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Non-Ethnic Inventor Sourcing of Immigrant Knowledge: The Role of Social Communities

Larissa Rabbiosi, Francesco Di Lorenzo, Anupama Phene, and Paul Almeida

Introduction

The international business literature suggests that global migration stimulates a process of knowledge circulation and includes several studies of the effects of knowledge flows related to immigrant inventors' innovative activities (e.g., Breschi et al., 2017; Choudhury, 2016; Oettl & Agrawal, 2008). This strand of work has focused so far largely on flows of knowledge enabled by ethnic ties between the immigrant inventor and his or her home country (Agrawal et al., 2008; Kerr & Lincoln, 2010; Saxenian, 2002). Work along these lines explores different types of ethnic community related knowledge flows—those that occur within broad ethnic communities (including flows from different locations worldwide), flows within the ethnic community in the immigrant inventors' host country, and flows within ethnic communities which include

L. Rabbiosi • F. Di Lorenzo (✉)
Copenhagen Business School, Copenhagen, Denmark
e-mail: lr.si@cbs.dk; fdl.si@cbs.dk

A. Phene
George Washington University, Washington, DC, USA
e-mail: anuphene@gwu.edu

P. Almeida
Georgetown University, Washington, DC, USA
e-mail: almeidap@georgetown.edu

A. I. Mockaitis (ed.), *The Palgrave Handbook of Global Migration in International Business*,
https://doi.org/10.1007/978-3-031-38886-6_19

home and host country members (Almeida et al., 2015; Breschi et al., 2017; Kapur, 2001; Marino et al., 2020).

Although in the U.S. immigrants from a range of ethnicities have contributed to positive economic gains, several studies highlight the particular influence of Indian and Chinese inventors—and especially in high-technology industries and regions (Kerr, 2007; Wadhwa et al., 2007). Based on their patenting and innovation activities, inventors from India comprise the second largest group (after Chinese inventors) of immigrant scientists and engineers (Saxenian et al., 2002). This significance of Indian inventors for innovativeness in high technology areas in the U.S. points to the importance of understanding the extent to which their innovativeness influences others. Previous studies show that immigrant communities, and Indian immigrant communities in particular, have important influences on entrepreneurship, trade and foreign direct investment (Kalnins & Chung, 2006; Rauch & Trindade, 2002; Shukla & Cantwell, 2018; Sonderegger & Täube, 2010), and that Indian inventors in high technology sectors exploit one another's knowledge and work intensively with fellow immigrants. We know also, that this tends to result in more valuable innovations (Almeida et al., 2015).

However, how ethnic Indian inventors' innovation activity affects their non-ethnic peers has attracted less research attention. It has been shown that inventor teams that include both ethnic and non-ethnic members enable flows of knowledge among team members from different cultures and that this leads to higher levels of knowledge recombination (Choudhury & Kim, 2019). Apart from this effect, we know little about other aspects that facilitate flows of immigrant knowledge held by ethnic inventor communities to inventors outside those communities. We suggest that Indian and other inventors belong to several social communities simultaneously. For instance, Indian inventors belong also to organizational, technological, and geographic communities by virtue of their employment, profession, and geographic location (Boschma, 2005). Drawing on insights from social identity and categorization theories (Tajfel, 1974; Tajfel & Turner, 1986), we suggest that common membership in a community allows non-Indian inventors to source knowledge from their Indian peers. In other words, in the same way that participation in an ethnic community facilitates intra-community flows of knowledge enabled by interaction and increased trust among community members (Almeida et al., 2015), the presence of Indians in other communities increases the chances of knowledge flows among the members of those communities including those belonging to other ethnic groups. Therefore, we suggest that the extent to which non-Indian inventors source knowledge from Indian inventors depends in part on the extent to which non-Indian inventors are exposed to Indians in the same organizational, technological, and geographic communities.

To explore flows of immigrant inventor knowledge outside the ethnic Indian community, we analyze data drawn from U.S. semiconductor industry patents to study the extent to which non-Indian inventors source knowledge from Indian inventors' patented inventions. Our data cover the period 1983 to 1998. Based on these data, we create matched samples of Indian and non-Indian inventors, and measure inventor knowledge sourcing based on backward citations. We use patent data to measure the percentage of Indian inventors in organizational and technological communities and employ U.S. Homeland Security data to measure the percentage of Indian immigrants in the geographic communities that include Indian and non-Indian inventors.

We find that both Indian and non-Indian inventors source knowledge from Indian immigrant inventors (immigrant knowledge), although as expected the extent of this activity is greater among Indian inventors. In line with our hypotheses, we find that for all three communities—organizational, technological, and geographic—a larger presence of Indians results in an increase in the immigrant knowledge sourced by non-Indian inventors. Overall, our results point to the positive role of ethnic Indians for enhancing innovativeness among both Indian and non-Indian inventors. We find that organizational, technological, and geographic communities facilitate knowledge flows both within communities and across the ethnic community boundaries.

We believe that our research makes several contributions. First, empirically, we add to previous research on immigrants and innovation by investigating the influence of Indian inventors' knowledge on other (non-Indian) inventors—an area of enquiry so far less addressed. Second, we highlight the facilitation mechanism provided by organizational, technological, and geographic communities. Third, we provide some implications for firms, managers, and policymakers. We suggest that it is important for managers and firms to be aware of the multiple communities to which their employees belong, and the knowledge flows and innovation activity they enable. Flows of knowledge within social communities that are beyond the firm's boundaries have potentially positive and negative implications for firm competitiveness, and firms should take account of this in their hiring and employee practices. The additional positive effects of immigrant inventors and even immigrant families highlighted by our findings should not be overlooked given the sensitivities of immigration in national policies. Our findings suggest that immigrant inventors contribute to the innovativeness of other inventors and that non-professional family members can also have an influence.

