigned to inventors residing in each region. Regional population data come from Gennaioli *et al.* (2014). *Right***:** Stability of regional innovation ranks. Circles represent one of the 1,549 regions in the dataset. Circles' sizes are proportional to average regional GDP over the period 1975-1993. Horizontal axis: number of patents filed between 1975 and 1993. Vertical axis: number of patents filed between 1994 and 2012. Colors refer to World Bank macro regions.

Figure 2: Patents in 1975 and 2012, by region



Notes: Total number of patents filed with the USPTO in 1975 and 2012 by region of residence of their inventors. Countries for which regional data is missing are colored gray even though a small number of inventors resides in these countries.

Conceptual framework and hypotheses

How new innovation clusters emerge is a topic of substantial debate. Some authors stress factors endogenous to the region. For instance, Feldman and Braunerhjelm (2006) point to entrepreneurial experimentation and local policies aimed at creating and maintaining a strong local knowledge base. Others point to the same Marshallian externalities (Marshall, 1890) that also drive the success of traditional industrial clusters or to face-to-face interactions among local firms and institutional actors that help reproduce at a systemic (i.e., cluster) level the organic learning processes otherwise confined to learning within individual firms (Storper and Venables, 2004).

However, globalization of R&D has added an extra layer of complexity to this discussion. As the global body of knowledge grows, it becomes increasingly distributed across people and places (Neffke, 2019). Under such conditions, clusters must combine their local 'buzz' with 'global pipelines' (Bathelt et al., 2004). These pipelines help a cluster tap into knowledge bases outside the region and mitigate against cognitive lock-in. They can be sustained by various types of global actors, from Diasporic Communities (Saxenian, 2007), to universities, star scientists (Zucker et al., 1998) and MNEs (e.g., Blomström and Kokko, 1999; Javorcick, 2004; Haskel et al., 2007; Keller and Yeaple, 2009; McCann and Acs, 2011; Crescenzi et al., 2015).

Our analysis will focus on these latter actors, MNEs. With their networks of R&D facilities, MNEs represent strong conduits for the diffusion of advanced technological know-how (Athreye and Cantwell, 2007). We therefore expect that cross-border R&D investments by MNEs help a region acquire new technological capabilities, providing the seed for new innovation clusters. This suggests the following hypothesis:

> **Hypothesis 1:** The development of R&D activities by foreign MNEs in a region leads to an increase in local patenting rates by domestic firms.

MNEs can also act as *anchor firms*. Anchor firms (Agrawal and Cockburn, 2003; Feldman, 2003) "attract skilled labor pools, specialized intermediate industries and provide knowledge spillovers that benefit new technology intensive firms in the region" (Feldman, 2003: 312). Moreover, anchor firms generate strong demonstration effects. When foreign MNEs innovate with local inventors, they manifest that adequate knowledge resources are present, aiding regional "self-discovery" (Hausmann and Rodrik, 2003). We hypothesize that these demonstration effects attract further MNEs to the region:

> **Hypothesis 2:** The development of R&D activities by foreign MNEs in a region attracts further MNEs that raise local innovation rates by setting up their own R&D activities.

However, spillovers from FDI are by no means automatic (Blomström and Kokko, 1999; Liu and Buck, 2007). To "[diffuse] knowledge and enhance collective learning in clusters" (Giuliani, 2007: 140), intra- and inter-firm international networks must become embedded in a region's local networks (Maskell and Malmberg, 1999). This raises an important, yet often ignored, question: Do foreign firms have an incentive to participate in local innovation networks?

One incentive for MNEs to invest abroad is that it allows them to access knowledge assets in other locations (Cantwell, 2005). This yields several benefits: by internationalizing their R&D activities firms can bring products to market faster (Von Zedtwitz and Gassmann, 2002), hire global talent at reduced costs (Lewin, Massini and Peeters, 2009), and tap into foreign centers of technological excellence (Cantwell and Janne, 1999). However, even if MNEs set up R&D centers abroad to tap into local knowledge and know-how – a strategy known as *strategic asset seeking* – this does not necessarily mean that they desire to engage in reciprocal collective learning. On the contrary, firms balance the benefits from inward knowledge spillovers with the costs of outward spillovers – i.e., of knowledge leaking to competitors (Shaver and Flyer, 2000; Cassiman and Veugelers, 2002). Alcacer and Chung (2007) therefore posit that MNEs try to maximize, not spillovers *per se*, but *net* spillovers. Because technology leaders have least to gain and most to lose from local knowledge sharing, they may not create many spillovers, in spite of their advanced knowledge assets. We therefore hypothesize:

> **Hypothesis 3:** The more technologically advanced the foreign MNE, the smaller the spillovers to the local economy will be.

If technology leaders indeed generate fewer spillovers, we would expect to find further evidence for this in the channels through which knowledge is transmitted between MNEs and local firms, such as local labor circulation (Song et al., 2003; Singh and Agrawal, 2011) and R&D collaborations. Furthermore, we would expect to find fewer traces of knowledge spillovers in patent citations. This yields the following set of hypotheses:

> **Hypothesis 4:** Ceteris paribus, technologically more advanced foreign MNEs (4a) exchange fewer R&D workers with local firms, (4b) engage in fewer technological collaborations with local firms and (4c) are less often cited as a source of know-how by local firms.

Why would technology leaders be better able to curb knowledge spillovers than others? On the one hand, technology leaders may be better positioned to do so than other firms. For instance, they may be able to pay higher salaries or use more sophisticated legal means to keep key R&D workers from leaving the firm. Technology leaders can also substitute for external collaborations by leveraging advanced internal knowledge assets through their own corporate networks (McCann and Mudambi, 2004). On the other hand, technology leaders can use their location decisions strategically to curtail spillovers. In line with this, Alcacer and Chung (2007) show that technologically advanced firms are more likely to avoid the vicinity of highly competent competitors than less advanced firms are. Under such circumstances, spillovers are kept at bay because there simply are few opportunities to hire workers from, or collaborate with, local firms. Although our data do not allow us to determine the full range of strategies technology leaders may employ to block outward spillovers, we can observe their location choices. We expect that advanced MNEs will locate their R&D activities in places with low absorptive capacity and less well-established innovation systems to mitigate risks of accidental knowledge spillovers by. This leads to the following hypothesis:

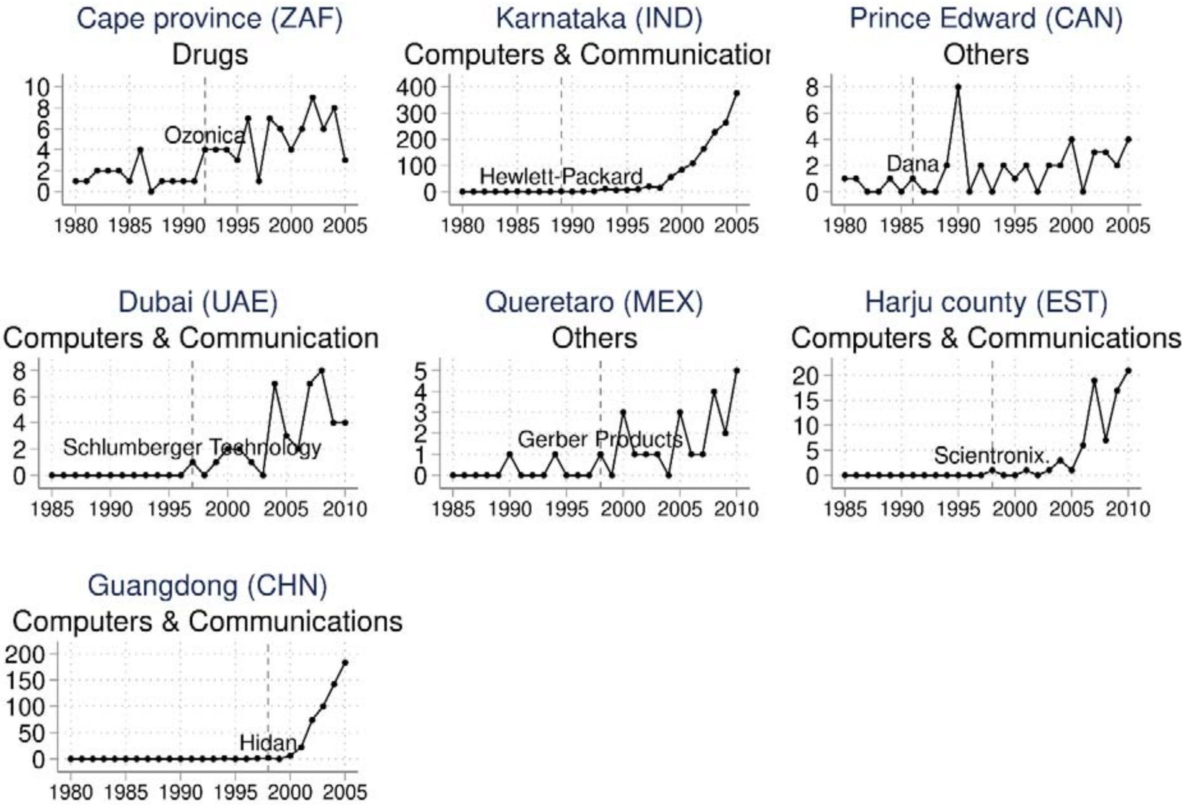
> **Hypothesis 5:** More technologically advanced foreign MNEs will locate disproportionately in less developed locations.

