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GLOBAL COLLABORATIVE PATENTS*

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We study the prevalence and traits of global collaborative patents for US public companies, where the inventor team is located both within and outside of the US. Collaborative patents are frequently observed when a corporation is entering into a new foreign region for innovative work, especially in settings where intellectual property protection is weak. We also connect collaborative patents to the ethnic composition of the firm's US inventors and cross-border mobility of inventors within the firm. The inventor team composition has important consequences for how the new knowledge is exploited within and outside of the firm.

The increased globalisation of R&D activities by US multinational companies over the last several decades is a striking trend. According to the Bureau of Economic Analysis, the share of R&D for US companies conducted by their foreign operations rose from 6% in 1982 to 14% in 2004. During this same time period, the unweighted average share of patents for US public companies that contained an inventor located outside of the US likewise rose from 6% in 1982 to 13% in 2004. These trends for US firms are matched by foreign firms locating an ever larger share of their innovative work in the US.

Our work considers several aspects of these trends. We specifically focus on global collaborative patents, which we define to be patents where at least one inventor is located outside of the US and at least one inventor is located within the US. We compare the origin and traits of these patents with global inventor teams to those where the inventors for the US firm are either all located abroad or all located in the US. We use the detailed filings from the US Patent and Trademark Office (USPTO) for all patents granted from 1975–2009. These filings include the names of the inventors of each patent, their employer, and their location. Specific locations are given for each inventor, which forms the basis for our classifications of patents. Patents with global inventor teams feature very prominently in the increased foreign inventive activity of US public companies. They rise from 1% of US public firm patents in 1982 to 6% in 2004, thereby accounting for a substantial portion of the observed overall growth in global inventive activity.

We find that by most conventional measures global collaborative patents tend to be strong innovations, equal to and sometimes exceeding the strength of the innovative work done by the same firm using inventor teams exclusively based in the US. Even more striking is the extent to which both of these groups outperform the patents developed by the firm abroad with exclusively foreign inventor teams. Global

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collaboration and inventor teams appear to reduce underperformance associated with the foreign innovation by US public companies. Compared to this latter exclusively foreign group, collaborative patents have more claims, backward citations within and outside of the firm, are more original, list more subclasses and have more novel technology combinations. Looking forward, collaborative patents are better cited within and outside of the firm. The main exception to these superior patterns is that exclusively foreign teams are better integrated into the future foreign-based innovations of the firm.

We further study how these collaboration trends link to the migration of scientific talent into the US. At the same time that R&D and patenting are becoming globalised, the US workforce in science and engineering is also becoming increasingly international and diverse. One measure, which we develop and utilise below, is the share of US-based patents that have inventors with non-Anglo-Saxon names. We use commercial databases of ethnic names to assign probable ethnicities to inventors. For example, innovators with the surnames Ming or Wang are assigned a high probability of being of Chinese ethnicity, while innovators with the surnames Banerjee or Patel are assigned a high probability of being of Indian ethnicity. Our empirical analysis shows that the employment of ethnic inventors by a US firm is tightly linked to its generation of collaborative patents. In many cases, these observed collaborations also exhibit a specific match between the ethnicity of the US-based inventor and the foreign region in which the other members of the inventor team are located. There are some indications that the overall impact of the patent and its integration into the company's future inventive work in the US are enhanced by these own-ethnicity collaborative matches, but the modest empirical strength of these results only admits tentative conclusions.

We also investigate the role of cross-border mobility of inventors in facilitating these collaborations. We find that a firm's choice to use an internal transfer can be intuitively and systematically related to its size and also the traits of the foreign location. For example, we show that poor use of the English language abroad is connected to a decline in collaboration only when a cross-border migration is not present. We also show tentative evidence that larger firms engage in greater use of internal migration and may receive some added gains, in terms of forward impact, from having done so. In terms of other conditions that predict collaboration, weak rule of law and poor intellectual property rights are the most prominent factors in our work.

There are several rationales or models for why collaborative patenting might be useful for conducting invention abroad. At least three related concepts focus on short-term or temporary needs. One frame focuses on learning about new locations, the match of a firm to the R&D capabilities of the region, and similar unknowns. Collaborative teams may be required for the learning process itself, or they may provide a form of protection or hedging as this learning process occurs. A second frame suggests that collaborative patenting may reduce entry costs into a new location, perhaps including the training of key personnel or foreign inventors for the innovative work. Relatedly, a careful fostering of the nascent invention team abroad may be necessary until its own critical mass is achieved. A third model suggests that collaboration is necessary for coordination of foreign activities with the other work of the multinational, perhaps giving way, with time, to independence as the interfaces are mastered. In each of these models, there are some scenarios where the importance and use of collaborative patenting fades with time in a country.

There are also several elements of global innovation that could give rise to long-term collaborative work. First, a foreign location may not have all of the specific skills or types of employees required for the firm's innovation; a parallel condition is that the foreign location is being targeted for a specific skill that is in short supply or too costly in US. One particularly common form of this split is when architecture-level work is conducted in the US and more detailed developments occur abroad where R&D personnel are less expensive. If much of the required knowledge remains tacit or is too expensive to codify fully, cross-border teams may be necessary to facilitate this arbitrage. Second, legal or cultural issues may require local partners as part of a multinational's expansion plan, due to either physical operations and sales or due to international patent laws. Third, in settings where the firm feels particular exposure, due to weak intellectual property rights, for example, the firm may want to keep some key technology pieces in the US, relying on collaborative teams rather than openly sharing sensitive information across borders to facilitate work. In these and similar scenarios, there can be a more permanent element to the collaboration.

We suspect that all of these conditions and more exist across the many settings that are included in our sample. On one hand, we document sizable declines in collaboration with elapsed time that the firm spends conducting innovation abroad in a region, which suggests that some entry-type mechanisms are involved. We also see some particular elements linked to uncertain environments that are consistent with the learning/protection stories. On the other hand, collaborative patents still account for a third or more of the patents in every region that we study, even after a decade of innovation by the multinational firm in that location. Moreover, our analysis of the forward impact of collaborative patents highlights a permanent opportunity to exploit. That is, we do not observe a performance penalty associated with collaborative teams that the firm would want to shed quickly, recognising though that we do not observe wage costs and all of the managerial inputs necessary. At least in terms of the attributes of developed patents, our results suggest some potentially powerful features of the model for longer-term use.

This article closely relates to the analysis by Foley and Kerr (2013) of the impact that ethnic innovators have on the global operations of US public firms. The earlier study identified that growth in the share of a firm's innovation performed by inventors of a particular ethnicity increases the share of that firm's foreign direct investment activity that is placed into countries related to that ethnic group. Foley and Kerr (2013) also found that ethnic inventors allow US multinationals to form new affiliates abroad without the support of local joint venture partners and thereby facilitate the disintegration of innovative activity (R&D and patents) across borders. The current study picks up in particular on the last theme of globalisation of innovative activity in these US multinational firms. It shows a particular connection of these US-based ethnic researchers to global collaborative patents, which accounts for much of the overall growth in global invention by US firms, and it quantifies the relative traits of these patents compared to other inventive activity undertaken by the firm.

This article also closely relates to and complements the work of Miguelez (2016). Miguelez (2016) documents the important role of high-skilled diaspora communities for the development of global inventor teams, using data from the World Intellectual Property Organisation (WIPO). Gravity models demonstrate how the global distribution of diaspora for a country govern technology flows and overseas R&D relationships, especially at low levels of formality. Our research fits within the global models of Miguelez (2016) and agrees with his broad empirical findings. By focusing on the US, we are able to isolate additional outcomes and spend greater time and attention on the comparison of collaborative patents to domestic and exclusively overseas inventive work conducted by the same firm, in order to assess performance outcomes. We also connect closely with the careful study of Branstetter *et al.* (2015) on the important role of cross-border co-invention teams among multinationals as a factor behind the rise of patenting in China and India (explaining, at times, the majority of patenting observed in these locations). Branstetter *et al.* (2015) show how collaborative patents outperform patents by indigenous firms, using interviews with researchers in multinational firms to verify the importance of cross-border teams. In this article, we consider a broader sample of work, allowing us to connect co-invention teams to traits of places, and we focus more attention on the comparison of collaborative patents to the core US-based work of the multinational.[1]

The current study contributes more broadly to academic, business and policy analyses of the issues surrounding global innovation. The globalisation of R&D activities has received considerable recent attention from diverse groups within and outside academia (Dalton *et al.*, 1999; Freeman, 2006, 2013; Zhao, 2006; Puga and Trefler, 2010). While early foreign R&D efforts by US firms focused on accessing foreign technologies and refining products so they were suitable for foreign markets, more recent efforts also attempt to tap into the large supply of foreign scientists and engineers regardless of their knowledge of specific foreign technologies (Niosi, 1999; von Zedtwitz and Gassmann, 2002; Thursby and Thursby, 2006; National Science Foundation, 2010). Freeman (2013) especially emphasises the globalisation of knowledge production, with reference to both multinational activity and also academia, and argues that global knowledge creation and diffusion is the leading factor governing the current patterns of trade, capital flows and immigration. As a specific example of these connections, a report on the Indian diaspora by the Government of India (2001) notes the key role that Indian Americans have played in promoting foreign direct investment into India by US multinationals, particularly in R&D-intensive sectors.

Collaborative patents, US-based ethnic innovators and internal migration of inventors could be especially valuable in starting, coordinating and connecting the global spread of inventive activity within firms. Beneficial channels that prior work has noted for ethnic networks include enhanced knowledge about products and services targeted at customers in foreign countries; stronger language skills and cultural sensitivity that would promote collaboration with innovators and business developers in foreign countries; specialised knowledge about how to enter specific foreign markets

[1] Related work on global teams and mobility for patenting includes Breschi and Lissoni (2001, 2009), Guellec and Van Pottelsberghe (2001), Griffith *et al.* (2004), Singh (2005), Maggioni *et al.* (2007), Bergek and Bruzelius (2010), Picci (2010), Alnuami *et al.* (2012), Huang *et al.* (2012), Krishna *et al.* (2012), Miguelez (2013), Miguelez and Moreno (2013), Montobbio and Sterzi (2013), Breschi *et al.* (2015) and Freeman and Huang (2015).

and conduct business locally; and better trust and sanctioning mechanisms. Each of these factors is essential to global business and yet can be quite difficult to construct in developing and emerging economies. Rauch and Trindade (2002) and subsequent work highlights the importance of these connections for companies making differentiated products; Saxenian *et al.* (2002) and Saxenian (2006) emphasise how global ethnic connections facilitate fragmented production, modular development and rapid product cycles; and Kerr (2008) stresses the role of ethnic innovators in settings where tacit knowledge is deeply important as opposed to codified information. To this end, we see evidence in the current project of global inventor teams being especially prevalent when US multinationals first enter into new markets, especially in contexts where intellectual property protection is weak.

To conclude, our novel findings contribute to several literatures by illustrating the role that firms play in linking ethnic networks, foreign direct investment and knowledge diffusion. Ethnic networks have been shown to play important roles in promoting international trade, investment and cross-border financing activity, with recent work particularly highlighting the role of educated and/or skilled immigrants.[2] Prior work has further emphasised how social and ethnic ties facilitate transfers of technology; individuals who are geographically mobile appear to play a significant role in these kinds of transfers.[3] Because the current article's findings illustrate a mechanism by which knowledge is transferred globally, it also adds to the research on the role that multinational firms play in the international diffusion of knowledge. In addition, the results inform a growing body of work that analyses firm decisions about whether to locate innovative activity in a single place or in multiple locations (Keller, 2004; Veugelers and Cassiman, 2004; Singh, 2004, 2005, 2007, 2008; MacGarvie, 2005; Branstetter, 2006; Zhao, 2006; Alcacer and Chung, 2007; Nachum *et al.*, 2008; Zhao and Islam, 2011; Ghemawat, 2011; Alcacer and Zhao, 2012). The current work also contributes to the growing number of studies on the economic impact of recent high-skilled migration to the US for work in US firms (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Mithas and Lucas, 2010; Peri and Sparber, 2011; Kerr *et al.*, 2014, 2015; Peri *et al.*, 2015).