Theory and Hypotheses

Inventors and Social Communities

Innovation rarely happens in isolation (Diemer & Regan, 2022); it tends to be the result of multiple interactions among inventors that allow access to and exchanges of knowledge (Almeida & Kogut, 1999). Research has shown how social communities allow the sharing of norms and values and provide the means for knowledge to circulate (Boschma, 2005; Brown & Duguid, 1991; Cooke & Kemeny, 2017). Ethnic inventors tend to have affiliations with their relevant ethnic community which includes members with the same national, cultural and/or ethnic background (e.g., Almeida et al., 2015; Choudhury & Kim, 2019; Marino et al., 2020). However, inventors participate also in organizational communities (inventors share the same organizational context), technological communities (inventors working in the same technological/research domain) and geographic communities (inventors located in the same geographic space) (Crescenzi et al., 2016). Membership of these social communities allows Indian inventors and non-Indian inventors to meet and interact which makes them important sources of knowledge for both inventor groups.

Kogut and Zander (1992) proposed the idea of the firm as a social community which facilitates flows of knowledge among firm members in a particular location and internationally. For example, in a multinational firm context, organizational membership allows flows of knowledge among members of the multinational in different countries and with different national origins (e.g., Almeida & Phene, 2004; Foley & Kerr, 2013; Rabbiosi & Santangelo, 2013). From a learning and knowledge perspective, not only does the organization evolve and change based on its employees, but the firm's members evolve by learning from the organization. This results in a convergence of learning and knowledge in both the individual and the organization (March, 1991). The firm's structures, systems, and common norms and culture (the organizational community) can promote receptiveness to and absorption of knowledge from different domains.

In addition to organizational communities, technological communities are important for connecting members and facilitating knowledge flows. For example, in the case of inventors with a common culture, early work in this area conducted by Crane (1972) describes how the 'invisible college of scientists' helps to diffuse knowledge beyond the firm's boundaries. Similarly, Rappa and Debackere (1992) demonstrate that verbal exchanges (conversations) between experts in the same technological areas (within and across firms) result in the sharing of information and know-how of interest to all the members of the group. Technological communities allow development and use of a specialized vocabulary, and a common set of routines and cognitive bonds among members (Garud & Rappa, 1994). Inventors' participation in a technological community results in the creation and spread of a distinct epistemic community (Cetina, 1999; Powell & Giannella, 2010) which increases the likelihood of knowledge flows among inventors (e.g., Caragliu & Nijkamp, 2016; Crescenzi et al., 2016).

The third type of social community that affects knowledge flows is based on co-location within a geographic area (Almeida & Kogut, 1999; Boschma, 2005). By creating the conditions for the development of social ties and networks relevant for learning (Jacobs, 1969; Marshall, 1890; Saxenian, 1996), geographic proximity enables effective transmission of knowledge (e.g., Fleming et al., 2007; Lobo & Strumsky, 2008). Co-located invention networks favor access to and exchanges of knowledge (Breschi & Lissoni, 2009). Case studies on regional clusters of small and medium sized firms in Italy (Piore & Sabel, 1984) and Baden-Wuerttemberg in Germany (Herrigel, 1993) indicate the significance of geographic communities for knowledge flows across the firms in those regions. A seminal work by Saxenian (1996) provides an ethnography of engineers located in Silicon Valley, and attributes their success to robust exchanges of knowledge among the individuals and firms in that location.

Individual interaction and trust building based on organizational, technological, and geographical community membership provides opportunities that extend across ethnic community boundaries. The part played by the social communities within these groups in enabling knowledge flows suggests that they may affect the extent to which non-Indian inventors source knowledge from Indian inventors. In the next section, we explore in more depth the conditions rendering non-Indian inventors more likely to source immigrant knowledge in organizational, technological, and geographic communities which cross ethnic community boundaries.

Communities as Mechanisms for Knowledge Flows

The sourcing of knowledge from Indian inventors requires non-Indian inventors to recognize, understand and assimilate immigrant knowledge. Each of these fundamental aspects of knowledge flows benefits from participation of non-Indian inventors in social communities that include Indian inventors.

The opportunities for non-Indian and Indian inventors to interact increases within a social community. Increased presence of Indian inventors in non-Indian inventors' organizational, technological, and geographic communities allows proximity between Indian and non-Indian inventors which promotes direct social interaction. Social relationships among the members of a community facilitate access to information and resources (Owen-Smith & Powell, 2004). These effects are explained by the basic propositions of social identity and categorization theories (e.g., Tajfel, 1974; Tajfel & Turner, 1986). Within each community discernible similarities such as a shared interest in the same technological field promote social bonds and social cohesion within the community and separation from dissimilar others. The social identification of members belonging to the same community increases their ability to recognize and accept the value of others' knowledge and reduces the costs of collaboration and knowledge transfer among members (Brown & Duguid, 2001; Kane, 2010; Kane et al., 2005). Even in the absence of direct interactions, social identification with the community facilitates opportunities for inter-person knowledge flows (Daft & Weick, 1984; Teece & Pisano, 1994). Overall, social proximity among non-Indian inventors and Indians enabled by membership of organizational, technological and/or geographic communities is likely to increase non-Indian inventors' familiarity with Indian inventors' attitudes, approaches, and knowledge, allow a better understanding of the ethnic community and promote greater appreciation of the value of the knowledge possessed by Indians. In turn, this can increase understanding of and receptivity to immigrant knowledge and may induce non-Indian inventors to search across ethnic community boundaries to acquire and use knowledge produced by Indian inventors.