Empirical methodology

Saxenian (2007) describes how some of the most prominent new centers of technological excellence originated with the help of foreign actors who connected these new locations to existing technology centers. Figure 3 corroborates this. It takes for each macro region of the world the location farthest above the 45-degree line of the right panel of Figure 1 and then shows how its patenting output evolved over time. Dashed vertical lines mark the first local patent assigned to a foreign MNE.

In most graphs, accelerations in innovation rates are preceded by a patent assigned to a foreign firm. Like Saxenian's case studies, these graphs first identify successful regions and then look for traces of foreign research activities in their past. However, this strategy risks selection bias. To avoid such bias we will identify all regions where foreign MNEs file patents with local inventors, regardless of whether they ever become successful innovation centers. Next, we compare growth paths of regions with such foreign R&D activities to otherwise similar counterfactual development paths in regions without foreign R&D activities.

Figure 3: Patent accelerations



Notes: Patenting output for region-technology cells with the largest growth in patenting rates. Titles list the name of the region and the broad technology class. Dashed vertical lines indicate the cell's first patent assigned to a foreign MNE.

Data

We use data on 6.0 million patents granted by the USPTO between 1975 and 2015 from PatentsView.[5] This datasets covers 3.6 million unique inventors with their geocoded places of residence and 314,366 unique primary assignee identifiers. We date each patent by its application year, not the year in which it was granted. Because the USPTO publishes patents with a processing lag, we limit the analysis to patent applications filed before 2013. Next, we assign all patents to one of 1,549 regions. This allows us to add data on GDP per capita at the national and regional levels, average years of education and population size taken from Gennaioli *et al.* (2014). Together, these regions cover 97.2% of all USPTO patents. Online Appendix A describes both datasets in detail.

[5] https://www.patentsview.org

Relying on patents as a measure of regional innovation output has some well understood limitations. (e.g, Archibugi, 1992; Crescenzi, *et al.*, 2017). For instance, patents only capture patented innovations, and their efficacy and use in protecting intellectual property varies across firms and sectors. Moreover, not all patented inventions are equally valuable and not all inventors contribute equally to an invention. Therefore, raw patent counts represent only a rough and possibly biased approximation of the technological capabilities of firms and regions.

In spite of these limitations, the USPTO patent database offers a unique lens on the internationalization of knowledge production. Its long coverage allows us to explore the emergence of new technology centers over the course of several decades, as well as the firms and inventors involved therein. Moreover, because the US represents the largest market in which firms can protect their intellectual property for most of the period under study, firms anywhere in the world have strong incentives to file their inventions with the USPTO. Finally, because patents are filed for the same market and with the same patent office, our data are highly comparable across regions and countries. However, because protecting inventions in the home market may be qualitatively different from protecting inventions in foreign markets, we exclude US regions (but not US firms!) and focus on new technology centers that emerge outside the US. This leaves patent data for 922,459 inventors, 25.6% of the total number of inventors.

Defining foreign research activities

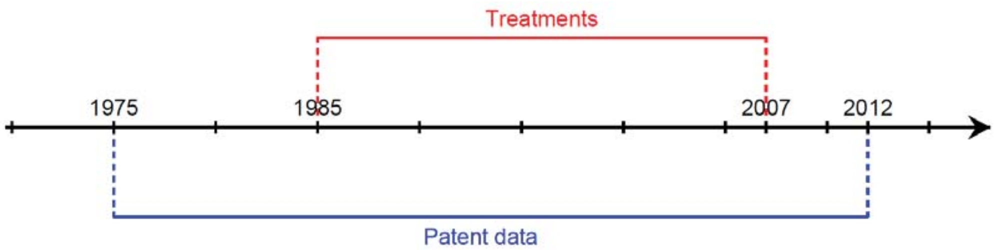
To identify foreign research activities, we select all patents whose inventors reside in a different country than the assignee's primary research location. These patents are considered as signs of foreign research activities. To determine an assignee's primary research – or home – location, we do not use the location of its headquarters as listed in PatentsView, but the modal country of residence of its inventors. This ensures that we identify the country in which an assignee carries out most of its R&D, not where it located its legal headquarters. For instance, we reclassify the phone maker ZTE from an American to a Chinese firm and the home furniture group IKEA from a Dutch to a Swedish firm. For sake of brevity, we will still refer to these primary research locations as companies' headquarters. Furthermore, we only use private-sector patents, excluding patents assigned to government agencies such as the *US Navy*, the *American Air Force* or the French *Commissariat à l'énergie atomique*. Finally, we limit the analysis to foreign R&D activities by firms based in the OECD, using the organization's 1985 composition.[6] This allows us to concentrate on

[6] That is: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Great-Britain, Greece, Iceland, Ireland, Italy, Japan, Luxemburg, The Netherlands, New-Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey and the United States. Because there are also lagging regions in OECD countries, we do include OECD regions among the potential hosts of foreign research activities.

knowledge diffusion from frontier to lagging regions. Moreover, it ensures that foreign research activities in different regions involve similarly advanced countries of origin.

We consider the first foreign patents, i.e., patent applications by local inventors but assigned to foreign, OECD-based, firms, as "treatments" to a technology in a region, where technologies refer to one of the 37 technological subcategories in Hall *et al*. (2001). Therefore, our sample in principle consists of all combinations of 1,549 regions and 37 technological subcategories, or 57,313 region-technology "cells". However, we drop all cells that had already hosted foreign R&D activities between 1975 and 1985. In the remaining cells, we record all patents filed by local inventors, from five years before to five years after a treatment. This limits our study to treatments between 1985 and 2007, as depicted in Figure 4.

Figure 4: Timeline of treatments



Notes: Data are available for patents filed between 1975 and 2012. The first ten years of this period are used to identify which region-technology cells are untreated, i.e., had no local patents assigned to foreign firms. For each treatment, we require an observation window from five years before to five years after the treatment.

Do these treatments coincide with actual FDI in a region? To verify this, we match treatments to firms in *ORBIS* using patent identifiers. *ORBIS* is a commercial database with information on some 200 million private companies worldwide. For nearly half (48.6%) of our treatments, we were able to find corresponding company branches in the *ORBIS* dataset in 2017. This match rate is high, given that *ORBIS* only covers company branches that are currently active, does not maintain a record of patents' previous owners if patents are sold and has incomplete coverage in some countries.