1. Dataset Construction and Description

This Section describes the patent data set developed for studying ethnic contributions and collaborative patenting. We first describe the patent data set and the assignment of

[2] Broad reviews of diaspora effects include Rauch (2001), Freeman (2006), Clemens (2009, 2011), Gibson and McKenzie (2011) and Docquier and Rapoport (2012). Evidence on foreign direct investment includes Saxenian (1999, 2002, 2006), Arora and Gambardella (2005), Buch *et al.* (2006), Kugler and Rapoport (2007, 2011), Bhattacharya and Groznik (2008), Docquier and Lodigiani (2010), Iriyama *et al.* (2010), Hernandez (2011), Javorcik *et al.* (2011), Nachum (2011), Rangan and Drummond (2011), Foley and Kerr (2013) and Huang *et al.* (2013). Evidence on trade includes Gould (1994), Head and Ries (1998), Rauch (1999), Rauch and Trindade (2002), Rangan and Sengul (2009), Hatzigeorgiou and Lodefalk (2011) and Kerr (2013).

[3] For example, Almeida and Kogut (1999), Kapur (2001), Rosenkopf and Almeida (2003), Kapur and McHale (2005*a*, *b*), Agrawal *et al.* (2006), MacGarvie (2006), Kerr (2008), Papageorgiou and Spilimbergo (2008), Oettl and Agrawal (2008), Nanda and Khanna (2010), Agrawal *et al.* (2011), Foley and Kerr (2013) and Ghani *et al.* (2014). Singh (2005), Obukhova (2009), Choudhury (2015) and Hovhannisyan and Keller (2015) study related forms of international labour mobility and technology diffusion.

inventor ethnicities. We then define collaborative patents and provide some descriptive statistics. We close with a depiction of inventor mobility across countries within firms. We describe in later Sections additional data included in our analyses as warranted.

1.1. *US Patent Data: Ethnicity*

Our analysis uses the individual records of all patents granted by the USPTO from January 1975 to May 2009. Each patent record provides information about the invention (e.g. technology classification, name of firm or institution) and the inventors submitting the application (e.g. name, city). Hall *et al.* (2001) provide extensive details about these data and Griliches (1990) surveys the use of patents as economic indicators of technology advancement. The data are extensive, with over eight million inventors and four million granted patents during this period. Approximately half of the USPTO patents are filed by inventors working in the US, while the other half are the patents made by foreign inventors that are registered with the USPTO.

While the immigration status of inventors is not collected, one can determine the probable ethnicities of inventors through their names. USPTO patents must list at least one inventor by name, and multiple inventors are often listed. Our approach exploits the idea that inventors with the surnames Chang or Wang are likely of Chinese ethnicity, those with surnames Rodriguez or Martinez of Hispanic ethnicity, etc. Two commercial ethnic name databases originally used for marketing purposes are utilised and the name-matching algorithms have been extensively customised for the USPTO data. The match rate is 99%. The process affords the distinction of nine ethnicities: Anglo-Saxon, Chinese, European, Hispanic, Indian, Japanese, Korean, Russian and Vietnamese. When there is more than one inventor associated with a patent, each individual is given an ethnicity assignment and then these are averaged.[4]

Figure 1(*a*) illustrates the rapidly evolving ethnic contribution to US technology development as a percentage of all patents granted by the USPTO. Table 1 provides the tabulated values. These descriptive statistics only use patents filed by inventors residing in the US as indicated by the city associated with the inventor. We group patents by the years in which they applied to the USPTO. For presentation purposes, Figure 1(*a*) does not include the Anglo-Saxon and European ethnic shares. They jointly decline from 90% of total US domestic patents in 1975 to 76% in 2004. This declining share is primarily due to the exceptional growth over the 30 years of the Chinese and Indian ethnicities, which increased from under 2% to 9% and 6%, respectively.

Figure 1(*b*) depicts the ethnic share of patenting by technology field, using the six main categories of Hall *et al.* (2001). For these purposes, we define 'ethnic share' to be

[4] Kerr (2007, 2010) provides further details on the matching process, lists frequent ethnic names and provides multiple descriptive statistics and quality assurance exercises. One quality assurance exercise regards the estimated ethnic composition of foreign patents registered with the USPTO. The resulting compositions are quite reasonable. About 90% of inventors filing from India and China are classified as ethnically Indian and Chinese, respectively. This is in line with what we would expect, as native shares should be <100% due to the role that foreign inventors play in these countries.

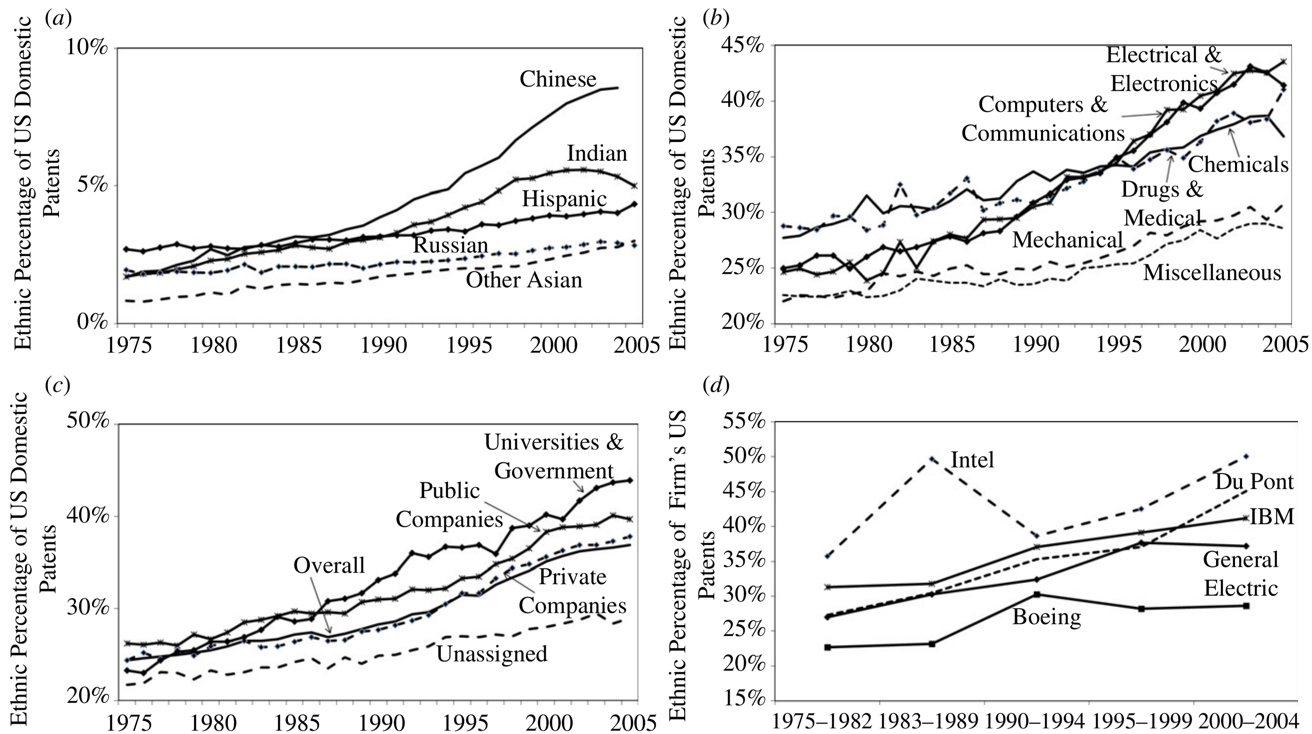

Fig. 1. *Trends in US Ethnic Innovation. Ethnic Shares (a) of US-based Patenting, (b) by Technology Field, (c) by Institution Type and (d) by Sample Firms*

Notes. (*a*) Trends are ethnic shares of patents filed by inventors residing in the US. Patents are grouped by application years. Anglo-Saxon (76%→63%) and European (16%→13%) shares are excluded for visual clarity. Other Asian contributions include Japanese, Korean, and Vietnamese inventors. (*b*) Trends are non-Anglo-Saxon ethnic invention shares by broad technology categories for patents filed by inventors residing in the US. Patents are grouped by application years. (*c*) Trends are non-Anglo-Saxon ethnic invention shares by broad institutional categories for patents filed by inventors residing in the US. Patents are grouped by application years. (*d*) Trends are non-Anglo-Saxon ethnic invention shares by selected firms for patents filed by inventors residing in the US. Patents are grouped by application years.

Table 1

Descriptive Statistics for Inventors Residing in US

	Ethnicity of inventor								
	Anglo-Saxon	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnamese
Panel (*a*): ethnic inventor shares estimated from US patent records, 1975–2004									
1975–9	74.8%	2.1%	15.6%	2.7%	2.0%	0.6%	0.3%	1.9%	0.1%
1980–4	73.4%	2.9%	15.1%	2.7%	2.6%	0.7%	0.4%	2.0%	0.1%
1985–9	72.2%	3.6%	14.6%	2.9%	3.1%	0.8%	0.5%	2.1%	0.2%
1990–4	70.0%	4.8%	14.1%	3.2%	3.9%	0.9%	0.6%	2.2%	0.4%
1995–9	66.4%	6.7%	13.6%	3.5%	5.2%	0.9%	0.7%	2.5%	0.5%
2000–4	63.1%	8.8%	13.0%	3.8%	5.9%	1.0%	0.9%	2.8%	0.6%
Chemicals	65.8%	7.3%	14.4%	3.2%	4.9%	0.9%	0.7%	2.5%	0.3%
Computers	62.9%	8.4%	12.6%	3.4%	7.5%	1.0%	0.7%	2.7%	0.7%
Pharmaceuticals	64.8%	7.2%	14.8%	3.9%	4.6%	1.1%	0.8%	2.6%	0.3%
Electrical	64.3%	8.3%	13.3%	3.3%	5.3%	1.0%	0.9%	2.8%	0.7%
Mechanical	72.8%	3.3%	14.2%	3.3%	2.8%	0.7%	0.5%	2.2%	0.2%
Miscellaneous	74.1%	2.9%	13.9%	3.6%	2.3%	0.6%	0.5%	1.9%	0.2%
Top cities as a percentage	WS (84)	SF (14)	MIL (21)	MIA (16)	SF (8)	SD (2)	BAL (2)	NYC (4)	AUS (2)
of city's patents	SLC (83)	LA (8)	NOR (19)	SA (9)	AUS (7)	SF (2)	LA (1)	BOS (4)	SF (1)
	NAS (82)	AUS (6)	STL (19)	WPB (6)	PRT (6)	LA (2)	DC (1)	HRT (4)	LA (1)
Panel (*b*): immigrant scientist and engineer shares estimated from 1990 US Census records									
Bachelor's share	87.6%	2.7%	2.3%	2.4%	2.3%	0.6%	0.5%	0.4%	1.2%
Master's share	78.9%	6.7%	3.4%	2.2%	5.4%	0.9%	0.7%	0.8%	1.0%
Doctorate share	71.2%	13.2%	4.0%	1.7%	6.5%	0.9%	1.5%	0.5%	0.4%

Notes. Panel (*a*) presents descriptive statistics for inventors residing in the US at the time of patent application. Inventor ethnicities are estimated through inventors' names using techniques described in the text. Patents are grouped by application years and major technology fields. Cities, defined through metropolitan statistical areas, include AUS (Austin), BAL (Baltimore), BOS (Boston), DC (Washington), HRT (Hartford), LA (Los Angeles), MIA (Miami), MIL (Milwaukee), NAS (Nashville), NOR (New Orleans), NYC (New York City), PRT (Portland), SA (San Antonio), SD (San Diego), SF (San Francisco), SLC (Salt Lake City), STL (St. Louis), WPB (West Palm Beach), and WS (Winston-Salem). Cities are identified from inventors' city names using city lists collected from the Office of Social and Economic Data Analysis at the University of Missouri, with a matching rate of 99%. Manual recoding further ensures all patents with more than 100 citations and all city names with more than 100 patents are identified. Panel (*b*) presents comparable statistics calculated from the 1990 Census using country of birth for scientists and engineers. Anglo-Saxon provides a residual in the Census statistics. Many US inventors with European names are native citizens.

the proportion of patents developed by non-Anglo-Saxon inventors. Ethnic shares are stronger and growing at a faster rate in high-tech fields than in the more traditional disciplines. By 2005, ethnic inventors residing in the US account for over 40% of inventions in the categories of electrical & electronics, computers & communications, and drugs & medical. On the other hand, they make up less than 30% in the categories of mechanical and miscellaneous.