Recognition, understanding and assimilation of immigrant knowledge is likely to depend on the inventor's reasons for participating in social communities. The literature suggests that this might depend on non-rational or instrumental motivations. Non-rational motivations are typical in ethnic communities where flows of knowledge build on social capital. Knowledge flows among members might be altruistic and rely on common values and norms which induce participants to share or transfer resources within the group on the basis of a shared ethnic identity (Almeida et al., 2015; Saxenian & Hsu, 2001), and not necessarily in expectation of a return or a reward (Nahapiet & Ghoshal, 1998). Instrumental motivations for joining a community in the expectation of gaining access to knowledge, are based on calculated and rational expectations and reciprocity. This means that membership of a social community is premised on mutual trust and compliance with the norms of reciprocity, that is, the expectation of some (not necessarily specific) kind of return at some point, for the resources shared (Kurzban & Neuberg, 2015) to avoid social sanctioning by the community (Portes, 1998).

Prior research suggests that participants use organizational, technological and geographic communities to enhance their economic well-being which includes access to innovation related knowledge (Dahl & Pedersen, 2004). For instance, Paruchuri and Awate (2017) demonstrate that inventors source organizational knowledge to support their creation of knowledge. Similarly, Owen-Smith and Powell (2004) describe how to increase their innovativeness individuals and groups working in biotechnology firms use informal collaborations to access knowledge from other institutions including firms, universities and government laboratories. The partner choices made by these individuals depend on the problem to be tackled and the complementary expertise they seek. Scientists collate lists of potential collaboration partners based on their knowledge and expertise and consult them about problems. Rogers (1983) describes the social exchanges among semiconductor engineers in Silicon Valley to share job and work related information useful for their careers and research. Knowledge is the currency allowing entry to these geographically, technologically, and organizationally mediated social groups whose members expect to receive and to provide knowledge. The motivation for this type of community participation appears to be instrumental and based on rational expectations of reciprocal exchanges of useful knowledge. Organizational, technological, and geographic social communities can include membership of multiple ethnicities not necessarily for altruistic reasons but for instrumental reasons related to effective sourcing of useful knowledge. If Indians are a useful source of knowledge in these communities, a larger Indian presence will provide non-Indian inventors with more opportunities to source knowledge.

Communities are also marked by dynamism and while social communities can vary in their degree of parochialism (Bowles & Gintis, 2004) they may enable participation in other communities. Membership in organizational, geographic and technological communities can and does change over time (Qin, 2015). Almeida and Kogut's (1999) work on semiconductor engineers shows that they move across geographic regions and between firms within the same region. As a result, the extent of Indian inventor participation in each of these communities is likely to vary, with consequences for their utility for non-Indian inventors' sourcing of immigrant knowledge.

Taken together, these arguments suggest:

Hypothesis 1: For non-Indian inventors, the sourcing of Indian immigrant inventor knowledge increases with the percentage of Indian immigrant inventors in the same organizational community.

Hypothesis 2: For non-Indian inventors, the sourcing of Indian immigrant inventor knowledge increases with the percentage of Indian immigrant inventors in the same technological community.

Hypothesis 3: For non-Indian inventors, the sourcing of Indian immigrant inventor knowledge increases with the percentage of Indian immigrants joining the same geographic community.

Method

Empirical Context and Data Sources

The Indian community in the U.S. is among the best educated national subgroups and includes many high-skilled science and technology workers, in particular. Since liberalization of its immigration law in 1965, the U.S. has experienced a steady inflow of skilled Indian professionals and students. This migrant inflow can be identified as: "The Early Movers" (1965–1979), Families (1980–1994), and "The IT Generation" (1995 to date) (Chakravorty et al., 2017, p. 29). The first group entered the U.S. based on their education and skills follow which family-related visas became an important entry category, with the families (spouses and children) and immediate relatives (parents, siblings, etc.) moving to join these highly skilled early movers. The third group, the IT workers, occurred due to the large involvement of Indians in computer systems and related services sectors. Their migration was pulled first by the "millennium bug" problem, and later by increased demand for computer and engineering-related labor in the U.S.

Whether early movers or later immigrants, Indians have emerged in the U.S. as a successful ethnic community with a high proportion of doctoral degree holders employed mostly in STEM (science, technology, engineering, mathematics) related jobs (Pew Research Center, 2013). Indian immigrants are contributing to overall U.S. innovative capacity and entrepreneurial activity, and the number of patents co-invented by Indians filed by U.S. firms in high-technology areas has increased (Almeida et al., 2015; Kerr, 2007; Saxenian, 1999). Given their education and work characteristics and their growing representation in patenting and innovation, we use Indian immigrant inventors in the U.S. as our empirical setting to study how and under what conditions immigrant knowledge flows to inventors outside the ethnic community. We focus on the semiconductor industry where ethnic Indian immigrant inventors play an important role.