To get a sense of how accurately we capture the timing and size of the investments associated with treatments, we also match treatments to greenfield R&D investment projects recorded in *fDi Markets* between 2004 and 2012. The fDi Markets database does not contain patent identifiers. We therefore match on company names instead. This allowed us to find investment projects for 173 (5.85%) treatments. The median of these treatments is associated with an investment of US$ 37.3 million and the creation of 207 jobs. However, this likely exaggerates the size of the typical treatment given the fDi Markets' bias towards large investment projects. Furthermore, we find that investment projects predated treatment patents by, on average, 1.7 years. This suggests that our treatments trail investments by between one and two years, which is reasonable given the expected time it takes for these investments to bear fruit. However, given that knowledge spillovers will also not be instantaneous, in practice we expect that treatment effects would emerge around the time we observe the filing of the foreign treatment patent.

Dependent variable

Our variable of interest is the patenting output by inventors who claim a region as their place of residence. If a patent lists multiple inventors living in multiple regions, we attribute a fraction $\frac{\#\, inventors\ on\ patent\ in\ region}{\#\, inventors\ on\ patent}$ to each region. Moreover, we focus our analysis on spillovers from treatment firms to other firms in a region-technology cell. We therefore disregard all patents assigned to "treatment firms": foreign firms to which the treatment patent was assigned.

To reduce distributional skew in a variable that equals zero in many cells and scales exponentially as regions' innovativeness increases, we use the Inverse Hyperbolic Sine (IHS) of a cell's patent count:

$$y_{r\theta t} = \ln \frac{1}{2}\left(P_{r\theta t} + \sqrt{1 + P_{r\theta t}^2}\right)$$

where $P_{r\theta t}$ represents the fractional count of patent applications filed in technology field θ in year t by inventors residing in region r. The advantage of this metric is that, unlike $\ln(0)$, $IHS(0)$ is well-defined, while the IHS rapidly approximates the natural logarithm: for $P_{r\theta t} \geq 3$, the difference between $\ln P_{r\theta t}$ and $IHS(P_{r\theta t})$ is below 2.5%.

Causal effects of foreign research activities

Foreign firms may not only help regions develop technological capabilities, they may also be attracted by such capabilities. As a consequence, the direction of causation between attracting FDI and developing technological capabilities is, *a priori*, unclear. To address this problem, we combine matching with difference-in-differences estimation. That is, we first select for each treated region-technology cell a set of untreated cells with otherwise similar characteristics. These matched cells offer counterfactual development paths for how the treated cells would have fared, had they not been treated. Next, we study whether the performances of treated and control cells diverge after the treatment.

The matching exercise uses a mixture of propensity score and exact matching. First, we estimate a cell's propensity to be treated using a probit regression with as explanatory variables the average years of education in the region and country, the region's population size, and several lags of country-level and region-level GDP per capita. The latter provide a flexible way to control for trends in income growth, which should in principle capture all improvements in a region's capability base that are directly relevant to its productivity. Next, we select up to five counterfactual cells in the exact same year and technology subcategory with propensity scores closest to the treated cell's. Finally, we require that treated and non-treated regions do not belong to the same country. This ensures that counterfactual cells are not treated indirectly, through within-country spillovers.

In a second step, we perform difference-in-differences estimation, using the following equation:

$$y_{r\theta t} = \alpha_{r\theta} + \sum_{k=-5}^{5} F_{r\theta}\tau_1^k + \sum_{k=-5}^{5} \tau_0^k + \gamma_t + \epsilon_{r\theta t} \tag{1}$$

where $\alpha_{r\theta}$ represents region-technology fixed effects, $F_{r\theta}$ a dummy for whether or not a region-technology cell was treated and γ_t year fixed effects. The parameters of interest are collected in τ_1^k. k encodes event time, and runs from -5 to +5, i.e., from five years before to five years after foreign research activities emerge in the patent data. They express the difference in average innovation output between treated and non-treated cells in each year. We report these coefficients graphically in Figures 5 and 6.

Note that we do not match cells on their pretreatment patenting performance. Therefore, before the treatment, patenting trajectories of treated and non-treated cells could be markedly different. If instead these pretreatment trajectories are indistinguishable, i.e., if $\hat{\tau}_1^k \approx 0$ for $k < 0$, this is a strong indication that the matching framework yielded adequate counterfactuals. Under such conditions, we will therefore consider the estimated treatment effects (i.e., the $\hat{\tau}_1^k$ parameters for $k > 0$) to be causal.

Findings

Difference-in-differences estimations

In total, we identify 5,731 treated region-technology cells, i.e., cells in which the first foreign research activities are detected between 1985 and 2007. This number drops to 3,134 after we exclude cells outside the matching support and cells without sufficiently close counterfactuals, based on a caliper of 0.0002. At this caliper, treated and non-treated cells have similar pretreatment trends. Stricter calipers do not yield improvements, but lead to less precisely estimated effects. On average, we add to each of these treated cells observations on 2.35 control cells.

Table 1 shows compares some key variables between treated and non-treated cells. Treated cells are on average substantially richer and more educated than non-treated cells. This corroborates our concern that foreign firms may be attracted to regions with advanced technological capabilities. Matching improves the balance between treated and non-treated cells for most variables, although some differences remain.

Table 1: Balance on observables

	Before matching			**After matching**		
Variable	**Treated**	**Control**	**t-stat**	**Treated**	**Control**	**t-stat**

		N=5,731	N=4,302		N=3,134	N=7,369	T-stat
Country	GDP/cap (2005 USD)	20,310	17,830	5.06	20,740	19,320	3.43
	Average yrs of education	8.66	8.36	3.53	8.58	8.46	1.67
	3-year av GDP/cap growth	2.53%	2.54%	-0.07	2.42%	2.61%	-2.71
Region	GDP/cap (2005 USD)	19,350	16,370	6.06	19,410	17,940	3.89
	Average yrs of education	8.62	7.92	6.77	8.5	8.38	1.38
	3-year av GDP/cap growth	2.41%	2.47%	-0.55	2.32%	2.44%	-1.66

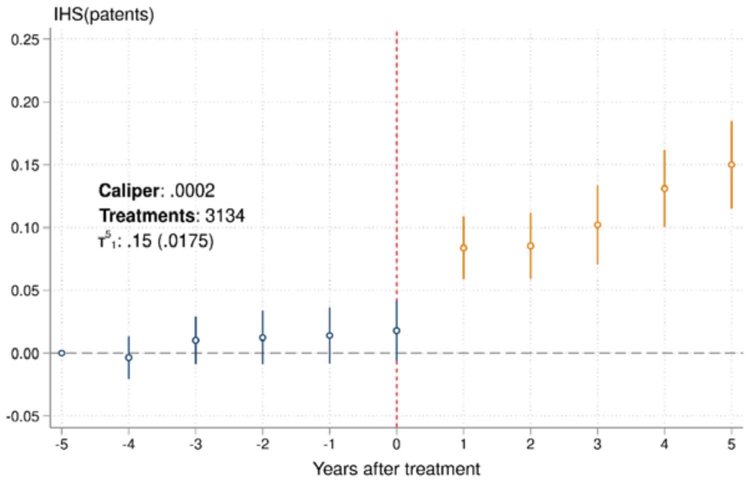
Notes: Treated cells are region-technology combinations where a foreign OECD-based firm starts patenting with local inventors between 1985 and 2007. The matched samples only retain matched treated and non-treated ("control") cells. The reported averages refer to the year preceding the treatment year for treated and matched controls and to 1996 –the year preceding the average treatment year – for cells in the non-treated column. GDP per capita is measured in 2005 Purchasing Power Parity (PPP) terms, and years of education are counted from primary school onward, for the population 15 years and older.