Figure 1(*c*) illustrates the growing ethnic contributions by type of institution. We classify patents issued to institutions using listed assignee names (e.g. Microsoft Corporation, Stanford University, US Department of Defense). Unassigned patents are those for which the property rights of the patent remain with the inventors themselves and account for about a quarter of patents. We separate public and private companies by whether a firm is a Compustat-listed company in 1989. We hold this group of public firms constant throughout the sample period to look at trends consistent for this group. Due in large part to greater visa sponsorships and engagement in research-oriented science, ethnic shares are largest for university patents. Publicly-listed companies follow closely behind in their share of ethnic inventors, which corresponds to the broadly observed trend that the degree of work visa sponsorship tends to grow with firm size. To some extent, migrants may also find larger firms more attractive for initial immigration choices due to greater employment stability, given that many visas like the H-1B are assigned to a specific firm-worker match.

We again focus on the US-based public companies for our analysis of collaborative patenting. Figure 1(*d*) plots the ethnic shares of patents for five large representative firms in this group. The differences in the levels of ethnic shares across firms align with the expectations one might have, with, for example, Boeing's share being lower due to employee citizenship requirements that are often made for defence-based work. Intel has the largest ethnic share in this group illustrated. All five corporations show growth in the share of their US-based patents that come from ethnic inventors. The Anglo-Saxon ethnic share declines from over 80% of US domestic patents for all public firms in the 1975–82 period to 68% in the 2000–4 period. Similar to the aggregate series in Figure 1(*a*), this declining share is primarily due to the growth in innovation among Chinese and Indian ethnicities, which increase from under 3% to 10% and 7%, respectively.

For the following geographic analysis, we define cities through the 281 metropolitan statistical areas. Cities are identified from the inventors' city names using city lists collected from the Office of Social and Economic Data Analysis at the University of Missouri, with a matching rate of 99%. Manual recoding further ensures all patents with more than 100 citations and all city names with more than 100 patents are identified. Table 1 shows that ethnic inventors are generally concentrated in immigration gateway cities closest to their home countries (e.g. Chinese in San Francisco, Hispanics in Miami). Not surprisingly, total patenting shares are highly correlated with city size; the three largest shares of US domestic patenting for 1995–2004 are from San Francisco (12%), New York City (7%), and Los Angeles (6%). Ethnic patenting is generally more concentrated, with shares for San Francisco, New York City, and Los Angeles being 22%, 10% and 9%, respectively. Indian and Chinese inventions are even further agglomerated. San Francisco shows exceptional growth from an 8% share of total US Indian and Chinese patenting in

1975–84 to 26% in 1995–2004, while New York City's share declines from 17% to 10%.

While the ethnic patenting data provide a tractable platform for examining migration and innovation, there are several limitations. Most importantly, our approach cannot distinguish between foreign-born inventors working in the US and later generations of immigrants. Nonetheless, the magnitudes of the inventor shares in our analysis still broadly match the immigrant shares for science and engineering calculated from the 1990 Census, as shown in panel (*b*) of Table 1. The European group is the clear exception, a point that we return to later.

1.2. *US Patent Data*: *Collaboration*

The focus of this article is on the traits and consequences of collaborative patents and their link to migrant inventors. Collaborative patents are defined as patents where at least one inventor is located inside the US and one inventor is located outside of the US at the time of the patent application. We contrast these global inventor teams against patents made by US public companies that:

(*i*) have all of their inventors located in the US or
(*ii*) have all of their inventors located outside of the US.

In some settings, we further isolate in this last group cases where a multi-country team exists for a US corporation that does not have a US-based inventor included in the team.

Our conceptual framework is one of a US-based company choosing to conduct global technology development. We accordingly need to be cautious in using our data set, given that many foreign firms also file for patents with the USPTO. We specifically restrict our sample to the patents of US public companies entering into patenting abroad after first patenting in the US. The link of patent assignees to US public firms uses the original match of Hall *et al.* (2001) and updates made by Foley and Kerr (2013). We drop non-US firms in Compustat even if a match to the USPTO data exists. The detailed inventor records begin in 1975. We require that we observe in 1975 or afterwards some measure of exclusively domestic patenting in the US before the firm files patents that include inventors in a specific foreign region for innovative work. Thus, we drop some firm-region pairs that have been continually conducting domestic and foreign patenting since before 1975. The final sample includes industrial patents with application years between 1985 and 2005, building off of patents granted through May 2009. The excluded period of 1975–84 is used for constructing traits of patents below.

Our analysis requires connecting inventor ethnicities to countries. Patents are assigned to one foreign country using the most frequent location of non-US inventors; ties are broken by the order of inventors listed on patents. Own-ethnicity collaborative patents are defined as collaborative patents where at least one inventor on the patent working in the US is of the same ethnicity as the country entered. There is a one-to-one mapping of ethnicity and country for five cases: India, Japan, Korea, Russia and Vietnam. In contrast, Chinese, European and Hispanic ethnicities each relate to more than one country. Chinese economies include Mainland China, Hong Kong, Macao, Singapore and Taiwan. European economies include Austria, Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, the Netherlands, Norway, Poland, Sweden and Switzerland. Hispanic economies include Argentina, Belize, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Philippines, Portugal, Spain, Uruguay and Venezuela.

Figure 2(*a*) shows the trend from 1985 to 2005 for collaborative patenting. The percentage expresses the fraction of patenting that is collaborative in nature among all patents filed by US public companies with inventors working in the eight ethnic regions identified in the ethnic-name approach. This share mostly rises over the 20-year period from about 30% of the patents by the firms in these foreign regions to 50%. Global inventor teams are clearly an important and growing component to the organisation of innovation in these US companies, equal in contribution by 2005 to situations where all inventors are residing abroad at the time of the innovative work. Branstetter *et al.* (2015) provide important related descriptions of cross-border teams for multinationals that are patenting in India and China specifically.

Figure 2(*b*) shows that the own-ethnicity share of collaborative patents is increasing as well. The growth of own-ethnicity collaboration accounts for over half (52%) of the total growth in collaborative patenting observed in Figure 2(*a*) and represents about 47% of collaborative patenting by the end of the period. This can be partly linked to the greater ethnic inventor shares among the scientists working in the US (Figure 1*a*) and the shift of global patenting by US public companies towards locations with a greater degree of collaboration (e.g. towards China and India and relatively away from Japan). Some of these features are quantified in our analysis below.

Figure 2(*c*) depicts a very interesting time pattern that exists within firms with respect to collaboration. The trend graph groups patents by how long the US public company has been conducting innovation in the ethnic region, from entry year up to 10+ years after entry. The sample overall is again predicated on the firm first conducting innovative work in the US. By starting our collaborative sample in 1985, each of the five horizontal divisions are populated across our sample period given our initialisation of the entry dates in 1975. Developing and emerging economies display a very high collaborative patent share at the time of firm initial entry, with over 70% of patents having at least one inventor located in the US. By contrast, about half of the patents are collaborative when US public companies first enter into Europe or Japan for innovative work. These differences across countries diminish over time after entry, and both groups have less than 45% of the patents being collaborative by the seventh year of the firm's operation abroad.[5]

Table 2 displays collaborative patenting shares and counts by ethnic region and time since firm entry into the specific region. In panel (*a*), the entry rates for collaborative patenting are highest in the Chinese economies and India, lowest in Europe and Japan. Most groups display the declining trend with respect to time in country that is

[5] We time these graphs and our analyses below from time since entry into the ethnic region for the cases where we have multiple countries mapping to an ethnic group. This is done to match our ethnic shares in the US and to reflect that much is learned about the region as a whole upon entry into it.

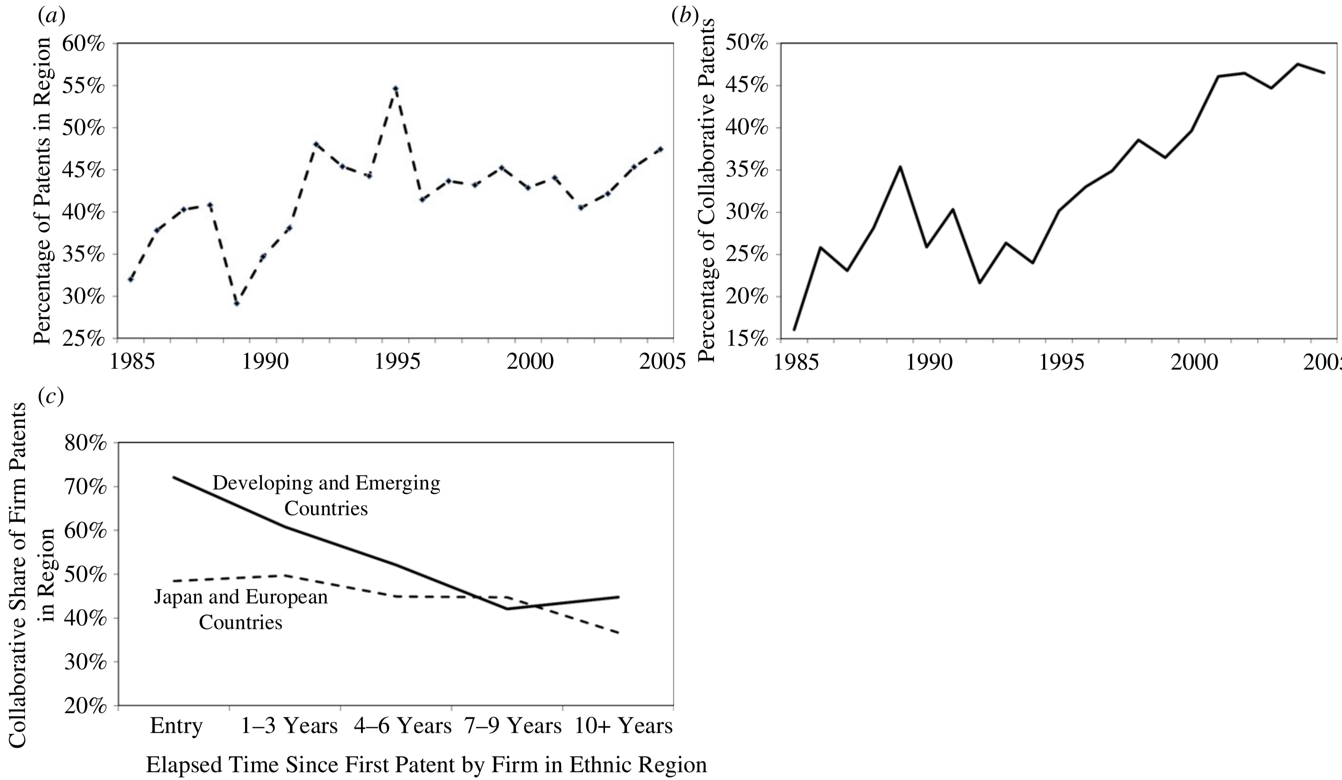

Fig. 2. *Trends in US Collaborative Patenting. (a) Collaborative Share of Patents in Region. (b) Own-ethnicity Share of Collaborative Patents. (c) Elapsed Time Since Foreign Entry by Firm*

Notes. (*a*) Trend depicts the share of patents that are collaborative in nature made by US public companies in regions identifiable with the ethnic-name matching algorithms. Collaborations are defined to be cases where at least one domestic US inventor coauthors the patent with at least one foreign inventor working in the region. (*b*) Trend depicts the own-ethnicity share of collaborative patents made by US public companies in regions identifiable with the ethnic-name matching algorithms. Own-ethnicity collaborations are defined to be cases where the domestic US inventor is of the same ethnicity as the foreign country in which the patent is being made. (*c*) Trend depicts the share of patents that are collaborative in nature made by US public companies in regions identifiable with the ethnic-name matching algorithms. The horizontal axis depicts the elapsed time since the firm first filed a patent with an inventor residing in the ethnic region.