Our dataset was constructed using the following sources of information. First, the National Bureau of Economic Research (NBER) database of the U.S. Patent and Trademark Office (USPTO) which allows us to identify patent applications by inventors with a U.S. location working in the semiconductor industry. These data are supplemented by information from the U.S. Department of Homeland Security (DHS) on the characteristics of Indian aliens who become permanent U.S. residents (immigrants).[1] We have ZIP (Zone Improvement Plan) codes for Indian immigrants' declared intended place of residence during this time period. We track this information for the period 1983–1997.[2] To compute the distribution of Asian Indians in each U.S. state and county we use U.S. Census data for 1980 and 1990.[3]

Sample

We constructed the sample using the data in Almeida et al. (2015). First, we identified 3228 Indian inventors during the longer period 1981–2002 and their 8984 semiconductor patents. Using NBER and USPTO patent data, we checked whether Indian inventors listed as first patent author were living in a U.S. inventor location during the period of observation. For the same sector and period, we identified 53,671 non-Indian inventors with a U.S. inventor

[1] These Indian permanent residents may be new arrivals or individuals already in the U.S. with temporary non-immigrant status (e.g., F-1, H-1, L-1).

[2] Since 1998, this information has been confidential.

[3] Census data differ from DHS data and refer to "Asian Indians" as individuals who were born in India (observed in the DHS data), American-born individuals with Indian ancestry, and individuals with Indian ancestry born-elsewhere. It is useful to examine the spatial distributions of Asian Indians in the Census data and Indian-born immigrants in the DHS data. Both show (very similar) spatial distribution of Asian Indians and India-born immigrants across U.S. states and counties. In 1990, 61% of Asian Indians were living in the states of California, New York, New Jersey, Illinois, and Texas and in 1983–1997, 62% of India-born migrants to the U.S. were living in the same five states. In 1990, the counties with Asian Indian presence amounting to 25% (and 25% of India-born immigrants) were Queens (New York State), Los Angeles (California), Cook (Illinois), Harris (Texas), Santa Clara (California) and Middlesex (New Jersey).

location listed as first patent author. Second, using NBER and USPTO data we extracted ZIP codes for inventor locations to identify county of residence in the U.S.[4] Then, for all inventors, we constructed yearly information on the community of Indian immigrants in the inventor's county of residence using DHS data. Since DHS data cover the period 1983–1997 and we use lagged values for our independent variables, the dataset resulted in 2184 Indian and 46,373 non-Indian inventors.

In order to control for unobserved factors that might affect patterns and rates of citations to immigrant knowledge by non-Indian inventors, and to achieve an identical number of inventors in both groups, we employed coarsened exact matching (CEM) with a "one-to-one" option. The idea behind this nonparametric matching method is to temporarily coarsen each variable into substantively meaningful groups (i.e., strata) to allow exact matching on the coarsened data, and then to retain only the original (uncoarsened) values of the matched data (Iacus et al., 2009, 2011). Several management and economics studies use CEM to deal with selection challenges (e.g., Azoulay et al., 2010; Campbell, 2012; Di Lorenzo & Van de Vrande, 2019). CEM reduces imbalances among the covariates between the groups of Indians and non-Indians which decreases statistical bias and improves causal interpretation of the effects. Our CEM procedure resulted in an exact matching between Indian and non-Indian inventors based on the following inventor covariates: total number of patents, patenting tenure, share of patents applied for and granted in semiconductor classes, county of residence, and year.[5] The CEM procedure significantly improved the imbalance between the Indian and non-Indian inventor groups; the overall imbalance provided by the L1 statistic moved from L1 = 0.826 to L1 = 0.501. From the initial 2184 Indian inventors, 35% are matched exactly. The resulting dataset at inventor-year level consists of 1528 inventors (764 Indian and 764 non-Indian) located in 116 different U.S. counties and observed between 1983 and 1998 for a total of 2230 observations. Although we test our hypotheses for the sample of matched non-Indian inventors, that is, 764 non-Indian inventors and 1116 observations, we conducted additional analysis and comparisons using the sample of Indian inventor observations.

[4] In order to map to DHS data and create a meaningful location match for Indian inventors we dropped inventors with missing ZIP code information and those with multiple ZIP codes in the same year.

[5] Following previous research using CEM (e.g., Di Lorenzo & Van de Vrande, 2019), we also exact-matched using the variable "matching year" which is the last year in each individual inventor time series and allows comparison and matching of Indian and non-Indian inventors along the selected covariates in the final years observed.

Variables

Our dependent variable is *immigrant knowledge sourced* which captures the knowledge sourced by the focal inventor from Indian inventors in each year. Following Almeida et al. (2015), we consider the inventor's patent portfolio in year t, and examine patents cited (backward citations) in this portfolio during the six years prior to year t. Our measure is the count of patents citing Indian inventors.[6]

Our independent variables consider the focal inventor's exposure to Indians in our three communities. First, we capture exposure to Indian inventors in the focal inventor's organizational community. The variable e*thnic organizational community* is the percentage of Indian inventors in all inventors granted semiconductor patents in the focal inventor's firm in year t − 1. Second, we capture exposure to Indians in the focal inventor's technological community by identifying the focal inventor's primary semiconductor technological class based on the three-digit semiconductor technology class in which the inventor patented the most in year t − 1. The variable *ethnic technological community* is the percentage of Indian inventors in all inventors with patents in the focal inventor's primary semiconductor technological class in year t − 1. Third, we measure the focal inventor's exposure to Indians in the geographic community by considering the focal inventor's county of residence. We include variables for two aspects of geographic community, namely professional and family milieux based on DHS data which classifies Indians transitioning to legal permanent resident status based on "class of admission" (i.e., status to immigrate to the U.S.). Classes of admission are mutually exclusive i.e., an immigrant can be classified in only one class. The U.S. immigration system includes a range of admission classes which fall into the following broad categories: (a) spouses and children of resident aliens or U.S. citizens, (b) other immediate relatives (e.g., siblings, parents) of resident aliens or U.S. citizens, (c) outstanding professionals and skilled workers, (d) other (e.g., refugees). We use categories (a) and (c) to capture the respective exposure to geographically situated Indian families and professionals. The variables *ethnic geographic professional community* and *ethnic geographic family community* are defined as the respective percentages in year t − 1 of outstanding professionals and skilled Indian immigrants in total Indian immigrants, and total Indian spouses and children in total Indian immigrants in the focal inventor's county.