These differences prove inconsequential for our difference-in-differences estimates, $\hat{\tau}_1^k$ (Figure 5). This is reflected in the fact that, before treatment, patenting output does not differ significantly between treated and non-treated cells. However, after the treatment, patenting rates in treated cells start outpacing the ones in non-treated cells. After five years, the local fractional patent count in treated cells exceeds its counterfactual by, on average, 0.15 IHS points. Using the natural logarithm to approximate the IHS, this means that patent counts in treated regions are about 16% ($e^{0.15} - 1 = 0.161$) above their counterfactuals.[7]

Figure 6 compares the effect on total patenting output in treated regions to the effect on patenting output by domestic firms only. The figure first replicates Figure 5, where the dependent variable is the IHS of all patents in a region, regardless of whether they were filed by domestic or foreign firms. This curve is shown in grey. The second curve plots the effect on local patents that were assigned to *domestic* firms only. This second curve isolates the effect of spillovers to the domestic economy.

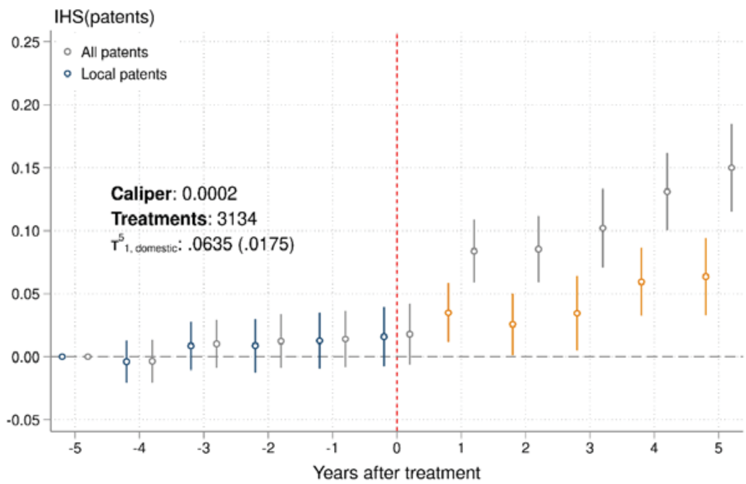
[7] Note that this excludes patents filed on behalf of the treatment firm itself. If we include these patents, the effect increases by 29 percentage points (pp) in t=1, 23 pp in t=2, and 12 pp in t=3. Treatment effects in t=4 and t=5 are all but unchanged, suggesting that the treatment firm's own contribution is limited in the longer term.

Figure 5: Difference-in-differences estimates: all local patents



Notes: Difference-in-differences estimates, $\hat{\tau}_1^k$. These estimates reflect the differences in the IHS of fractional patent count between treated and control cells in the matched sample of 3,134 treated and 7,369 control cells. Vertical lines depict 95% confidence intervals, using standard errors clustered by region. Point estimates that are statistically significantly different from zero ($p = 0.05$) are shown in orange, insignificant point estimates in blue.

Figure 6: Difference-in-differences estimates: patents by domestic firms



Notes: Idem Figure 5 for patenting output by domestic firms. Estimates of Figure 5 in grey for comparison.

The spillover effect, i.e., the effect on domestic patenting, is substantially smaller than the total effect.[8] Five years after the treatment, patenting rates by domestic firms in treated regions lie just 0.0635 IHS points,

[8] Note that the pretreatment trends are the same in both curves by construction: we imposed that neither treated nor control regions host foreign research activities before t=0.

about 7%, above those in non-treated regions. This corroborates Hypothesis 1: when foreign MNEs start R&D activities in a region, patenting output by domestic firms tends to rise.

The difference between the treatment effects on total patenting and on domestic patenting must be attributed to further foreign firms following the treatment firm into the region. This can be interpreted as a signaling effect: the entry of the first foreign MNE signals to other foreign firms that it is possible to successfully develop R&D activities in the region. This signaling effect is larger than the spillover effect. Of the overall effect of 16%, only 7% is due to increased patenting by domestic firms. The remaining 9% consists of elevated patenting by foreign MNEs.[9] This corroborates Hypothesis 2: the entry of foreign MNEs attracts further foreign entrants who contribute to a region's patenting output.

Heterogeneity in treatment effects

Do all treatments yield similar spillovers? To explore this within a difference-in-differences framework, we would need to estimate separate difference-in-differences curves for different subsamples. The modest number of treatments in our sample makes such a strategy impractical. Instead, we exploit the fact that the difference-in-differences graphs break down into a flat part until the treatment year and a more-or-less linear increase thereafter. This suggests that we can collapse the data into a period before and after the treatment and estimate the following cross-sectional regression equation:

$$\Delta y_{r\theta t} = \tau F_{r\theta} + F_{r\theta} Z_{r\theta} \gamma_1 + Z_{r\theta} \gamma_0 + X_{r\theta t-1} \beta + \eta_{r\theta t}$$

where $\Delta y_{r\theta t} = y_{r\theta t+5} - y_{r\theta t-1}$ represents the growth in the IHS of patenting in region r and technology θ from one year before to five years after the treatment and matrix $X_{r\theta t-1}$ includes control variables. The treatment dummy, $F_{r\theta}$, is interacted with various variables, collected in the matrix $Z_{r\theta}$, that describe a cell's macro-region, technology or treatment firm. This allows exploring heterogeneity in treatment effects along these dimensions.

Table 2 summarizes results. Uneven columns report the effect on total patenting, even columns on patenting by domestic firms. All models control for all variables used in the propensity scores calculations, as well as for year and country fixed effects. The first two columns show that foreign research activities increase overall patenting output by about 14% five years after the treatment.[10] The effect on domestic firms'

[9] That is not to say that the treatment effect on patents of foreign firms is 9%. Because, by definition, before treatment the number of patents assigned to foreign firms is zero, this effect does not exist. Given that the total effect is $\frac{P^{for}_{r\theta t+5}+P^{loc}_{r\theta t+5}}{P^{loc}_{r\theta t-5}} = \frac{P^{for}_{r\theta t+5}}{P^{loc}_{r\theta t-5}} + \frac{P^{loc}_{r\theta t+5}}{P^{loc}_{r\theta t-5}} \approx 1.16$, we have: $\frac{P^{for}_{r\theta t+5}}{P^{loc}_{r\theta t-5}} \approx 1.16 - 1.07 = 0.09$. Patenting by foreign firms thus raise the treatment effect by about another 9 pp. Due to Jensen's inequality, the effect will in fact be somewhat larger.

[10] Treatment effects are calculated as $e^{\hat{\tau}} - 1$, where $\hat{\tau}$ the treatment effect. Note that for small $\hat{\tau}$ $e^{\hat{\tau}} - 1 \approx \hat{\tau}$.

patenting is just 6%. The difference between the two estimates is due to patents filed by local inventors on behalf of other foreign firms that entered the region.

Columns 3 and 4 interact the treatment dummy with macro-region dummies. Treatment effects are strongest in East Asia and in the omitted category, Europe and Central Asia. Here, foreign research activities increase overall patenting by 23% and 11% respectively and patenting by domestic firms by 13% and 4%. Point estimates for South Asia are also large, but imprecisely estimated. In contrast, cells in the MENA region experience no significant treatment effects.

Columns 5 and 6 interact the treatment dummy with dummies for six broad technology classes, with "other" as the base category. Large and significant treatment effects exist in medical, electrical and computer technologies.

Finally, we identify all treatments by firms who are technology leaders. To do so, we count the number of patents filed between 1975 and 1985 on behalf of each firm in our dataset. Firms ranked in the top 5% for this count in their technology category will be considered technology leaders. Tables B.1-B.6 in Online Appendix B list ten technology leaders for each of six aggregate technology categories. To contrast technology leaders to other foreign MNEs, we create two further classes: firms in the 6^{th}-19^{th} percentile and firms in the bottom 80% of their technology class.