Table 2

Firm Entry and Collaborative Patenting Trends by Region

	Patents within foreign countries grouped by ethnicity							
	Chinese	European	Hispanic	Indian	Japanese	Korean	Russian	Vietnamese
Panel (*a*): share of patents that are collaborative with inventors based in the US								
Entry year	70%	42%	66%	84%	46%	61%	63%	100%
Years 1–3	59%	47%	60%	66%	45%	63%	62%	
Years 4–6	53%	43%	60%	49%	38%	56%	63%	
Years 7–9	48%	42%	71%	25%	39%	76%	73%	
Years 10+	43%	37%	49%	49%	31%	65%	69%	
Panel (*b*): share of patents that are collaborative with own-ethnicity inventors based in the US								
Entry year	23%	18%	15%	34%	3%	4%	35%	0%
Years 1–3	21%	17%	7%	29%	2%	17%	56%	
Years 4–6	31%	15%	15%	27%	3%	12%	41%	
Years 7–9	34%	17%	14%	15%	2%	24%	63%	
Years 10+	19%	16%	11%	30%	2%	9%	51%	
Panel (*c*): count of observations in cell								
Entry year	223	408	137	98	270	71	48	2
Years 1–3	249	562	115	85	218	46	109	0
Years 4–6	321	725	108	132	173	25	46	0
Years 7–9	461	794	93	198	223	21	49	0
Years 10+	562	4,142	311	152	1,014	34	61	0

Notes. Table displays collaborative patenting shares and counts by ethnic region and time since firm entry into the specific region. The sample is comprised of US public companies entering into patenting abroad after first patenting in the US. The sample includes industrial patents with application years between 1985 and 2005, building off of patents granted through to May 2009. Collaborative patents are defined as patents where at least one inventor is located in the US and one inventor is located outside the US. Patents are assigned to one foreign country using the most frequent location of non-US inventors; ties are broken by the order of inventors listed on the patent. Own-ethnicity collaborative patents are defined as collaborative patents where at least one inventor on the patent working in the US is of the same ethnicity as the country entered.

graphed in Figure 2(*c*), although Korea and Russia are flatter or slightly rising (at quite high overall rates of collaboration). Panel (*b*) of Table 2 shows the own-ethnicity shares. These own-ethnicity shares partly link to the size of the ethnic group in the US, with Japan having a very low own-ethnicity collaborative share due to the limited number of ethnic Japanese inventors in the US. Own-ethnicity contributions are strongest in the Chinese, Indian and Russian economies.[6]

Our analysis at several points considers inventor team size alongside that of collaborative patents. Figure 3(*a*) shows the broad increase in team sizes of

[6] An interesting extension is the degree to which collaborative patents are connected to patents having multiple assignees (e.g. due to a joint venture). We are able to assemble some data to help understand these features, although we cannot do so for the full sample period. For patents with application years 2000–5, we observe evidence of multiple assignees at the following rates: 0.6% for patents with US domestic-only teams, 4.7% for collaborative patents, and 1.4% for foreign non-collaborative patents (and 3.8% for patents with multi-country non-US teams). These statistics show that multiple assignee patents are connected to the rise of collaborative patents but that they do not account for a large portion of the rise in these collaborative teams. We also observe some measure of substitution between use of own-ethnicity inventors and multi-assignee structures. Breaking down the 4.7% base rate for collaborative patents, it is 3.4% for own-ethnicity collaborative work and 5.7% for collaborative work that does not involve ethnic connections. This pattern is similar to the broader finding in Foley and Kerr (2013) that US ethnic inventors facilitate foreign direct investment that depends less on local partners than foreign entry that is conducted without this resource.

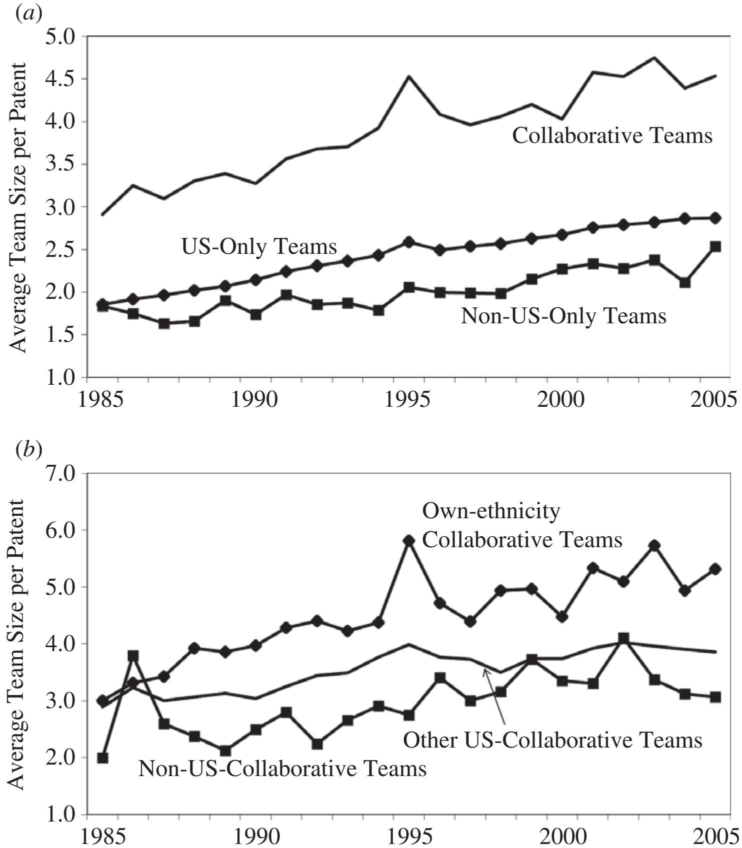

Fig. 3. *Trends in Inventor Team Sizes. Inventor Team Size by (a) Patent Type and (b) Collaborative Types*
Notes. (*a*) Trend depicts the average number of inventors per patent type for US public companies. Collaborations are defined to be cases where at least one domestic US inventor coauthors the patent with at least one foreign inventor working in the region. (*b*) Trend depicts the average number of inventors per patent type. Own-ethnicity collaborative patents have a US-based inventor of the same ethnicity as the foreign region; other US collaborative patents do not have this ethnicity connection; and non-US collaborative teams are multi-country teams for US corporations that do not include a US-based inventor.

collaborative, foreign non-collaborative and US domestic patents. The substantial growth in average team size for patenting reflects the very general trend towards larger teams in the development of scientific knowledge (e.g. Wuchty *et al.*, 2007). Throughout our sample period, the team sizes for collaborative patents are at least one person larger than those for US domestic patents. This differential remains pretty constant in relative terms, as both series experience a net growth of about 55% in terms of team size from 1985 to 2005. This consistent relative differential means that the raw numerical gap between the two series increases, as the 20-year period exhibits a team size growth of 1.02 members for US domestic patents and 1.63 members for collaborative patents. By contrast, foreign non-collaborative patents for US multinationals show a more modest growth and smaller teams.

Figure 3(*b*) provides some additional detail regarding collaborative patents. We break apart our collaborative patent series into own-ethnicity collaborative teams *versus* those that do not possess this ethnic connection. The interesting feature here is that own-ethnicity collaborative teams tend to be larger than the others, with some widening of the gap over time. We also plot, in this Figure, the trend for multi-country teams for US corporations that do not include a US-based inventor as a comparison point. The sample size here is smaller – 436 patents compared to 2,023 and 3,298 for own-ethnicity and other US-connected collaborative teams, respectively – and hence some caution is warranted for the annual values. Nevertheless, these exclusively foreign teams appear to have a roughly similar average size and trend to US collaborative patents.

1.3. *US Patent Data*: *Inventor Mobility*

Extensions to our analysis consider the cross-border mobility of inventors within and outside firms. This added perspective provides incremental insights on the development of collaborative teams and the heterogeneity in their effectiveness. Unfortunately, the USPTO patent data do not uniquely identify each inventor, instead only providing their names. We rely on the work of Li *et al.* (2014), which uses name disambiguation techniques to probabilistically assign unique inventor identifiers. This work is becoming the foundation of a number of studies seeking to identify unique inventors and their mobility with the USPTO patent data. Breschi *et al.* (2014) describe similar work being done with the European Patent Office records and provide a broader literature review.

This work is probabilistic and several features of the matching process are important to note in our setting. The first, and perhaps most important, aspect is that name disambiguation works best when names are very distinctive. A central challenge in the ethnicity context is that many ethnicities have very concentrated naming patterns (e.g. the surnames Lee and Park for Koreans). This concentration is very advantageous with respect to assigning ethnicities but it makes disambiguation harder. Second, geography is often used in these analyses to help isolate individual inventors, and we suspect that the international migration that occurs outside of multinationals may be harder to capture than what occurs within companies. Finally, and likely not very important, some inventors use different first names depending upon location, as Asians in particular may select an Anglo-Saxon first name when working in the US. This would be harder for the procedures to capture but we also think this issue is rather small in our context. Li *et al.* (2014) provide a broader discussion. To address these concerns and other typical uncertainties with these naming procedures, we report below two sets of statistics that use the upper and lower bounds on match certainty that are developed by Li *et al.* (2014). As we reach extremely similar conclusions at both bounds, we believe our data platform is in a good position to move forward.

Figure 4(*a*) and (*b*) present some visual depictions of the role of internal transfers in multinationals for explaining the levels and trends of collaborative patents. In terms of levels, we observe that for about 30% of all collaborative patents one or more of the team members have moved across borders, as we can observe it in the patent database (and thus this forms a lower bound for the complete share). This share dips somewhat

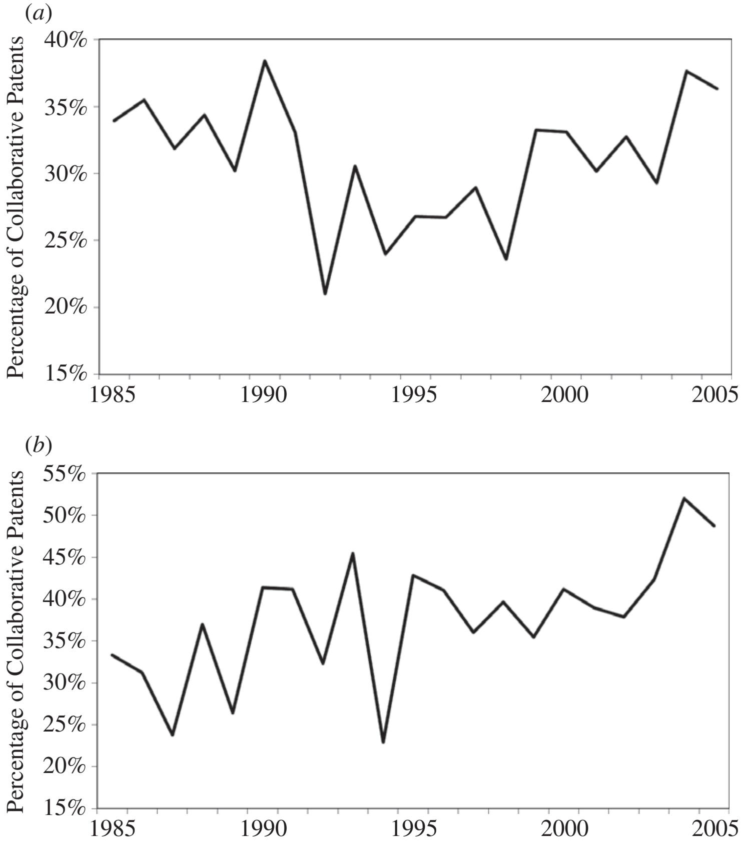

Fig. 4. *Trends in Cross-border Inventor Mobility Shares. (a) Share of Collaborative Patents with Mover. (b) Share of Own-ethnicity Patents with Mover*

Notes. (*a*) Trend depicts the share of collaborative patents made by US public companies that involve one or more inventors moving across borders. (*b*) Trend depicts the share of own-ethnicity collaborative patents made by US public companies that involve one or more inventors moving across borders. Own-ethnicity collaborations are defined to be cases where the domestic US inventor has an ethnic name matching the foreign country in which the patent is being made.

in the middle of our sample period but does not show a very sharp general trend, especially in comparison to the other trends observed for collaborative patenting. This sag is common to multiple foreign regions and not due to any single location. In the majority of cases, moving inventors are present in the US in the first years that they patent. Figure 4(*b*) shows that movers constitute a more prominent feature in the level and trend of own-ethnicity collaborative patenting. On the whole, given their mostly stable contributions to each category, the absolute growth rates for collaborative patents display trends similar to the aggregate series documented in Figure 2(*a*) and (*b*). They thus play a significant role in facilitating the increase of collaborative patents to 6% of US patents, but they are not the sole factor and can provide interesting insights into the influence of team composition.

2. Empirical Findings

This Section describes our empirical work. We first quantify country, technology, and firm-level traits associated with collaborative patenting. We then compare collaborative patenting to other patents made by US public companies.

2.1. *Predictors of Global Collaborative Patents*

We begin with estimates of whether a patent that includes foreign inventors is collaborative. The sample is comprised of the patents of all US public companies entering into patenting abroad after having first patented within the US. The sample includes industrial patents with application years between 1985 and 2005. Patents included in the sample have at least one inventor working outside of the US in one of the eight regions identifiable with the ethnic-name approach described above. Thus, the sample models the choice between using an exclusively foreign inventor team *versus* a global inventor team with a connection to the US. As noted earlier, patents are assigned to one foreign country using the most frequent location of non-US inventors; ties are broken by the order of inventors listed on patents.