[6]To obtain a more complete picture of immigrant knowledge flows, we also considered patents with at least one Indian inventor and classified these as knowledge sourced from an Indian inventor.

To rule out competing mechanisms we included the following control variables. An inventor's propensity to source knowledge from an ethnic community might be explained by overall knowledge sourcing behavior. Accordingly, we control for knowledge sourced by the focal inventor from the organizational, technological, and geographic communities. *Organizational knowledge sourced by the inventor* is the percentage of backward citations (filed between years t − 6 and t) in the inventor's patent portfolio (in year t) to patents assigned to the focal inventor's firm. Similarly, *technological knowledge sourced by the inventor* is the percentage of backward citations (filed between years t − 6 and t) in the inventor's patent portfolio (in year t) in the inventor's primary three-digit semiconductor technology class. *Geographic knowledge sourced by the inventor* is the percentage of backward citations (filed between years t − 6 and t) to the inventor's patent portfolio (in year t) to inventors living in the focal inventor's state.

At the focal inventor level, we control also for *inventor productivity* which is the total number of patents filed by the inventor between years t − 6 and year t, and *inventor technological breadth* which is the standard deviation of the technological classes in the focal inventor's portfolio of patents applied for in year t − 1. Both these characteristics might influence the inventor's ability to source immigrant knowledge. Since collaborations are important for knowledge sourcing, we control for *inventor collaboration propensity* as the average number of coinventors named on the focal inventor's patents in year t − 1, and *inventor ethnic collaboration propensity* is the average number of Indian inventors (collaborators) named the focal inventor's patents in year t − 1.

Finally, we control for other contextual factors. The sourcing of immigrant knowledge might be influenced by the quality of the knowledge created by Indian inventors and exposure to the Indian community in the county of residence. We include *immigrant knowledge quality* computed as the average number of forward citations received by Indian patents in year t − 1. Based on U.S. census data, for each county we compute the variable *Indian population in county* as the percentage of Asian Indians in the county's total population in year t − 1.

Results

Our variable of interest *immigrant knowledge sourced*, is a count variable characterized by a typical right-skewed citations data distribution which calls for a negative binomial regression model to test our hypotheses. We rule out possible non-independence of observations within groups and estimate robust

Table 19.1 Correlation matrix and summary statistics

Sample of Non-Indian Inventors (*N* = 1116)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Immigrant knowledge sourced														
(2) Ethnic organizational community	0.068													
(3) Ethnic technological community	0.184	0.219												
(4) Ethnic geographic professional community	0.192	0.033	0.125											
(5) Ethnic geographic family community	0.079	–0.009	–0.050	0.178										
(6) Technological flows to inventor	0.064	0.076	0.173	0.040	–0.024									
(7) Organizational flows to inventor	0.093	0.014	–0.001	–0.011	–0.054	–0.046								
(8) Geographic flows to inventor	0.080	0.002	0.083	0.076	0.048	0.008	0.463							

(*continued*)

Table 19.1 (continued)

Sample of Non-Indian Inventors (*N* = 1116)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(9) Inventor productivity	0.378	0.111	0.174	0.158	0.041	0.122	0.097	0.102						
(10) Inventor collaboration propensity	0.148	0.043	0.109	0.056	−0.025	−0.007	0.104	0.059	0.240					
(11) Inventor ethnic collaboration propensity	0.134	0.304	0.120	0.026	−0.002	0.015	−0.006	0.047	0.169	0.354				
(12) Inventor technological breadth	0.381	0.060	0.175	0.113	−0.005	0.061	0.083	0.096	0.574	0.229	0.191			
(13) Immigrant knowledge quality	−0.106	−0.138	−0.445	−0.148	0.076	0.029	−0.016	−0.074	−0.104	−0.102	−0.112	−0.131		
(14) Indian population in county	0.024	0.145	0.312	0.186	0.052	−0.026	−0.015	0.265	0.079	0.068	0.024	0.107	−0.315	
Mean	7.839	0.058	0.054	0.161	0.395	0.503	0.106	0.207	0.896	1.411	0.094	−0.928	2.899	0.013
Std. Dev.	22.202	0.067	0.024	0.093	0.075	0.293	0.169	0.203	0.795	1.539	0.338	0.647	0.301	0.011

Sample of Indian Inventors (N = 1114)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Immigrant knowledge sourced														
(2) Ethnic organizational community	–0.057													
(3) Ethnic technological community	0.147	–0.030												
(4) Ethnic geographic professional community	0.108	–0.005	0.153											
(5) Ethnic geographic family community	0.018	0.009	–0.008	0.176										
(6) Technological flows to inventor	0.055	0.002	0.180	0.019	0.009									
(7) Organizational flows to inventor	0.067	–0.171	0.033	0.022	–0.077	–0.040								
(8) Geographic flows to inventor	0.099	–0.005	0.097	0.111	0.000	0.025	0.481							
(9) Inventor productivity	0.341	–0.096	0.167	0.085	0.003	0.148	0.129	0.140						