Although technology leaders arguably have most to offer in terms of technological know-how, their treatments affect local innovation rates significantly less than those of lower-ranking firms. The treatment effect on overall patenting (column 7) halves when the treatment firm is a technology leader compared to treatments by mid-tier firms or firms at the bottom of the patenting distribution. These differences are even more striking when focusing on patenting by domestic firms (column 8). Whereas foreign firms at the bottom of the patenting distribution raise domestic patenting rates by about 9%, technology leaders generate no such spillovers whatsoever. This difference in treatment effects barely changes when all interaction terms enter the model simultaneously (columns (9) and (10)). This corroborates Hypothesis 3: The more advanced the MNE, the smaller the spillovers to the local economy are.

Table 2: Analysis of effect heterogeneity

	(1) all	(2) domestic	(3) All	(4) domestic	(5) all	(6) domestic	(7) all	(8) domestic	(9) all	(10) domestic
Treatment effects										
T	0.132***	0.0585***	0.103***	0.0395**	0.0477	0.0126	0.159***	0.0867***	0.0427	0.0158
	(0.0136)	(0.0125)	(0.0176)	(0.0164)	(0.0294)	(0.0281)	(0.018)	(0.0167)	(0.0327)	(0.0314)
T×East Asia			0.101***	0.0833**					0.104***	0.0866***
			(0.0353)	(0.0327)					(0.0348)	(0.0324)
T×L. America			-0.0163	-0.0217					-0.00524	-0.0144
			(0.0332)	(0.0276)					(0.0333)	(0.0277)
T×MENA			-0.204**	-0.0147					-0.124	0.0321
			(0.08)	(0.0283)					(0.0866)	(0.0439)
T×South Asia			0.0904	-0.0458					0.0675	-0.0561
			(0.0763)	(0.0597)					(0.0746)	(0.0611)
T×SS Africa			0.0325	0.022					0.0373	0.0249
			(0.0786)	(0.0765)					(0.0798)	(0.0781)
T×Mechanical					0.0694	0.0345			0.0725	0.0369
					(0.0479)	(0.0459)			(0.0479)	(0.046)
T×Chemical					0.0125	0.0026			0.0194	0.00931
					(0.0405)	(0.0387)			(0.0407)	(0.0388)
T×Computers					0.199***	0.0936**			0.207***	0.103**
					(0.0445)	(0.041)			(0.0447)	(0.0413)
T×Medical					0.174***	0.142***			0.173***	0.141***
					(0.0497)	(0.0463)			(0.0498)	(0.0464)
T×Electrical					0.0908**	0.0445			0.0957**	0.049
					(0.0415)	(0.0384)			(0.0417)	(0.0385)
T×Top 5							-0.0795***	-0.0760***	-0.0869***	-0.0758***
							(0.0284)	(0.0262)	(0.0287)	(0.0266)
T×Top 6-19							-0.00184	-0.0296	-0.000705	-0.0254
							(0.052)	(0.0464)	(0.0522)	(0.0466)
Control variables										
Matching vars?	yes	yes	Yes	yes	yes	yes	yes	yes	yes	yes
Country FE (46)	yes	yes	Yes	yes	yes	yes	yes	yes	yes	yes
Year FE (21)	yes	yes	Yes	yes	yes	yes	yes	yes	yes	yes
Statistics										
# observations	10,476	10,476	10,476	10,476	10,476	10,476	10,476	10,476	10,476	10,476
R^2	0.077	0.066	0.079	0.067	0.09	0.073	0.079	0.068	0.093	0.075

Notes: ***: p<.01; **: p<.05, *: p<.1. Dependent variable: growth in IHS of fractional patent count from one year before to five years after treatment. Uneven columns count all local patents, even columns ("domestic") only patents assigned to domestic firms. MENA: Middle-East and North Africa, SS Africa: Sub-Saharan Africa. Top 5 is a dummy variable that codes treatments by MNEs in the top 5% of their technology's patenting distribution, Top 6-19, codes treatments by MNEs in the 6^{th} to 19^{th} percentile of this distribution. Standard errors, clustered at the matched group level, in parentheses.

Spillover channels

If it is true that technology leaders generate fewer spillovers than lower-ranking firms, we should be able to corroborate this by looking at spillover channels and patent citations. Below, we focus on two well-known channels through which knowledge spillovers materialize: technological alliances and labor circulation. Next, we look at citation patterns. Finally, we analyze the location choices of foreign firms.

Alliances

Do technology leaders engage in fewer local alliances abroad than lower-ranking MNEs? To answer this question, we collect all patents assigned to potential treatment firms. That is, we take all patents assigned to OECD-based MNEs that were filed by inventors outside the MNEs' home countries. Next, we create one dummy variable that takes a value of one if these patents are the result of a collaboration, i.e., if the patent lists multiple firms as assignees and another dummy that identifies collaborations with domestic firms. We regress both dummy variables on a dummy that captures whether a firm is a technology leader.

Table 3 reports results. The upper panel reports estimates from Linear Probability Models (LPMs), while the lower panel reports marginal effects from logit regressions. Columns (1) and (3) show the unconditional association between firms' propensity to engage in alliances and their being a technology leader. On average, technology leaders are 3.1 percentage points (pp) less likely to engage in alliances, which is equivalent to 63% of the average alliance rate ("baseline propensity"). Technology leaders are also underrepresented in alliances with domestic firms: technology leaders are 1.2 pp less likely to engage in such alliances than other firms, equivalent to 52% of the average domestic alliance rate. We reach similar conclusions when adding control variables or when using a logit specification.

Labor mobility

Working at MNEs allows workers to acquire advanced skills and organizational know-how that become available to local firms once these workers leave the MNE (Poole, 2013; Csáfordi et al., 2018). To explore whether technology leaders and lower-ranking MNEs differ with respect to labor circulation in their foreign R&D locations, we use the disambiguated inventor identifiers in PatentsView to approximately map how inventors move between firms.

Table 3: Alliances

	All alliances		Alliances with domestic firms	
	(1)	**(2)**	**(3)**	**(4)**
Baseline alliance propensity	0.0512		0.0228	
Linear probability models				
Top 5% treatment firm	-0.031***	-0.027***	-0.012***	-0.016***
	(0.0078)	(0.0074)	(0.0042)	(0.0057)
Dummies MNE's HQ country?		Yes		Yes
Destination country dummies?		Yes		Yes
Technology category dummies?		Yes		Yes
# Observations	15,772	15,772	15,772	15,772
R^2	0.007	0.060	0.002	0.035
Logit regressions				
Top 5% treatment firm	-0.031***	-0.019***	-0.012***	-0.007***
	(0.0078)	(0.0043)	(0.0042)	(0.0021)
Dummies MNE's HQ country?		Yes		Yes
Destination country dummies?		Yes		Yes
Technology category dummies?		Yes		Yes
# Observations	15,772	15,772	15,772	15,772
Pseudo R^2	0.023	0.137	0.012	0.169

Notes: ***: p<.01; **: p<.05, *: p<.1. Dependent variable: dummy variable for if patent lists at least one other firm (alliance, columns (1) and (2)) or one other domestic firm as a co-assignee (alliance with domestic firms, columns (3) and (4)). Sample: all patents by potential treatment MNEs in regions outside an MNE's home country. Baseline alliance propensity: average likelihood that a patent is the result of an alliance. Columns (2) and (4) control for fixed effects for treatment firms' home countries, for the countries of treated regions and for six broad technology categories. Standard errors, clustered at the region level, in parentheses.

First, we ask how often foreign firms bring their own inventors to R&D locations abroad. To do so, we identify all inventors who filed patents outside their firm's home country (and outside the US) and then ask if they also filed an earlier patent with this same firm inside its home country. Next, we determine whether this was more often the case for inventors of technology leaders than for inventors of lower ranking firms. Because the likelihood of observing job switches depends on how many patents inventors file, we control for the total patenting output throughout an inventor's career. Furthermore, we add dummies for the firm's home country and for the inventor's country of residence.

Results are reported in Table 4. Being a technology leader has a positive and significant effect on the likelihood that inventors are sourced from a firm's headquarters. The LPM shows that technology leaders source inventors 1.8 pp more often from their headquarter locations than technologically less advanced MNEs. The logit regression yields a comparable marginal effect. Technology leaders thus bring more of their own experienced inventors to their foreign R&D locations than lower ranking MNEs do.