We develop seven basic traits for each country. The measures are taken as an average over the period studied when time variant. Log GDP *per capita* describes the overall economic development of the country. The second metric is a binary variable for low or very low English language proficiency in the country as measured in EducationFirst's English Proficiency Index (http://www.ef.com/epi/). The third is the log distance between the US and the foreign country measured using the great circle distances between capital cities. The fourth is an index for rule of law taken from La Porta *et al.* (2002). This metric is on a six-point scale, with higher values representing stronger rule of law. The fifth is an index for the protection of intellectual property rights taken from Park (2008). This metric is on a five-point scale, with higher values representing stronger protection. We next include a general measure of patenting integration of the country with the US as measured by the log total patents *per capita* that the country files with the USPTO. This measure includes all foreign firms, inventors, and governments that file patents with the USPTO for intellectual property protection. Finally, we measure the share of this foreign patenting that is being done in the specific subcategory of the patent in question. This models the degree to which collaboration is seeking to overcome 'voids' in the composition of local innovation talent or institutions for the focal technology.

Online Appendix Table A1 provides univariate correlations. The raw likelihood of collaborative patenting is most visibly connected to patenting by firms in places where rule of law is weak, intellectual property rights are not well protected and scientific integration with the US is low. Collaborative patenting is also associated with poorer and developing countries and places with low average proficiency in the English language. By contrast, connections to distance or local patenting composition are less apparent. These connections, especially to the legal rights established abroad, make intuitive sense. At the level of the firm and in accordance with our descriptive graphs, collaboration is declining in the time that the firm has been in the foreign location, increasing in the patenting size of the firm, and increasing in the share of the firm's US innovative workforce of ethnic origin.

For a more-rigorous assessment, we estimate a linear probability model of the form:

$$(0,1)\mathit{Collaborative}_p = \boldsymbol{\eta}_{jt} + \beta \mathbf{X}_{cj} + \gamma \mathbf{Z}_{ft} + \epsilon_p, \tag{1}$$

where p indexes patents. Each patent p is linked to an application year t, non-US country c, technology j, and firm f. The dependent variable $(0,1)\mathit{Collaborative}_p$ is an indicator variable for a collaborative patent. The vector $\boldsymbol{\eta}_{jt}$ contains technology-year fixed effects. The vector $\mathbf{X}_{cj}$ contains traits of countries and technologies that we relate to the prevalence of collaborative patenting. We eventually employ country-year fixed effects to fully control for these features, but it is interesting to first quantify the broad patterns of the data. Finally, the vector $\mathbf{Z}_{ft}$ contains traits of the US firm at the time of the patent application. These traits include factors like how long the firm has been conducting innovation in the foreign country and the ethnic share of its US-based inventor workforce. The regressions estimated are unweighted, have 11,737 observations, and cluster standard errors by country.

Column 1 of Table 3 models the seven basic traits noted above. The coefficient patterns across the country-level variables are interesting and the legal protections continue to stand out the most. Collaborative patenting tends to be less common in countries characterised by strong rule-of-law and better intellectual property rights. These patterns could be reflective of collaboration being important when entering into uncertain environments, which was hinted at by the firm entry timing noted earlier. Once we condition on these two legal variables, collaboration is more likely when countries have a higher GDP *per capita*. This is a robust pattern evident in many permutations – the univariate correlation of collaborative patenting to developing and poorer countries came through channels connected to weaker property rights. Similarly, the strength of these property rights accounts for the univariate correlations noted for patents *per capita* and English proficiency. Links to distance are again not evident. These correlations, of course, are far from causal, and other correlated traits of countries (e.g. education levels) may be more important. The correlations nonetheless demonstrate a consistent pattern over these traits that provide additional confidence in the types of analyses undertaken.

Column 1's estimation and those that follow include technology-year fixed effects, with the technology aggregation for these fixed effects being defined at the sub-category level of the USPTO system (36 groups). Unreported estimates relax this structure and instead include indicator variables for broad types of technologies. These specifications show that collaboration tends to be higher in the chemicals and drugs categories of the USPTO system.

Column 2 adds in our first firm-level trait, which is the number of years since the firm began patenting in the foreign ethnic region. This measure ranges from zero (time of entry) to ten years or longer. It has a strong negative coefficient, measuring a 1.7% decline in the absolute probability of the patent being collaborative with each additional year of operation in the foreign country. At the bottom of Table 3, we compare the coefficient to the 0.43 mean of the dependent variable. One additional year since the first patenting activity in the region is associated with a 4.0% lower likelihood of collaborative patenting in relative terms.

Table 3

Traits Associated with Collaborative Patenting

	Dependent variable is (0,1) for collaborative patent						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country traits							
Log GDP *per capita*	0.106	0.089	0.091	0.086	0.154		
	(0.029)	(0.029)	(0.029)	(0.029)	(0.034)		
(0,1) low English proficiency	−0.032	−0.031	−0.033	−0.042	−0.046		
	(0.028)	(0.026)	(0.025)	(0.026)	(0.032)		
Log distance to US	−0.006	−0.035	−0.034	−0.037	0.020		
	(0.032)	(0.032)	(0.035)	(0.035)	(0.046)		
Rule of law, six-point	−0.082	−0.065	−0.065	−0.062	−0.086		
scale with six being highest	(0.020)	(0.019)	(0.020)	(0.020)	(0.030)		
IPR protection, five-point	−0.140	−0.130	−0.128	−0.126	−0.166		
scale with five being highest	(0.033)	(0.031)	(0.030)	(0.030)	(0.030)		
Log patents *per capita* that	0.003	0.006	0.005	0.003	0.005		
are filed in USPTO system	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)		
Share of national patenting	−0.496	−0.368	−0.365	−0.377	0.339		
conducted in same field	(0.344)	(0.343)	(0.340)	(0.336)	(0.401)		
Firm traits							
Years since firm began		−0.017	−0.016	−0.016	−0.010	−0.017	−0.017
patenting in foreign location		(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Years since firm began			−0.004	−0.004	−0.006	−0.004	−0.004
patenting abroad			(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Log patent count by			0.008	0.005	−0.001	0.008	0.005
firm worldwide in year			(0.009)	(0.008)	(0.011)	(0.008)	(0.008)
Ethnic share of domestic				0.211	0.228		0.186
US inventors in year				(0.055)	(0.080)		(0.058)
Technology-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Compustat covariates					Yes		
Country-year fixed effects						Yes	Yes
Mean of dependent variable		0.432	0.432	0.432	0.432	0.432	0.432
ß [years in location]/DV mean		−0.040	−0.037	−0.037	−0.024	−0.039	−0.040
ß [US ethnic share]/DV mean				0.488	0.528		0.431

Notes. Table considers conditions associated with collaborative patenting. The sample is comprised of US public companies entering into patenting abroad after first patenting in the US. The sample includes industrial patents with application years between 1985 and 2005, building off of patents granted up to May 2009. Collaborative patents are defined as patents where at least one inventor is located in the US and one inventor is located outside the US. The dependent variable is a binary indicator for a collaborative patent. Patents included in the sample have at least one inventor working outside the US. Patents are assigned to one foreign country using the most frequent location of non-US inventors; ties are broken by the order of inventors listed on patents. Tech-year fixed effects are defined at the sub-category level of the USPTO system. Regressions are unweighted, have 11,737 observations, and cluster standard errors by country. Compustat covariate sample includes 7,769 observations and controls for log worldwide sales, employment and R&D expenditures of the firm.

Column 3 expands the analysis to consider additional traits of the firm's global patenting efforts. We control for time since the firm began patenting abroad inclusive of all foreign operations. We also control for the log worldwide patent count by the firm in the application year. These additions lower slightly the coefficient estimate on the years since entry into the foreign ethnic region. There is a positive correlation between the global patent count of the firm and the frequency of collaborative patenting but this is not measured precisely.

Column 4 further adds the share of the firm's US domestic inventors who are of non-Anglo-Saxon ethnic origin. This measure is highly predictive of collaborative patents, suggestive of the special role that migration can have in fostering global inventor teams. An increase in this share by 10% (e.g., from 20% to 30%) connects to a 2.1% increase in the absolute probability of the patent being collaborative. In relative terms, this increase is about 5%. The inclusion of this explanatory factor also diminishes the initial importance of the global patent count of the firm, as larger firms also have a higher ethnic share of their inventor workforce.

Column 5 includes further controls for firm size that we can derive from Compustat – the log values of firm worldwide sales, employment and R&D expenditure. We can only construct these metrics for two-thirds of our sample (7,769 observations) and, hence, we consider them as a robustness exercise. The emphasised results are robust to these control variables and the overall time since the firm began to patent abroad becomes more important in the presence of these controls.

Columns 6 and 7 show very similar results when including country-year fixed effects that remove all local conditions. We also find similar results in several unreported robustness checks. For example, the patterns are similar when weighting each patent such that each firm receives the same overall weight in the regressions. The patterns are also similar if using the log ethnic inventor count in the US rather than the share-based measure. Firm-level explanatory variables show similar statistical significance when clustering standard errors by firm. Finally, we continue to observe the importance of our key explanatory factors (i.e. entry timing, size of the company's US ethnic scientific workforce) when splitting the sample by dimensions such as firm size, level of economic development, level of intellectual property protection, and local technology composition and when looking separately at the upper and lower halves of the distributions.[7]

Table 4 repeats the analysis in Table 3 but now considers as the outcome variable a (0,1) indicator variable for an own-ethnicity collaborative patent. Among country traits, intellectual property rights remain the most important predictor. Focusing mostly on the firm-level traits at the bottom of the Table, the coefficient patterns are quite similar. The coefficients are smaller but this mostly reflects the lower variation and sample mean on this own-ethnicity dimension. In relative terms, the effect for years after entering the foreign region is quite comparable to Table 3. The absolute and relative frequency for own-ethnicity collaboration is not surprisingly higher for firms that have a larger ethnic workforce share in the US.

Table 5 introduces firm fixed effects in the models of collaborative patenting and own-ethnicity collaboration in columns 1 and 3, respectively. Not surprisingly, the measures for time since foreign entry are accounted for by the firm-specific fixed effects. Growth over time in the total patenting of the firm is associated with lower collaboration rates, while we observe a relatively large boost from growth in the size of the company's ethnic workforce in the US. Columns 2 and 4 further interact the various firm measures with the GDP of the country where the foreign patenting takes

[7] This comparability focuses on our firm-level patterns. We also considered sample splits regarding the country traits in estimations without country fixed effects. These exercises did not yield very insightful information and the most important variation we exploit in this regard is across the full sample.

Table 4

Traits Associated with Own-ethnicity Collaborative Patenting

	Dependent variable is (0,1) for own-ethnicity collaborative patent						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country traits							
Log GDP *per capita*	0.039	0.035	0.034	0.028	0.003		
	(0.044)	(0.045)	(0.045)	(0.043)	(0.037)		
(0,1) low English proficiency	0.027	0.027	0.027	0.017	−0.015		
	(0.040)	(0.039)	(0.039)	(0.039)	(0.039)		
Log distance to US	−0.068	−0.075	−0.078	−0.082	−0.083		
	(0.037)	(0.036)	(0.035)	(0.035)	(0.044)		
Rule of law, six-point scale	0.010	0.014	0.016	0.020	0.052		
with six being highest	(0.042)	(0.042)	(0.043)	(0.042)	(0.037)		
IPR protection, five-point	−0.070	−0.067	−0.064	−0.061	−0.077		
scale with five being highest	(0.035)	(0.034)	(0.033)	(0.033)	(0.029)		
Log patents *per capita* that	−0.018	−0.018	−0.018	−0.020	−0.019		
are filed in USPTO system	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)		
Share of national patenting	−0.400	−0.368	−0.355	−0.369	0.099		
conducted in same field	(0.305)	(0.304)	(0.304)	(0.306)	(0.279)		
Firm traits							
Years since firm began		−0.004	−0.005	−0.005	−0.003	−0.005	−0.006
patenting in foreign location		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Years since firm began			0.000	0.001	−0.001	0.000	0.001
patenting abroad			(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Log patent count by firm			0.006	0.002	0.003	0.009	0.006
worldwide in year			(0.007)	(0.007)	(0.008)	(0.007)	(0.006)
Ethnic share of domestic				0.253	0.235		0.231
US inventors in year				(0.059)	(0.073)		(0.056)
Technology-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Compustat covariates					Yes		
Country-year fixed effects						Yes	Yes
Mean of dependent variable		0.162	0.162	0.162	0.162	0.162	0.162
ß [years in location]/DV mean		−0.026	−0.032	−0.033	−0.016	−0.033	−0.034
ß [US ethnic share]/DV mean				1.556	1.447		1.420

Notes. See Table 3. The dependent variable is a (0,1) indicator variable for at least one inventor on the patent working in the US being of the same ethnicity as the country entered.

place. These interactions tend to be less important overall. They show that the declines in collaboration with firm patent growth are especially pronounced in developing and emerging economies. Also, the size of the ethnic workforce in the US matters less for collaboration when the GDP of the foreign country is greater. This reflects the particular strength of this channel observed in Table 2 for countries such as China, India and Russia.