(continued)

Table 19.1 (continued)

Sample of Indian Inventors (N = 1114)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(10) Inventor collaboration propensity	0.137	–0.151	0.054	0.015	–0.054	0.018	0.113	0.065	0.172					
(11) Inventor ethnic collaboration propensity	0.184	0.071	0.208	0.008	–0.008	0.069	0.076	0.032	0.149	0.421				
(12) Inventor technological breadth	0.360	–0.105	0.123	0.123	0.009	0.014	0.105	0.065	0.462	0.220	0.154			
(13) Immigrant knowledge quality	–0.093	0.026	–0.481	–0.126	0.083	0.004	–0.032	–0.061	–0.123	–0.072	–0.116	–0.125		
(14) Indian population in county	0.043	0.107	0.304	0.224	0.042	0.091	–0.051	0.274	0.118	0.095	0.159	0.106	–0.309	
Mean	14.008	0.169	0.06	0.157	0.396	0.551	0.091	0.200	0.965	1.392	0.282	–0.931	2.899	0.013
Std. dev.	45.585	0.214	0.022	0.091	0.078	0.279	0.152	0.203	0.784	1.396	0.582	0.645	0.299	0.011

Correlations greater than 0.050 are significant at least at $p < 0.10$

standard errors and the variance-covariance matrix by clustering at the individual inventor level.

Table 19.1 summarizes the descriptive statistics and correlations of the variables used in our analysis for the samples of non-Indian and Indian inventors.

On average, the extent of immigrant knowledge sourcing is around 7.8 citations for a non-Indian inventor (6.5% of the inventor's total backward citations) and 14 citations (10.6% of the inventor's total backward citations) for an Indian inventor. This suggests that Indian inventors' use of immigrant knowledge is approximately twice that of non-Indian inventors ($p < 0.01$). In terms of potential exposure to Indians in different communities we also find differences between Indian and non-Indian inventors. On average, the possibility of interactions with Indians in the workplace (*ethnic organizational community*) is twice as high for Indian compared to non-Indian inventors (0.169 vs 0.058; $p < 0.01$). The results for the variable *ethnic technological community* and the t-test of mean values (0.054 vs 0.060; $p < 0.01$) suggest that the difference in the exposure to potential interactions with Indians within their technological community between the two groups of inventors is significant but relatively small (0.006).[7]

In relation to the control variables, the results for knowledge sourced from their technological, organizational, and geographic communities, and average number of collaborators are similar for Indian and non-Indian inventors. However, for collaboration with Indian inventors the results differ significantly with Indians more likely to collaborate with other Indians.

Table 19.2 reports the results of our models.

Before discussing our hypotheses, we consider model 1 which includes the full sample, that is, the combined sample of non-Indian and Indian inventors. The coefficient of the dummy variable *Indian inventors* is positive and statistically significant ($p < 0.05$) suggesting that Indian inventors draw more on knowledge patented by Indian inventors than do non-Indian inventors. This result is in line with prior findings which suggest ethnicity facilitates access to and flows of knowledge among co-ethnic group members (Agrawal et al., 2008).

Next, we consider the implications of immigrant knowledge for the sample of non-Indian inventors (models 2–7). Model 2 is the baseline model which includes the control variables. We find that the greater the exposure of non-Indian inventors to Indians in different communities, the greater the amount

[7] There is no difference between Indian and non-Indian inventors in terms of *ethnic geographic professional community* and *ethnic geographic family community* which is as expected due to the exact matching on *county of residence* between Indian and non-Indian inventors which smooths differences at the county level between the two groups.

Table 19.2 Negative binomial regression for ethnic community knowledge sourced by non-Indian inventors

	Full Sample	Sample of Non-Indian Inventors						Sample of Indian Inventors	Full Sample
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Indian inventor	0.388**								0.438***
	(0.157)								(0.150)
Ethnic organizational community			4.486***				3.973**	–0.516**	–0.0614
			(1.464)				(1.545)	(0.253)	(0.260)
Ethnic technological community				28.16***			30.22***	17.44***	23.81***
				(4.814)			(4.808)	(4.284)	(3.747)
Ethnic geographic professional community					2.886*		3.576***	1.401	2.390***
					(1.542)		(1.229)	(0.954)	(0.890)
Ethnic geographic family community						5.021***	3.588***	0.864	2.638**
						(1.154)	(1.085)	(1.488)	(1.060)
Technological flows to inventor	(0.157)	0.572	0.437	–0.104	0.697**	0.677**	–0.0591	0.304	0.176
	0.490*	(0.384)	(0.381)	(0.346)	(0.352)	(0.341)	(0.282)	(0.286)	(0.208)
Organizational flows to inventor	(0.257)	1.965*	1.886	1.778	2.088*	1.753*	1.564*	–1.192**	0.603
	0.515	(1.193)	(1.192)	(1.082)	(1.207)	(1.013)	(0.851)	(0.492)	(0.587)
Geographic flows to inventor	(0.676)	0.502	0.636	0.776*	0.211	0.553	0.678	1.324***	0.823***
	0.955***	(0.537)	(0.534)	(0.467)	(0.510)	(0.529)	(0.431)	(0.392)	(0.310)
Inventor productivity	(0.345)	0.736***	0.706***	0.865***	0.664***	0.722***	0.739***	0.823***	0.790***
	0.766***	(0.116)	(0.117)	(0.100)	(0.107)	(0.102)	(0.0936)	(0.0865)	(0.0652)
Inventor collaboration propensity	(0.0714)	0.0640	0.0907**	0.0793*	0.0615	0.0751*	0.102**	0.0463	0.0694**