Table 4: Inventor sourcing from headquarter country

	LPM	logit
Baseline HQ sourcing propensity	0.023	
Top 5% firm	0.0177***	0.0140***
	(0.0031)	(0.0019)
ln(total # patents by inventor)	0.0078***	0.0056***
	(0.0010)	(0.0007)
Dummies MNE's HQ country?	Yes	Yes
Technology category dummies?	Yes	Yes
Destination country dummies?	Yes	Yes
# Observations	421,392	421,392
R^2 / pseudo R^2	0.016	0.050

Notes: ***: p<.01; **: p<.05, *: p<.1. Dependent variable: dummy variable for whether an inventor patented in the treatment firm's home country before patenting with that same firm abroad. The sample consists of all inventors who file a patent outside the primary assignee's home country between 1975 and 2012 (excluding the US). *Top 5% treatment firm*: dummy variable for whether the MNE ranks in the top 5% in its technology category. 2.4% of patents have multiple assignees. In these cases, the dummy's value is determined by the rank of the patent's primary assignee. *Total # patents by inventor*: total number of patents across an inventor's career. *Baseline HQ sourcing propensity*: average likelihood that inventors are sourced from their firm's headquarters. LPM: linear probability model, logit: marginal effects of a logit specification evaluated at regressor sample averages. Standard errors, clustered at the region level, in parentheses.

Table 5: Local job-switching patterns

	Domestic to foreign		Foreign to domestic		Foreign to foreign	
	(1)	(2)	(3)	(4)	(5)	(6)
	LPM	logit	LPM	Logit	LPM	logit
Baseline propensity	0.1711		0.0872		0.1979	
Top 5% firm	-0.0490***	-0.0410***	-0.0161***	-0.0151***	-0.0457***	-0.0510***
	(0.0083)	(0.0055)	(0.0048)	(0.0046)	(0.0087)	(0.0170)
ln(total # patents by inventor in tech-reg cell)	0.1537***	0.0854***	0.0177***	0.0124***	0.1255***	0.1030***
	(0.0189)	(0.0057)	(0.0052)	(0.0038)	(0.0113)	(0.0077)
Dummies MNE's HQ country?	Yes	Yes	Yes	Yes	Yes	Yes
Technology category dummies?	Yes	Yes	Yes	Yes	Yes	Yes
Destination country dummies?	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	36,416	36,416	36,416	36,416	36,416	36,416
R^2 / pseudo R^2	0.214	0.250	0.038	0.067	0.108	0.106

Notes: ***: p<.01; **: p<.05, *: p<.1. Dependent variable: dummy variable for whether a local inventor in a region-technology cell: (a) first patents for a domestic firm and then for a foreign firm (columns (1) and (2)), (b) first patents for a foreign firm and then for a domestic firm (columns (3) and (4)) or (c) first patents for a foreign firm and then for another foreign firm (columns (5) and (6)). When inventors file patents for several firms, the earliest patent determines the direction of the move. Sample and control variables as in Table 5. *Top 5% firm*: dummy variable for whether the foreign firm is a technology leader. In columns (5) and (6), the dummy refers to the origin firm. *Baseline propensity*: average likelihood that an inventor makes the job switch at hand. Standard errors, clustered at the region level, in parentheses.

Do technology leaders also exchange fewer inventors with other firms in the local economy? To answer this question, we select all inventors who file two patents or more in a region-technology cell, at least one of which for a foreign firm. We control for the inventor's total number of patents in the cell to account for the fact that the more patents an inventor files, the easier it is to detect job switches.

Results, shown in Table 5, are striking. Technology leaders exchange workers with other firms in the local economy at a much lower rate than lower ranking MNEs do. The rate at which they hire inventors from domestic firms (columns (1) and (2)) is 4.9 pp lower, against an average mobility rate of 17%. Furthermore, inventors leave technology leaders for domestic firms at a 1.6 pp lower rate (baseline rate: 9%) and for other foreign firms at a 4.6 pp (baseline rate: 20%) lower rate than lower ranking MNEs.

Citations

Knowledge spillovers may also leave traces in citation patterns. Although citations do not necessarily imply knowledge flows, a large literature starting from Jaffe *et al.* (1993) has interpreted the fact that patents disproportionally cite other patents filed in nearby locations as a sign that knowledge flows are geographically bounded. Following this literature, we analyze whether treatment patents of foreign technology leaders are cited less within the local economy than those of lower-ranking MNEs.

To do so, we match all patents in treated regions to observationally similar patents in other regions, using propensity-score matching (see Online Appendix C). The more often the treatment patent is cited by patents in treated cells than by control patents, the stronger are the local knowledge spillovers. We estimate this spillover intensity once for patents in cells treated by technology leaders and once in cells treated by MNEs in the bottom 95 percentiles of the patenting distribution.

Table 6 compares results in these two samples. Both samples suggest that local knowledge spillovers exist: treatment patents are cited more often by local patents than by control patents. However, whereas treatment patents of technology leaders are cited twice as often by local than by control patents, at 5.1, this same ratio is substantially higher for patents of lower-ranking firms. This suggests that technology leaders generate markedly fewer spillovers than less prominent MNEs.

The same pattern emerges when we focus on spillovers to domestic firms only (i.e., when we focus on citations by domestic firms). However, because no control patents cite any of the treatment patents, we cannot calculate the citation ratio in this case. Nevertheless, the absolute numbers of citations (8-1 versus 1-0) still suggest that lower-ranking firms generate more spillovers than technology leaders.

Table 6: Citations on local patents to treatment patent

	All		Domestic		Foreign	
	T5 cells	**B95cells**	**T5 cells**	**B95cells**	**T5 cells**	**B95cells**
Patents in treated cells	0.005%	0.02%	0.004%	0.018%	0.009%	0.045%
	(6)	(46)	(5)	(38)	(1)	(8)
Control patents	0.002%	0.004%	0.003%	0.004%	0%	0.006%
	(3)	(9)	(3)	(8)	(0)	(1)
N	125,609	234,278	115,549	216,478	10,060	17,800
T/C ratio	2	5.11	1.67	4.75	undefined	8

Notes: Percentage of patents in treated cells and of control patents that cite the treatment patent. T5 cells: region-technology cells treated by a technology leader and matched controls. B95 cells: region-technology cells treated by other firms and matched controls. All: all patents in treated cells and their controls; Domestic: patents by domestic firms only; Foreign: patents by foreign firms only. Absolute numbers of citing patents in parentheses. T/C ratio: ratio of citation propensities of patents in treated cells to control patents.

Location choice

Alcacer and Chung (2007) suggest that firms choose investment locations strategically to balance the costs and benefits of technology spillovers. These authors show that whereas technologically less advanced firms preferentially locate in regions with high absorptive capacity, technology leaders tend to steer clear from such locations.

Table 7 corroborates Alcacer and Chung’s findings. It shows that the socio-economic structure of regions treated by technology leaders differs markedly from regions treated by technologically less advanced MNEs. Technology leaders tend to choose regions with lower levels of GDP per capita, lower levels of schooling, and lower patenting rates than less advanced firms. That is, Table 7 supports Hypothesis 5: technology leaders locate in regions with low levels of absorptive capacity. Note that these low levels of absorptive capacity may in themselves already explain why technology leaders do not exchange many workers and engage in few technological alliances in the local economy: in the regions where they invest, opportunities to do so are low. However, our data do not allow us to determine whether this is the only strategy technology leaders employ to avoid interactions with local firms.