The online Appendix reports two important robustness checks on these estimations. First, Appendix Tables A2, A4 and A6 repeat Tables 3–5 using a probit model instead of our linear probability specification (1). These probit models yield very similar results. Where modest differences occur, they only serve to strengthen the conclusions that we can draw from the reported estimations.

In Appendix Tables A3, A5 and A7, we replicate our core model – specifically column 4 from Tables 3 and 4 and columns 1 and 3 from Table 5 – when we drop each

Table 5

Panel Estimates of Collaborative Patenting

	DV is (0,1) for collaborative patent		DV is (0,1) for own-ethnicity collaborative patent	
	(1)	(2)	(3)	(4)
Years since firm began patenting in foreign location	0.000	0.001	−0.001	0.000
	(0.003)	(0.003)	(0.002)	(0.002)
× Log GDP *per capita*		0.000		0.001
		(0.003)		(0.001)
Years since firm began patenting abroad	0.009	0.008	0.004	0.003
	(0.004)	(0.004)	(0.003)	(0.003)
× Log GDP *per capita*		−0.003		−0.003
		(0.002)		(0.003)
Log patent count by firm worldwide in year	−0.028	−0.031	−0.006	−0.007
	(0.013)	(0.012)	(0.010)	(0.010)
× Log GDP *per capita*		0.021		0.005
		(0.009)		(0.006)
Ethnic share of domestic US inventors in year	0.185	0.206	0.219	0.266
	(0.074)	(0.078)	(0.066)	(0.056)
× Log GDP *per capita*		−0.067		−0.169
		(0.056)		(0.054)
Technology-year fixed effects	Yes	Yes	Yes	Yes
Country-year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Mean of dependent variable	0.432	0.432	0.162	0.162
ß [US ethnic share]/DV mean	0.429	0.478	1.351	1.639

Note. See Tables 3 and 4.

ethnic region from the sample one at a time. These results also prove quite similar. Most important, all of the firm-level explanatory factors are very robust across variants. The only exception is a weaker relationship of collaborative patents to ethnic inventor shares when excluding Europe and including firm fixed effects; on the other hand, the importance of own-ethnicity patenting in this setting rises. This heightened connection of US ethnic inventors to joint ethnic patenting when excluding Europe is not very surprising and could simply indicate that ethnic linkages are less important for US corporations when establishing R&D operations in Europe, or that we are able to measure these ethnic linkages less precisely and, in some real sense, the process of assimilation links these two possible factors together. Excluding Europe has a larger impact on our country-level covariates, although the central connection of collaborative patenting to settings where the rule of law and IPR protections are weak remains quite prominent.

The recent literature on international knowledge spillovers often highlights special US connections for China and India (Branstetter *et al.*, 2015; Breschi *et al.*, 2015; Freeman and Huang, 2015). Given their high-profile nature, we also test dropping the Chinese and Indian regions at the same time in these online Appendix Tables. We find overall very similar results when jointly excluding these two countries. It is worth noting that our panel begins well before the very large rise of these two countries, and so generally they are not that pivotal to our analysis – although they do fit the concepts and overall patterns quite well. This parallels similar findings by

Miguelez (2013) about the broad applicability of diaspora for co-invention networks beyond the China and India cases.

2.2. *Role of Cross-border Mobility within Firms*

Table 6 next layers inventor migration into these analyses. Column 1 of Table 6 repeats our base estimation for collaborative patents from column 4 of Table 3. Columns 2–4 then separate this outcome variable into three mutually exclusive, collectively exhaustive categories:

(*i*) collaborative patents that include a within-company move of one or more inventors across borders;
(*ii*) collaborative patents that do not include an internal move but have one or more inventors that have moved across borders outside of the firm; and
(*iii*) collaborative patents for which we have no evidence of a move.

Given this data structure, the coefficients and means of the dependent variables across columns 2–4 add up to column 1.

Focusing on the country traits, some very intriguing differences are evident. First, the negative partial correlation associated with a country having low English proficiency works entirely through a reduced likelihood of a collaborative patent that does not involve a cross-border mover, with no impact for the cases where mobile inventors are present in the team. This is quite consistent with these mobile team members lowering entry barriers connected to language, business practices and so on. By contrast, companies are less likely to have a within-firm mover involved in the team, relative to the other collaborative forms, when distance to the US is greater or when the foreign location does not offer extensive patenting in the same field. This particular reduction could descend from less inherent advantage to shifting the resource over locations or to lower supply of potential movers within the firm.

Looking at the firm-level traits, bigger patenting firms appear to exploit internal moves much more than small firms, with increases in firm size almost exactly balanced on the two margins of columns 2 and 4 (i.e. teams using internal moves *versus* teams with no movers evident). This is interesting but it should be treated with caution given the obvious issue of us measuring mobility through the patent data itself. It could be that firms with few patents are still transferring employees across locations but that they do not show up in our patent data until they are located in the US. To disentangle these features fully, we would need to access broader employment records of the firms. That said, we find it unlikely that this strong symmetry on the two margins would be purely due to measurement error. Just as interesting, the connection of collaborative patents to the ethnic share of US domestic inventors appears most prominently, in relative terms, for teams where external-to-company moves are evident.

Columns 5–8 have a similar structure for own-ethnicity collaborative patents; to keep a manageable number of divisions, we do not distinguish here whether the cross-border mover(s) is the same individual or not as the inventor(s) with the own-ethnicity connections. The results are overall quite comparable, with the most noticeable difference being that distance shows its most important impact in the collaborative teams that do not include a moving individual. In other words, the establishment of a

Table 6

Collaborative Patenting and Inventor Mobility

	Dependent variable is (0,1)for collaborative patent with indicated traits:				Dependent variable is (0,1) for own-ethnicity collaborative patent with indicated traits:			
	Base estimation	Include a within-company move	Include an external-to-company move	Does not include a move	Base estimation	Include a within-company move	Include an external-to-company move	Does not include a move
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country traits								
Log GDP *per capita*	0.086	0.028	0.010	0.049	0.028	0.019	0.006	0.003
	(0.029)	(0.018)	(0.006)	(0.026)	(0.043)	(0.020)	(0.006)	(0.025)
(0,1) low English proficiency	−0.042	0.028	0.004	−0.073	0.017	0.034	0.002	−0.019
	(0.026)	(0.030)	(0.011)	(0.027)	(0.039)	(0.022)	(0.005)	(0.020)
Log distance to US	−0.037	−0.051	0.012	0.002	−0.082	−0.023	0.004	−0.063
	(0.035)	(0.033)	(0.005)	(0.032)	(0.035)	(0.016)	(0.006)	(0.020)
Rule of law, six-point scale with six being highest	−0.062	−0.027	−0.010	−0.025	0.020	0.001	−0.007	0.026
	(0.020)	(0.019)	(0.006)	(0.019)	(0.042)	(0.018)	(0.006)	(0.020)
IPR protection, five-point scale with five being highest	−0.126	−0.054	0.003	−0.075	−0.061	−0.028	0.000	−0.034
	(0.030)	(0.031)	(0.010)	(0.032)	(0.033)	(0.020)	(0.005)	(0.018)
Log patents *per capita* that are filed in USPTO system	0.003	0.008	0.000	−0.005	−0.020	−0.004	−0.001	−0.015
	(0.017)	(0.016)	(0.004)	(0.016)	(0.020)	(0.009)	(0.003)	(0.011)
Share of national patenting conducted in same field	−0.377	−0.819	0.093	0.349	−0.369	−0.658	0.022	0.267
	(0.336)	(0.261)	(0.067)	(0.448)	(0.306)	(0.187)	(0.043)	(0.255)
Firm traits								
Years since firm began patenting in foreign location	−0.016	−0.006	0.000	−0.010	−0.005	−0.002	0.000	−0.003
	(0.004)	(0.004)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
Years since firm began patenting abroad	−0.004	0.002	−0.003	−0.003	0.001	0.001	−0.001	0.001
	(0.004)	(0.003)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
Log patent count by firm worldwide in year	0.005	0.018	0.003	−0.016	0.002	0.012	0.001	−0.011
	(0.008)	(0.005)	(0.003)	(0.006)	(0.007)	(0.004)	(0.002)	(0.004)
Ethnic share of domestic US inventors in year	0.211	0.044	0.047	0.119	0.253	0.064	0.029	0.160
	(0.055)	(0.050)	(0.018)	(0.055)	(0.059)	(0.032)	(0.013)	(0.039)

Table 6
(*Continued*)

	Dependent variable is (0,1)for collaborative patent with indicated traits:				Dependent variable is (0,1) for own-ethnicity collaborative patent with indicated traits:			
	Base estimation	Include a within-company move	Include an external-to-company move	Does not include a move	Base estimation	Include a within-company move	Include an external-to-company move	Does not include a move
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.432	0.110	0.022	0.299	0.162	0.056	0.010	0.096
ß [years in location]/DV mean	−0.037	−0.050	−0.004	−0.035	−0.033	−0.042	0.015	−0.033
ß [US ethnic share]/DV mean	0.488	0.403	2.147	0.398	1.556	1.147	2.804	1.657

Notes. See Tables 3 and 4. Estimates separate collaborative patents by whether a member of the collaborative patent team appears to have moved across borders, either within the company or outside of it. Within-company moves are identified through the inventor patenting with the same firm in multiple countries; external-to-company moves are identified through inventors moving across firms and borders. Inventor moves are determined through the upper-bound designations from Li *et al.* (2014). The online Appendix shows very similar outcomes using lower-bound designations. Columns 2–4 add up to column 1, and columns 6–8 add up to column 5.

long-distance own-ethnicity collaboration typically involves a within-company or external move. These estimations use the upper-bound designations of Li *et al.* (2014) for defining unique inventors, and online Appendix Table A8 shows very similar results when using the lower-bound designations. Online Appendix Table A9 also shows very similar results when incorporating firm fixed effects into the analyses.

In summary, inventor mobility within and outside of firms clearly connects to collaborative patenting, although it does not fully explain it (and likewise collaborative patenting does not fully explain inventor mobility choices). The reported contrasts with respect to the traits of foreign countries and the characteristics of sponsoring firms are both fascinating and intuitive. We hope that future research picks up on these themes and builds them out, as several of these moderating factors are worthy of their own study (in addition to some we have yet to identify).

2.3. *Consequences of Global Collaborative Patents*

We turn next to a quantification of the traits of global collaborative patents compared to the other patents filed by US public companies at the USPTO. To this end, we build a larger sample that also includes the domestic patents filed by these companies. We estimate a linear regression of the form:

$$Y_p = \boldsymbol{\eta}_{jt} + \boldsymbol{\psi}_{ft} + \beta(0,1)Collaborative_p + \gamma(0,1)ForeignNonCollaborative_p + \epsilon_p, \qquad (2)$$

where p again indexes patents. The dependent variable Y_p is one of a set of standard traits about patents that we consider. The two regressors in our base estimations are indicator variables for a collaborative patent (global inventor team) and for a foreign non-collaborative patent. The vector $\boldsymbol{\eta}_{jt}$ contains technology-year fixed effects, and the vector $\boldsymbol{\psi}_{ft}$ contains firm-year fixed effects. The β and γ coefficients are thus measured against patents for the firm where all inventors are located in the US. The estimates are unweighted, have around 400,000 observations for most traits and cluster standard errors by firm.

Table 7 considers the traits of collaborative and non-collaborative patents observable at the time of patent grant, in comparison to patents granted to inventor teams where all workers are in the US. Column headers indicate the specific trait considered. Panel (*a*) presents the means of the studied traits for reference. Throughout this Table and the next Table, caution should be exercised when considering these means, as the patents in the groups may come from different technology areas and time periods. In most cases, regardless, the group means closely align with the regression analyses. Panel (*b*) then provides a specification (2) with just technology-year fixed effects, while panel (*c*) includes both technology-year and firm-year fixed effects. In both cases, we provide the β and γ coefficients that compare collaborative and non-collaborative international patents to US domestic patents. We likewise report the relative effects of the β and γ coefficients to the average value observed for US domestic patents. Finally, we report the t-test for a linear difference between the collaborative and non-collaborative coefficients ($\beta - \gamma$). Values greater than two indicate that the collaborative coefficient is statistically larger than the non-collaborative coefficient, and the opposite is true for values less than negative two.