	0.0531	(0.0438)	(0.0453)	(0.0469)	(0.0392)	(0.0417)	(0.0418)	(0.0516)	(0.0344)
Inventor ethnic collaboration propensity	(0.0384)	0.172	–0.0689	0.0193	0.249	0.169	–0.113	0.328***	0.182*
	0.287***	(0.169)	(0.181)	(0.152)	(0.190)	(0.153)	(0.182)	(0.119)	(0.0990)
Inventor technological breadth	(0.0977)	0.347***	0.373***	0.221**	0.308***	0.351***	0.219**	0.435***	0.329***
	0.426***	(0.0951)	(0.0947)	(0.100)	(0.0927)	(0.0879)	(0.104)	(0.105)	(0.0803)
Immigrant knowledge quality	(0.0890)	–0.112	–0.106	0.875***	–0.188	–0.377	0.652**	0.414	0.477**
	–0.124	(0.261)	(0.254)	(0.296)	(0.266)	(0.266)	(0.291)	(0.293)	(0.224)
Indian population in county	(0.215)	7.785	1.800	1.339	10.99	10.90	–2.333	–8.540	–4.268
	0.755	(10.57)	(10.51)	(10.91)	(9.511)	(9.627)	(9.964)	(7.389)	(7.031)
Constant	(7.241)	0.736	0.600	–3.630***	0.420	–0.627	–5.280***	–1.490	–3.510***
	1.035	(0.879)	(0.875)	(1.034)	(0.933)	(0.810)	(0.932)	(1.082)	(0.759)
Observations	2230	1116	1116	1116	1116	1116	1116	1114	2230
Clustered Errors	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald Chi2	290.3	204.1	216.1	346.4	235.4	258.1	521.9	256.7	608.9
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of immigrant knowledge sourced by non-Indian inventors. Model 3 supports hypothesis 1. The coefficient of *ethnic organizational community* is positive and significant at $p < 0.01$ suggesting that knowledge sourced from Indian inventors by non-Indian inventors increases with the number of Indian inventor patenting in the organizational context of the focal inventor. In model 4, the coefficient of *ethnic technological community* is positive and significant at $p < 0.01$ suggesting that exposure to Indian inventors is important also in the relevant technological context of the non-Indian inventor; this supports hypothesis 2. Our results also support hypothesis 3 that exposure to Indians through membership of the same geographic community promotes knowledge sourcing by non-Indian inventors from Indian inventors. The coefficients of *ethnic geographic professional community* and *ethnic geographic family community* are positive and significant ($p < 0.1$ and $p < 0.01$, respectively). That is, the greater the exposure to Indian professionals and (interestingly) Indian families in the U.S. county of residence the greater the amount of immigrant knowledge sourced by non-Indian inventors. These results are confirmed by model 7 which includes all the independent variables.

Model 8 provides the results for exposure to the organizational, technological, and geographic communities for our matched samples of Indian inventors. Since each focal Indian inventor is a member of the ethnic Indian community, we find different patterns for Indian inventors' exposure to interactions with other Indians for knowledge sourcing from the other communities. For an Indian inventor sourcing immigrant knowledge, what matters is exposure to other Indian inventors in the technological community, and co-inventing with other Indian inventors both of which are positive and statistically significant ($p < 0.01$). However, increased exposure to Indian inventors patenting in the organization seems detrimental to immigrant knowledge sourcing which might be explained in part by competition. As the number of Indian inventors in the organizational community increases, Indian inventors may reduce their sourcing of immigrant knowledge to differentiate themselves in terms of their knowledge creation compared to other Indian organizational peers. For Indian inventors, colocation with immigrant professionals and immigrant families for promoting potential interactions and facilitating knowledge sourcing is less important—shown by the lack of significance of the variables *ethnic geographic professional community* and *ethnic geographic family community*. The existing embeddedness of Indian inventors in their ethnic community might remove the need for participation in geographic communities to source immigrant knowledge.

Robustness Checks

We conducted some robustness checks (results available upon request). First, since our sample was constructed using CEM which allows a one-to-one exact matching procedure we matched one non-Indian inventor to one Indian inventor. However, our results are robust to different matching alternatives such as a many-to-one matching which allows more than one non-Indian inventor to be matched to an Indian inventor and matching of inventor locations based on the same state rather than the same county. Second, we conducted an ordinary least squares (OLS) estimation and obtained results largely consistent with our main results.

Although full investigation of the relationship between our dependent variable *immigrant knowledge sourced* and the innovation quality of non-Indian inventors is beyond the scope of the present study, preliminary testing using our data suggests a positive correlation between knowledge sourced from Indian inventors and innovation quality for non-Indian inventors which is similar to the effects found by Almeida et al. (2015) in their study of Indian inventors. This initial evidence is reassuring and corroborates the importance of studying how and to what extent immigrant knowledge spills over outside the ethnic community.