Table 7: Location choices

	Top 5% (N=1,073)	Bottom 80% (N=1,798)
Regional GDP/cap (2005 USD)	18,610 (330)	20,610 (280)
Country GDP/cap (2005 USD)	19,930 (350)	21,940 (290)
Population (millions)	5.22 (0.47)	4.53 (0.33)
Average education	8.24 (0.08)	8.80 (0.06)
GDP growth	2.46% (0.08)	2.48% (0.06)
Patents per 1,000,000 inhabitants	1.44 (0.23)	1.73 (0.21)

Notes: Mean regional characteristics of cells treated by technology leaders and lower-ranking firms in the year before the treatment. The sample consists of all treated cells used in the impact analysis (N=3,134). 1,073 cells are treated by top 5% firms, 1,798 cells by bottom 80% firms. 263 cells are treated by firms in between (their summary statistics are not shown). Standard errors in parentheses.

Conclusion

We have investigated the link between R&D activities of foreign multinationals and patenting in host regions, using data on regions that cover almost the entire world and four decades of innovation output. We find that the initiation of R&D activities by foreign multinationals has a sizeable and positive effect on local innovation rates. The combination of knowledge spillovers to domestic firms and the attraction of new foreign firms to the region sets the host economy on a trajectory of persistently higher innovation rates. However, host economies benefit less from R&D activities of technology leaders than of lower-ranking MNEs. This perhaps surprising finding corroborates a theoretical conjecture according to which technology leaders aim to maximize net, not total, spillovers. In support of this conjecture, we find that technology leaders tend to invest in regions with lower absorptive capacity than lower ranking firms. Possibly because of this, technology leaders are also found to engage in fewer alliances and exchange fewer workers with domestic firms.

Our paper has certain limitations related to the intrinsic shortcomings of studying innovation through patent data and to the rudimentary characterization of firm strategies. Moreover, we cannot exclude that a *change* in regional conditions both attracts foreign firms and increases local innovation output in a region. Without a source of exogenous variation in R&D investments, our estimates may therefore still suffer from some bias. However, we believe that this bias is justifiable against the increased external validity that moving beyond analyzing individual regions or countries to compare the emergence of new centers of technological excellence across the globe affords.

The paper also advances our conceptual understanding of how such new technology centers emerge. It does so by systematically linking insights from the economic geography literature on innovation clusters, from international economics and international business on MNEs' location choices and the impact of FDI, and from strategic management on MNEs' incentives to participate in local learning processes. The resulting framework yields a set of hypotheses on the formation and growth of innovation clusters. Crucially, it suggests that to understand knowledge circulation in clusters, we cannot ignore the incentives and strategic choices of the involved actors. Instead of assuming that global and local learning processes unfold organically, researchers of cluster dynamics should carefully consider the trade-offs that firms and other actors face.

Finally, the paper offers relevant lessons for public policy. Foreign firms’ R&D activities can help regions acquire new technological capabilities. However, whether such learning materializes depends not only on local innovation systems and absorptive capacities, but also, and crucially, on the type and strategic considerations of these foreign firms themselves. Whereas policy makers often focus their efforts on attracting technology leaders to their regions, our study suggests that the value of attracting such flagship FDI may be overestimated. A more prudent approach would focus on less visible players. This may not only require less generous incentives, but also generate more spillovers to the local economy.

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Online Appendix A: Data

US Patents. Patent data come from PatentsView, a database born out of a collaboration between American universities and the US government, and spearheaded by the USPTO. It was created in 2012 by the USPTO, the US Department of Agriculture, the American Institutes for Research, New York University, the University of California at Berkeley, and two data firms.

The PatentsView database is built upon the raw text and XML patent files held by USPTO.[11] The data contains unique inventor identifiers, geo-coordinates of their location of residence at the time of applying for a patent, the technological classes of the patents, the name of the original assignees at the time of the grant, their foreign status (US or non-US), and their citations to other patents.[12] We use the universe of patents granted between 1975 and 2012. This covers 6.0 million patents, granted to 3.6 million distinct inventors. The patent data is arranged at the patent-inventor level (one, unique patent-inventor couple per row). We keep all recorded institutional assignees in the data.[13] There are up to 13 of them for a single patent.[14]

Two features of the PatentsView database are essential for our purpose: (i) assignee, inventor and location names are algorithmically disambiguated, and (ii) its wide time coverage enables the study of technology diffusion over nearly four decades (1975-2012).[15] We provide an overview of the disambiguation procedures performed by the PatentsView team below.

Disambiguation. PatentsView uses probabilistic methods to determine whether inventors with the same name are indeed the same person. Assignees are also probabilistically disambiguated in a similar way. Addresses are disambiguated using geographical APIs.

Assignees. First, minor typos and misspellings are removed from company names using a probabilistic string matching algorithm. Second, the main disambiguation relies on string matching algorithms (see PatentsView website for details).

[11] The raw patent files are publicly available at developer.uspto.gov/data or patents.reedtech.com.

[12] Additional information on inventors' gender, patents' summary text, technology classification references such as WIPO, CPC or IPCR, descriptions of tables and figures, patents' examiners, and the lawyers in charge of applications are made available by PatentsView. We do not use this data in the paper.

[13] Most studies using patent data only use the first assignee. In our context, this would miss collaborations between firms at the frontier and less advanced firms. We would underestimate the total number of patents filed for foreign firms if only the first assignees were used to determine foreign intervention.

[14] Among the 6 million patents, only 3 have 13 assignees. Two of them–7100279 and 7780143–are assigned to 13 distinct Japanese firms. The other–US8965747–is assigned to 12 Chinese and Northwestern University, which is the only institutional assignee on this patent.

[15] This feature makes it more attractive than the commonly used NBER patent citation data (Hall *et al.*, 2001).

Locations. Locations are disambiguated by querying MaxMind and Google's Geocoding API, regarded as the industry standard to convert typical addresses (such as "Houghton Street, London") into geographic coordinates (such as "latitude: 51.5136, longitude: -0.1169").

Inventors. Inventor names are arguably the hardest field of the data to disambiguate. They are disambiguated via Discriminative Hierarchical Coreference, a machine learning technique that groups different spellings of a same author together via hierarchical trees, using information on the set of co-inventors of one author, the companies she patents for, her locations of residence and the title of her patents. Details can be found on the PatentsView website. The patents are classified into 259,465 Cooperative Patent Classification (CPC) subgroups that are mapped to 37 technological sub-categories and 6 broad technological categories (Hall *et al.*, 2001): the 6 broad categories are Chemicals, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical, and Others. The data can be accessed and downloaded freely from the PatentsView website. Because several new patent classes have been introduced since Hall *et al*.'s publication, we manually assign 74 of these new classes to subcategories. As a result, only 2.1% of patents do not have a subcategory, 92% of which lack patent classes in the original data. We use a patent's primary technological subcategory to determine a region-technology cell's technology.

As the disambiguation of assignees, locations and inventors is an ongoing effort, and as the disambiguation methods are continuously refined, the same patent datasets downloaded at different times are likely to have slightly different identifiers for firms, places and people.

Subnational data. Next, we assign the patent-inventor couples to 1,549 regions for which we have data on GDP per capita (at the national and the regional level), average years of education and population. The data is described and used in Gennaioli *et al.* (2014), and it is available discontinuously from 1960 to 2010 for most regions. Typically, two data points in a region would be 5 years apart. We linearly interpolate missing values between any two available values, so as to have data for each year. The regions for which we have observables cover 97.2% of the USPTO patents. Based on the disambiguated locations of inventors, we assign each latitude-longitude pair associated with the location of residence of inventors to a regional polygon via a spatial join algorithm.[16]

The map below, taken from Gennaioli *et al.* (2014), shows the geographical coverage of the regional data. We are indebted to Nicola Gennaioli, Rafael La Porta, Florencio Lopez De Silanes, and Andrei Shleifer for sharing their data and shapefile.

[16] `geoinpoly` in STATA, by Robert Picard.