Table 7

Traits of Collaborative Patents at the Time of Patent Grant, Comparison to US Domestic Patents

	Number of inventors worldwide	Number of foreign inventors	Number of claims listed	Number of backward citations made	Number of external backward citations made	(0,1) majority of backward citations are self-cites	Originality score for backward citations	Number of subclasses listed	(0,1) for subclasses being a novel combination
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel (*a*): means of groups									
Collaborative mean	4.164	1.604	19.142	14.057	11.862	0.096	0.451	3.646	0.714
Non-collaborative mean	2.107	2.107	15.652	10.173	8.811	0.059	0.387	3.130	0.664
US domestic patent mean	2.452	0.000	16.869	12.809	10.803	0.089	0.455	3.887	0.747
Observations	400,132	400,132	400,072	400,132	400,132	400,132	391,799	400,132	364,477
Panel (*b*): estimation with tech-year fixed effects									
(0,1) Collaborative patent	1.518	1.601	1.462	−0.909	−0.707	0.004	−0.024	−0.047	−0.016
	(0.095)	(0.044)	(0.329)	(0.665)	(0.568)	(0.009)	(0.008)	(0.054)	(0.011)
(0,1) Non-collaborative patent	−0.416	2.103	−1.896	−4.547	−3.691	−0.022	−0.078	−0.338	−0.045
	(0.095)	(0.085)	(0.635)	(0.615)	(0.567)	(0.009)	(0.015)	(0.066)	(0.014)
ß [collaborative]/US patent mean	0.619	n.a.	0.087	−0.071	−0.065	0.045	−0.053	−0.012	−0.021
ß [non-collaborative]/US patent mean	−0.170	n.a.	−0.112	−0.355	−0.342	−0.247	−0.171	−0.087	−0.060
t-test: ß [collab.] − ß [non-collab.] = 0	17.23	−5.79	5.59	5.86	5.39	2.84	4.06	3.95	1.89
Panel (*c*): estimation with tech-year and firm-year fixed effects									
(0,1) Collaborative patent	1.536	1.594	0.983	−1.289	−1.149	0.006	−0.022	−0.075	−0.016
	(0.083)	(0.047)	(0.308)	(0.616)	(0.513)	(0.008)	(0.007)	(0.048)	(0.010)
(0,1) Non-collaborative patent	−0.350	2.121	−1.517	−3.925	−3.229	−0.017	−0.053	−0.251	−0.033
	(0.085)	(0.092)	(0.563)	(0.509)	(0.443)	(0.007)	(0.007)	(0.051)	(0.009)
ß [collaborative]/US patent mean	0.626	n.a.	0.058	−0.101	−0.106	0.067	−0.048	−0.019	−0.022
ß [non-collaborative]/US patent mean	−0.143	n.a.	−0.090	−0.306	−0.299	−0.191	−0.116	−0.065	−0.044
t-test: ß [collab.] − ß [non-collab.] = 0	16.47	−5.77	4.55	4.14	3.87	2.37	3.85	2.71	1.34

Notes. Table compares traits of collaborative patents with global inventor teams, non-collaborative patents where inventors are exclusively located outside the US and domestic patents where all inventors are located in the US. The sample is comprised of patents filed by US public companies entering into patenting abroad after first patenting in the US. The sample includes industrial patents with application years between 1985 and 2005, building off of patents granted up to May 2009. Technologies are defined at the sub-category level of the USPTO system. Regressions are unweighted and cluster standard errors by firm.

Columns 1 and 2 of Table 7 begin with some simple statistics about the number of inventors listed on the patent. As shown earlier in Figures 3(*a*) and (*b*), it is clear that collaborative foreign patents have a larger number of inventors per patent than the two other types. On average, they have 4.2 inventors per patent, compared to 2.5 for domestic patents. Some of this difference reflects technology and time period differences but a difference of about 1.5 inventors remains in the regression-based formats. Column 2 shows that non-collaborative patents have a larger number of foreign inventors than collaborative patents, while unreported estimates show that the domestic teams of collaborative and US-based inventor teams are pretty similar in terms of size. Put differently, exclusively US-based inventor teams tend to be larger than exclusively foreign-based inventor teams. Collaborative patents retain almost all of the typical US-based team size and add a little more than 1.5 foreign inventors on average, for a much larger total invention team.

Columns 3–9 of Table 7 provide additional traits of patents that are observable at the time of the patent grant. Column 3 considers the number of claims that the patent makes, which some prior work takes as an indicator of patent quality. There is a strict ordering in this case: collaborative patents, followed by US domestic teams, followed by non-collaborative foreign teams. The relative effects are on the order of 5–10% and are statistically significant.

Columns 4–7 consider metrics based upon the backwards citations the patent makes to prior work. We consider the total number of citations, the number of citations made to prior external work outside of the firm producing the focal patent, whether the majority of the backward citations are to the firm's own prior work and finally an originality score for the firm's backward citations. The originality score follows Hall *et al.* (2001) as one minus a Herfindahl index over the technology classes that are cited in the patent. A larger score on the originality index indicates that the patent draws from a broader distribution of prior technologies in its work. One pattern is strongly evident across these four metrics: non-collaborative patents display a smaller number of citations and a narrower cited technology base compared to collaborative patents or to US domestic patents. Collaborative patents also tend to display more of these features compared to US domestic patents, but these differences are substantially weaker in economic size and statistical strength.

Columns 8 and 9 next look at the subclasses of technologies listed on the patent. Each patent lists one or more patent technology subclasses, which is the most detailed level of the USPTO system with over 150,000 separate technologies identified. Non-collaborative foreign patents tend to have fewer listed subclasses, while the other two types of patents are comparable to each other. Non-collaborative patents are also less likely to have a novel combination of subclasses (Strumsky *et al.*, 2011, 2012; Akcigit *et al.*, 2013), while collaborative patents are marginally less than US domestic patents. Thus, at the time of application, the traits of collaborative patents typically fall in between those of patents with exclusively US- or foreign-based teams, with collaborative work usually looking more like US-based teams. The most noticeable exceptions are team size and the number of patent claims being made, where collaborative patents rank substantially higher than either of the other groups.

Table 8 continues this estimation approach and considers the forward citations that the various types of patents receive. In this context in particular, the focus should be on

Table 8

Traits of Collaborative Patents in Terms of Forward Citations Received, Comparison to US Domestic Patents

	Count of forward citations received	Count of forward citations, normalised	Generality score of forward citations	External citations received: Total count	External citations received: Count outside of US	External citations received: Count inside of US	Internal self-citations received: Total count	Internal self-citations received: Count outside of US	Internal self-citations received: Count inside of US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel (*a*): means of groups									
Collaborative mean	9.646	1.250	0.404	8.276	2.204	6.071	1.383	0.220	1.163
Non-collaborative mean	7.327	0.991	0.355	6.271	2.032	4.239	1.072	0.405	0.667
US domestic patent mean	11.603	1.175	0.442	9.895	2.244	7.461	1.726	0.081	1.645
Observations	393,174	393,174	393,174	393,174	393,174	393,174	389,069	389,069	389,069
Panel (*b*): estimation with tech-year fixed effects									
(0,1) Collaborative patent	0.884	0.065	−0.009	1.002	0.461	0.540	−0.119	0.146	−0.266
	(0.399)	(0.054)	(0.010)	(0.368)	(0.086)	(0.356)	(0.127)	(0.029)	(0.111)
(0,1) Non-collaborative patent	−1.786	−0.184	−0.057	−1.383	0.230	−1.613	−0.400	0.332	−0.732
	(0.371)	(0.072)	(0.012)	(0.316)	(0.150)	(0.275)	(0.144)	(0.058)	(0.108)
ß [collaborative]/US patent mean	0.076	0.055	−0.020	0.101	0.205	0.072	−0.069	1.802	−0.162
ß [non-collaborative]/US patent mean	−0.154	−0.157	−0.129	−0.140	0.102	−0.216	−0.232	4.099	−0.445
t-test: ß [collab.] − ß [non-collab.] = 0	5.67	4.19	4.12	5.49	1.48	5.44	2.58	−4.17	5.58
Panel (*c*): estimation with tech-year and firm-year fixed effects									
(0,1) Collaborative patent	0.769	0.038	−0.008	0.815	0.404	0.411	−0.048	0.112	−0.160
	(0.382)	(0.045)	(0.009)	(0.359)	(0.098)	(0.342)	(0.071)	(0.020)	(0.061)
(0,1) Non-collaborative patent	−1.747	−0.202	−0.045	−1.463	0.124	−1.587	−0.287	0.281	−0.568
	(0.242)	(0.047)	(0.006)	(0.223)	(0.100)	(0.188)	(0.082)	(0.042)	(0.073)
ß [collaborative]/US patent mean	0.066	0.032	−0.018	0.082	0.180	0.055	−0.028	1.383	−0.097
ß [non-collaborative]/US patent mean	−0.151	−0.172	−0.102	−0.148	0.055	−0.213	−0.166	3.469	−0.345
t-test: ß [collab.] − ß [non-collab.] = 0	7.01	3.64	4.23	6.68	2.31	6.15	2.50	−3.80	5.01

Notes. See Table 7. Columns 1–3 present worldwide counts and traits of citations received by the patent. Normalised counts divide the citation count by the average for the patent class and application year. Columns 4–6 present traits of citations made by patents external to the original assignee, while columns 7–9 present traits internal to the original assignee. The sample in columns 7–9 is conditional on at least some patenting later being conducted by the assignee. Counts of citations in columns 5–6 and 8–9 allow citing patents with inventors in multiple countries to be counted twice.

the regression-based analysis since these forward citations accumulate with time. As collaborative patents are a much more recent phenomenon, their raw citation counts tend to be naturally lower. Column 1 begins with the total count of forward citations received. Column 2 provides a normalised count where the raw count is divided by the average for that patent class and application year (the difference to the technology-year fixed effects is that the sub-category level used for technology-year fixed effects is more aggregated at 36 divisions *versus* over 450 patent classes). Non-collaborative patents have lower future citation counts than domestic or collaborative patents. There is some suggestive evidence that collaborative patents may also outperform their domestic peers but this effect is not statistically significant in column 2. Column 3 reports a generality index, which is the mirror image of the originality index in Table 7. Non-collaborative patents tend to be cited by a more concentrated technology set in the future.

Columns 4–9 of Table 8 next disaggregate the patent's forward citations on two dimensions:

(*i*) internal *versus* external to the patenting firm and
(*ii*) inside *versus* outside the US.

External citations are often used to assess the value or broader impact of patents. Internal citations provide insights on the degree to which the firm itself builds upon the focal invention. This may differ across firm locations due to awareness of inventions, priorities established for technological development and other reasons. The sample in the latter three columns is restricted to cases where we observe at least one subsequent patent by the firm in a later year than the focal patent's application year, so that there is at least some opportunity for an internal citation to occur. Given that our focus is on large public firms with high patent frequency, this restriction is not very important.

Column 5 shows that collaborative and non-collaborative patents receive more non-US external citations than domestic-only patents. Collaborative patents may, if anything, have an edge in this dimension compared to non-collaborative patents but these differences are small and statistically weak. By contrast, column 6 shows a substantial reduction in the external impact within the US for non-collaborative patents. Thus, the location of the inventors within the firm correlates strongly with the location where the external impact of the patent is experienced, and a distributed team of collaborative inventors connects with external impacts both within and outside of the US.

Columns 7–9 show a mostly similar pattern for impacts within the firm as measured by future self-citations. Column 8 again shows that inventors outside of the US, now the firm's own inventors, build more on work that was conducted with inventors outside of the US. Likewise, column 9 again shows that inventions developed with inventors in the US have a greater subsequent impact on the firm's US-based inventions. The main difference to columns 4–6 comes through the relative position of the collaborative patents. For external impact, collaborative patents display a 'best of both worlds' coefficient pattern that indicates greater impact in both locations than is seen for patents created by exclusively domestic or foreign teams. For internal impact, a trade-off instead exists. Collaborative patents have more impact for the firm's future technology development outside of the US than patents by an exclusively US-based team but less than those by an exclusively foreign team. The opposite is true for the firm's future technology development in the US and these differences are all statistically significant.

We turn now to several robustness checks and extensions on the patterns. First, we return to the team size estimates that started Table 7. Throughout Tables 7 and 8, the relative effects are meaningful in size but not extraordinary, often of the order of 10–20%. In most cases, we also observe a performance advantage for collaborative patents. A natural question is the degree to which these advantages come from different inputs into collaborative patents (e.g. R&D dollars, managerial attention). While we generally do not observe these inputs, we do observe the inventor team size. Inventor team size for collaborative patents tends to be 60% (or more) larger than for the other types of patents. Thus, estimates that measure traits on a 'per inventor' basis (e.g. forward citations per inventor) will find an underperformance by collaborative patents. We hesitate to make such an adjustment for two reasons. First, we do not know the amount of time each inventor placed into the effort and it could be that larger team size comes with fewer hours per inventor. Second, we also lack a very clear scale for measuring the complete return differences to the firm across these traits (e.g. it is not clear whether a 10% higher rate of internal citations translates into more or less than 10% of internal benefits to the firm).

Nonetheless, to provide some basis for this comparison, panel (*a*) of Table 9 extends panel (*c*) of Table 8 to include inventor team size-year fixed effects.[8] For these fixed effects, we code the maximum team size at 5+ inventors on a patent. As per the prior discussion, this additional control weakens (and in some cases eliminates) many of the differences observed between domestic US patents and those with collaborative teams. In other words, similarly-sized teams of exclusively US-based inventors perform more like those of collaborative patents. On the other hand, the differences between these groups and non-collaborative foreign inventors remain. It is thus important to keep the differences in inventor contributions in mind when noting the performance advantages of collaborative patents but the big differences compared to exclusively foreign inventor teams are not explained by the adjustment.

Panel (*b*) of Table 9 provides a second extension. We modify the analysis to consider own-ethnicity collaborations (i.e. at least one US-based inventor matches the ethnic region of the firm's overseas inventors) versus those across ethnic lines. We do not have a very strong prior about the direction of these patterns. For example, one could hypothesise that ethnic-based collaborations improve communication across borders and thereby boost patenting outcomes. However, it seems equally plausible that some of the potential team diversity benefits are lost in own-ethnicity collaborations. The results in panel (*b*) of Table 9 suggest that own-ethnicity collaborations have somewhat stronger external and internal impacts in the US, with the differences outside of the US more muted.

[8] For completeness, online Appendix Table A10 documents this exercise and the next three extensions for the initial traits of patents evaluated in Table 7. Similarly, Appendix Table A11 includes two extra outcome variables (i.e. normalised forward citation counts, generalised score of forward citations) not reported in Table 9.

Table 9

Extensions on Table 8

	Count of forward citations received	External citations received: Total count	External citations received: Count outside US	External citations received: Count inside US	Internal self-citations received: Total count	Internal self-citations received: Count outside US	Internal self-citations received: Count inside US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel (*a*): panel (*c*) of Table 8 with team size-year fixed effects							
(0,1) Collaborative patent	−0.086	0.163	0.283	−0.121	−0.252	0.106	−0.358
	(0.399)	(0.373)	(0.103)	(0.346)	(0.078)	(0.021)	(0.068)
(0,1) Non-collaborative patent	−1.532	−1.299	0.154	−1.453	−0.237	0.283	−0.519
	(0.240)	(0.219)	(0.101)	(0.180)	(0.081)	(0.042)	(0.071)
Panel (*b*): panel (*c*) of Table 8 with separate ethnicity-based collaborative interactions							
(0,1) Own-ethnicity collaborative patent	1.334	1.243	0.242	1.000	0.090	0.123	−0.033
	(0.614)	(0.566)	(0.145)	(0.631)	(0.103)	(0.031)	(0.091)
(0,1) Other collaborative patent	0.417	0.548	0.504	0.044	−0.134	0.105	−0.239
	(0.484)	(0.454)	(0.123)	(0.373)	(0.094)	(0.025)	(0.089)
(0,1) Non-collaborative patent	−1.748	−1.463	0.124	−1.588	−0.287	0.281	−0.568
	(0.243)	(0.223)	(0.100)	(0.189)	(0.082)	(0.042)	(0.074)
Panel (*c*): panel (*c*) of Table 8 with separate non-US collaborative interactions							
(0,1) Collaborative patent	0.773	0.818	0.403	0.414	−0.047	0.111	−0.159
	(0.382)	(0.359)	(0.098)	(0.341)	(0.071)	(0.020)	(0.061)
(0,1) Foreign non-collaborative patent	−1.689	−1.408	0.117	−1.525	−0.282	0.271	−0.553
	(0.244)	(0.228)	(0.101)	(0.193)	(0.082)	(0.037)	(0.072)
(0,1) Foreign collaborative patent	−2.711	−2.321	0.211	−2.532	−0.403	0.391	−0.795
	(1.206)	(1.183)	(0.186)	(1.086)	(0.152)	(0.135)	(0.154)
Panel (*d*): panel (*c*) of Table 8 with separate internal migration collaborative interactions							
(0,1) Collaborative patent with inventor migrating internationally within firm	1.062	1.106	0.207	0.899	−0.043	0.104	−0.147
	(0.764)	(0.738)	(0.194)	(0.836)	(0.151)	(0.028)	(0.132)
(0,1) Other collaborative patent	0.731	0.814	0.540	0.274	−0.086	0.123	−0.209
	(0.472)	(0.442)	(0.129)	(0.350)	(0.077)	(0.024)	(0.065)
(0,1) Non-collaborative patent	−1.836	−1.502	0.116	−1.618	−0.336	0.248	−0.584
	(0.248)	(0.233)	(0.104)	(0.199)	(0.073)	(0.037)	(0.072)

Notes. See panel (*c*) of Table 8. Panel (*a*) further includes inventor team size-year fixed effects, with a category maximum of 5+ inventors on a team. Panel (*b*) separates the collaborative patent regressor by whether the ethnicity of the US-based inventor matches that of the foreign region. Panel (*c*) separates the non-collaborative regressor by whether the foreign inventor team is located in two or more non-US countries. Panel (*d*) separates the collaborative patent regressor by whether or not the inventor team includes a within-firm inventor migration. Panel (*d*) also includes fixed effects for a collaborative patent with an external-to-the-firm inventor move and main effects for patents with these types of movements, which are reported in online Appendix Table A11.

Panel (*c*) of Table 9 reports estimations that isolate multi-country non-US inventor teams within our patent pool that do not contain US-based inventors. It is important to remember here that these are only US-based companies, and thus we are not considering inventor teams for Siemens, Sony, Nokia etc. that have foreign-based headquarters. The very interesting outcome is that these foreign collaborative teams perform even more unlike US-connected collaborative patents than the foreign patents that have teams in a single location. In terms of initial traits, which are reported in online Appendix Table A10, these patents with non-US multi-country teams look pretty much the same as patents produced by teams located in a single non-US country, excepting inventor counts. But looking forward, these non-US multi-country teams are even less likely to have an external or internal impact in the US and even more likely to have external impact outside the US than the foreign teams that are located in a single country.

We do not seek to explain this pattern in detail, as the results are not precise enough to make a big fuss about just yet. We are able to conclude from this exercise that the differences we observe for collaborative patents with US-connected teams are not due to generic features that come from multi-country teams, which is an important fact to highlight. An important avenue for future work is to assemble a deeper data set with multinational companies headquartered in many countries and then test more broadly this phenomena with information about country pairs and headquarters. Such a platform would likely require incorporating non-USPTO patents. This would be the necessary next step to begin separating whether the patterns we observe descend from a US fixed effect (which would hold true for a Sony or Siemens patent involving an inventor team located in France and the US) or a feature that relates to the collaborative team being connected to the headquarters country (which happens in this case to be the US). Based upon case studies and anecdotal evidence, we suspect the latter factor is the more important of the two but this remains an open question.

Online Appendix Table A11 considers whether these outcomes are heightened or diminished by the role of internal transfers being a part of the inventor team. We allow separate indicators for collaborative patents with an internal-to-the-firm transfer and collaborative patents with no evidence of cross-border mobility. We also include fixed effects for a collaborative patent with an external-to-the-firm inventor move and main effects for patents generally that include these types of mobile inventors; these additional elements are imprecisely estimated and reported in online Appendix Table A11. The robust insight is that our collaborative patenting results are evident in both types of collaborative patents, validating the results as a general feature of the collaboration process. The point estimates might also suggest that internal-to-the-firm mobility is associated with greater forward knowledge use in the US by the firm and a smaller differential to foreign patents outside of the US. These differences, however, are far from statistically significant and are at best indicative of what might lie ahead as bigger samples and longer time horizons emerge. We also believe that truly answering these questions requires marrying patent data with cross-border employment records for multinational firms (Choudhury, 2015) to provide a more comprehensive view of inventor teams and mobility.

Finally, the recent nature of these collaborative patents raises the potential for our results to be sensitive to how one handles the citation truncation at the end of the sample period. An alternative approach to controlling for technology-year fixed effects is to explicitly create uniform time horizons over which future citations are calculated. We implement both three- and five-year horizons in online Appendix Table A12. The comforting conclusion from those extensions is that the effects remain very similar with all of these alternative treatments. Further, a comparison of the quantified relative impacts across the shorter time horizons with our full-horizon effects also suggests that there is no obvious trend to these outcomes over the time span used, with some margins growing while others shrink modestly.

3. Conclusions

The globalisation of innovation is proceeding at an exceptionally fast pace. Many US public companies conduct significant overseas R&D and global inventor teams have become surprisingly prominent – on average, 6% of the worldwide patents of US multinational corporations in 2004. We find that the ethnic composition of the firm's US-based inventive workforce is an important factor in whether the firm engages in international collaboration. Collaborative patents are also frequently observed when a US public company is entering into a new foreign region for innovative work. This is particularly true in markets where intellectual property protections are weak. In a large fraction of these cases, an inventor moving across borders within the firm is evident. On the whole, the strategy appears to be a sound one. Collaborative patents tend to perform similarly to patents developed by the same companies using exclusively US-based teams and both of these groups are stronger than those developed with exclusively foreign inventor teams. The nature and location of the inventor team has lasting effects on how the patent is used within the firm and the degree to which the firm's subsequent inventive efforts build upon the technologies.

There are several important managerial implications from this work. First, it emphasises the importance of forethought about team design and goals for innovative work when spreading overseas. One often hears discussions of cheaper R&D being conducted abroad and many firms and managers later express disappointment at the results achieved. Our work shows that collaborative teams may provide a particularly attractive middle ground to this trade-off, even beyond the facilitation of initial entry. Second, our citation analysis reveals the imperfect sharing of knowledge across units within multinational companies. This is commonly discussed with respect to operational issues and our citation work goes further and emphasises it with respect to knowledge creation and the ability of inventors to build upon the past work of the firm. Managers desiring to increment their firm's knowledge base both domestically and abroad may need to staff projects with inventors from both locations. In general, our findings emphasise the importance of actively building absorptive capacity for knowledge within organisations across the firm's own units.

In terms of policy implications, some fairly clear themes emerge that are not exclusive to this work–for example, better rule of law and IPR protection encourage better scientific integration with the US through these multinationals, though there are many other justifications for these policy objectives, too. More distinctive to our work and related studies like Miguelez (2016) and Branstetter *et al.* (2015) is the emphasis on cross-border migration for influencing technology transfer across countries and the building of local bases for innovation. The results of this study do not build a conclusive case for 'brain gain' type effects due to out-migration, as we do not conduct detailed counterfactual analyses of what could have occurred had the individuals stayed (Agrawal *et al.*, 2011; Breschi *et al.*, 2015). That said, our study makes clear that use of cross-border teams is a very attractive technique for multinationals conducting innovation abroad and careful thought by nations about short-term travel policies, multinational employee transfer visas and similar features may have a big impact as multinationals weigh their options.

Looking forward, more research is certainly worthwhile in this emerging domain. To revisit some of the pieces highlighted, we see particular advantages in efforts to unite patent data with internal employment records of multinationals. This work can be in the form of single-company studies or utilisation of large-scale employer-employee data sets that are becoming available. Second, we hope that future work can build a platform that includes many countries and multinationals headquartered in many locations. Such a framework would allow us to separate the particular importance of headquarters locations from the fixed attributes of some nations for inventive work. Going beyond, most studies in this domain focus on patent- or country-level traits and more explicit consideration of a firm's overall strategy to multinational innovation is desirable. This would be especially powerful if linked to information on operational data and other performance outcomes.

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Additional Supporting Information may be found in the online version of this article:

Appendix A. Additional Empirical Results.
Data S1.

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