Figure A.1: Coverage of regional data

Online Appendix B: Technology leaders by technology class

Tables B.1 to B.6 show the ten most innovative firms in the period 1975 to 1985 in terms of patenting output by technological category. Technology categories follow the NBER classification developed by Hall, *et al.* (2001). The tables show how many patents a firm produced in the technology category over the 1975-1985 period, both in levels and as a share of the global total, as well as how many "foreign investments" the firm made in the period 1985-2002. A foreign investment is detected when a firm files a patent with inventors residing abroad. From 1985 to 2007, there are 1,385 foreign investments in Chemicals, 1,768 in Computers & Communications, 1,136 in Drugs & Medical, 1,851 in Electrical & Electronics, 1,377 in Mechanical and 1,544 in Other technologies (mainly consisting of low-tech classes such as Apparel & Textile, Heating technology, Furniture & House Fixtures and Agriculture & Food).

Table B.1: Chemical

Rank	**Company**	**Patent count**	**Share of total**	**Foreign investments**	**Share of total**
1	Bayer Aktiengesellschaft	3496	2.32%	20	1.44%
2	Ciba-Geigy Corporation	2672	1.78%	13	0.94%
3	E. I. Du Pont de Nemours and Company	2558	1.70%	13	0.94%
4	The Dow Chemical Company	2521	1.68%	12	0.87%
5	General Electric Company	2256	1.50%	24	1.73%
6	BASF Aktiengesellschaft	2137	1.42%	17	1.23%
7	Hoechst Aktiengesellschaft	2135	1.42%	5	0.36%
8	Phillips Petroleum Company	2089	1.39%	2	0.14%
9	Exxon Research & Engineering Co.	2000	1.33%	3	0.22%
10	Mobil Oil Corporation	1796	1.19%	1	0.07%

Table B.2: Computers and Communications

Rank	**Company**	**Patent count**	**Share of total**	**Foreign investments**	**Share of total**
1	International Business Machines	2292	4.30%	137	7.75%
2	Canon Kabushiki Kaisha	1539	2.89%	7	0.40%
3	Hitachi, Ltd.	1390	2.61%	13	0.74%
4	U.S. Philips Corporation	1223	2.29%	40	2.26%
5	Siemens Aktiengesellschaft	1163	2.18%	26	1.47%
6	Bell Telephone Laboratories, Incorporated	1119	2.10%	0	0.00%
7	RCA Corporation	975	1.83%	0	0.00%
8	Motorola, Inc.	913	1.71%	27	1.53%
9	Texas Instruments Incorporated	751	1.41%	36	2.04%
10	Sony Corporation	694	1.30%	0	0.00%

Table B.3: Drugs and Medical

Rank	Company	Patent count	Share of total	Foreign investments	Share of total
1	Merck & Co., Inc.	878	2.38%	4	0.35%
2	Bayer Aktiengesellschaft	838	2.27%	5	0.44%
3	Ciba-Geigy Corporation	617	1.67%	3	0.26%
4	Eli Lilly and Company	497	1.35%	1	0.09%
5	American Cyanamid Company	429	1.16%	3	0.26%
6	Pfizer Inc.	423	1.14%	0	0.00%
7	E. R. Squibb & Sons, Inc.	402	1.09%	2	0.18%
8	Beecham Group Limited	388	1.05%	0	0.00%
9	The Upjohn Company	343	0.93%	0	0.00%
10	Hoffmann-La Roche Inc.	332	0.90%	1	0.09%

Table B.4: Electrical and Electronic

Rank	Company	Patent count	Share of total	Foreign investments	Share of total
1	General Electric Company	3575	3.52%	46	2.49%
2	RCA Corporation	2864	2.82%	0	0.00%
3	Westinghouse Electric Corp.	2571	2.53%	5	0.27%
4	Hitachi, Ltd.	2366	2.33%	11	0.59%
5	U.S. Philips Corporation	2342	2.30%	40	2.16%
6	Siemens Aktiengesellschaft	2335	2.30%	37	2.00%
7	International Business Machines	1575	1.55%	38	2.05%
8	Tokyo Shibaura Denki Kabushiki Kaisha	1173	1.15%	0	0.00%
9	Xerox Corporation	1160	1.14%	8	0.43%
10	Motorola, Inc.	1093	1.08%	38	2.05%

Table B.5: Mechanical

Rank	Company	Patent count	Share of total	Foreign investments	Share of total
1	General Motors Corporation	1699	1.31%	3	0.22%
2	Nissan Motor Co., Ltd.	1696	1.31%	0	0.00%
3	Robert Bosch GmbH	1461	1.13%	26	1.89%
4	Caterpillar Tractor Co.	1237	0.96%	0	0.00%
5	General Electric Company	1187	0.92%	15	1.09%
6	Toyota Jidosha Kogyo Kabushiki Kaisha	1173	0.91%	0	0.00%
7	Honda Giken Kogyo Kabushiki Kaisha	1153	0.89%	0	0.00%
8	Hitachi, Ltd.	900	0.70%	4	0.29%
9	Westinghouse Electric Corp.	771	0.60%	0	0.00%
10	Canon Kabushiki Kaisha	755	0.58%	3	0.22%

Table B.6: Other Technologies

Rank	Company	Patent count	Share of total	Foreign investments	Share of total
1	General Electric Company	969	0.88%	13	0.84%
2	The Singer Company	578	0.53%	4	0.26%
3	Minnesota Mining and Manufacturing	524	0.48%	7	0.45%
4	Mobil Oil Corporation	496	0.45%	3	0.19%
5	Phillips Petroleum Company	478	0.44%	1	0.06%
6	E. I. Du Pont de Nemours and Company	443	0.40%	5	0.32%
7	Caterpillar Tractor Co.	435	0.40%	0	0.00%
8	General Motors Corporation	431	0.39%	3	0.19%
9	Nippon Gakki Seizo Kabushiki Kaisha	418	0.38%	0	0.00%
10	Halliburton Company	406	0.37%	3	0.19%

Online Appendix C: Citation analysis

In this appendix, we provide details about the matching algorithm used in the patent citation analysis. We focus on citations to the treatment patent, removing all citations added by patent examiners as these do not reflect technological spillovers. We first collect all patents in treated region-technology cells filed after the treatment patent. Next, we match these patents to similar patents outside the treated cell, using a mix of propensity score and exact matching. First, we match exactly on patent class (using the 1112 USPC main classes, assigned at the time that the patent was granted) and macro-region. Next, we refine these matches using propensity score matching with citation counts, number of inventors, and year of application of the patent as matching controls. To ensure that matches are close enough, we impose a 0.0002 caliper. Finally, we prohibit certain matches. First, matched patents may not come from the same company, inventor or country as the treatment patent(s). This prevents that citation patterns reflect national, cultural or linguistic preferences, or firm- or inventor-specific knowledge. Second, we exclude matched patents filed over twenty years after the treatment patent(s). Figure C.1 summarizes the process.

We repeat this procedure, once for patents assigned to domestic firms and once for patents assigned to foreign firms in treated regions. This yields two matched samples. Next, we split these samples into two parts: the first contains patents in cells treated by technology leaders (T5 firms) and their statistical twins. The second contains patents and matched counterparts in cells treated by lower-ranking firms, which we define as firms in the bottom 95 percentiles of the cumulative patenting distribution between 1975 and 1985 (B95 firms). We now compute the following citation ratio:

$$r_{is} = \frac{c_{r\theta s}(\, F_{r\theta}^{i} = 1)}{c_{r'\theta' s}(\, F_{r'\theta'}^{i} = 0)}$$

where i is the rank of the treating firm(s) (either T5 or B80) and s the status of the citing patents (domestic, foreign or all patents). $c_{r\theta s}(\, F_{r\theta}^{i} = 1)$ represents the number of citations $c_{r\theta s}$ from patents in treated cells ($F_{r\theta}^{i} = 1$) to the treatment patent. The denominator counts citations from matched patents. The larger this ratio, the greater the local spillovers are compared to the baseline scenario captured by the control patents. To determine which foreign firms generate the largest knowledge spillovers in treated regions, we compare the citation ratios in T5-treated (r_{T5s}) to those in B95-treated cells (r_{B95s}).

Figure C.1: Citation analysis