Discussion and Conclusions

Research at the intersection of the international business and innovation literatures has for long emphasized the importance of ethnicity as a mechanism for the transfer of knowledge between inventors. Shared language and sense of identity and similar norms promote trust and reciprocity and reduce information costs, allowing easier knowledge flows among inventors in the same ethnic community (Agrawal et al., 2008; Breschi et al., 2017; Kerr, 2008; Oettl & Agrawal, 2008; Saxenian, 1999). It has been shown also that the sourcing of knowledge from ethnic communities enhances the quality of the innovations produced by immigrant inventors (Almeida et al., 2015). However, if it remains within the ethnic community the significance of immigrant knowledge will be limited. Our research goes beyond a "community-centered perspective" (Lissoni, 2018) and proposes and explores a new perspective on immigrant inventors by considering the influence of their knowledge outside the ethnic community (e.g., Choudhury & Kim, 2019). We draw on insights in the sociology literature to explore how ethnic inventors' knowledge is disseminated. Since knowledge flows are socially situated (Brown & Duguid, 1991), we posit that socialization processes which allow inventors outside the ethnic community to interact with the members of that community serve to straddle ethnic community boundaries and enable knowledge sourcing. In line with previous work, we focus on three communities—the organizational, technological, and geographic communities—in which inventors are embedded simultaneously and where socialization takes place (Boschma, 2005).

The overall finding that the knowledge created by the Indian inventors contributes as prior knowledge to non-Indian inventors' innovations constitutes an important contribution to scholarship. This area tends to be overlooked—the dominant focus being on immigrant knowledge influencing other members of the ethnic community. In other words, our study complements and extends work on innovation and entrepreneurship (Almeida et al., 2015; Choudhury, 2016; Elo et al., 2019; Kenney et al., 2013), and foreign investment (Foley & Kerr, 2013; Hernandez, 2014; Miguelez, 2017) which focuses on ethnic community interactions and the benefits that accrue to ethnic community members as a result of community membership. For instance, Rauch and Trindade (2002) show how ethnic Chinese communities support trade across borders through the sharing of knowledge related to markets and supply and by sanctioning which discourages opportunistic behavior by the community. Similarly, Shukla and Cantwell (2018) show that the presence of immigrants in the host country influences its patterns of foreign investment; and in the area of entrepreneurship, the success of the "motel industry" has been shown to be shaped by the sharing of knowledge and preferred access to capital among ethnic Indians (Kalnins & Chung, 2006). In a high technology and innovation context, Saxenian (2002) discusses the existence of a variety of Chinese and Indian professional associations in Silicon Valley, aimed at sharing scientific and technical information and enabling co-operation between engineers and scientists within the ethnic community. She documents the role of associations for facilitating cross-generation mentoring and resources to facilitate entrepreneurial activity. In the patent and knowledge creation space, Agrawal et al. (2008), provide evidence of co-ethnicity in increased flows of knowledge represented by citations. They show also that co-location seems to serve a similar purpose by supporting the development of social capital.

Our research builds on these studies and suggests that different communities—organizational, technological, and geographic—play a part in disseminating inventor knowledge from the ethnic community to inventors outside that community. Specifically, we suggest that organizational, technological, and geographic communities can bridge ethnic community boundaries and enable social interactions. We contribute to research on social communities by investigating the implications of simultaneous embeddedness in different communities for flows of knowledge across ethnic community boundaries. Crescenzi et al. (2016) show that inventors within the same organization are more likely to collaborate. We complement this finding by showing that organizational communities can bridge ethnic community boundaries. Specifically, our results suggest that the presence of Indian inventors in the organizational community is more likely to increase the probability of socialization with non-Indians and lead in turn to knowledge flows. We support the view that geographically situated social communities facilitate flows of immigrant knowledge to members outside the ethnic community. We argue that embeddedness in co-located professional and family communities triggers interactions with Indians and enables a better understanding of the ethnic community and a greater appreciation of the knowledge available within it. This evidence echoes previous findings on the importance of family communities for the geographic distribution of skilled labor (Dahl & Sorenson, 2010).

From a policy perspective, the issue of immigrant inventors and their contribution to host economies has been the subject of controversial debate on immigration. Despite evidence of the benefits reaped by the host economy from the presence of high skilled immigrants, questions remain about the negative effects such as the crowding out from science and engineering of native born scientists and inventors (Stephan & Levin, 2001). In the current climate, policy decisions appear to be driven by concerns about the negative effects of immigration which are resulting in greater scrutiny of the H1B visa program that allows immigrant inventors to work in the U.S., and recent increased suspension of premium fast track processing of these visas (Da Silva, 2018). Our study provides evidence which should be informative for policy makers. Our findings build on work which challenges the idea of the displacement (of natives) effects of immigration (Kerr & Lincoln, 2010; Moser et al., 2014) and suggests the positive benefits for the non-Indian community based on the knowledge created by Indian inventors—effects which are enhanced by the increased presence of immigrant inventors and their families in organizational, technological and geographic communities. In particular, our findings about the role of ethnic geographically situated professional communities echo empirical evidence on the reduced flows of knowledge due to policies that limit the international mobility of skilled workers and students (Orazbayev, 2017). Thus states, professional associations and organizations should exploit the presence of immigrant inventors and their family members in order to obtain the benefits for the wider community.

Our research has some limitations. Our findings for the flow of immigrant knowledge beyond community members might not be generalizable directly to other ethnic groups than the Indian community. An interesting extension to our work would be to study other ethnic immigrant communities (Chinese, Russian) which show predominantly skilled migration. It would be interesting also, to explore whether our results could be replicated for other destination countries for example, by studying the sourcing of immigrant knowledge in the UK—another important destination country for Indian immigrants. Theoretically, we posit that the presence of Indians in the organizational, technological, and geographic communities of non-Indian inventors promotes knowledge sourcing from the ethnic community through interactions and social processes. Our results point to the importance of a greater presence of Indians in the communities of non-Indian inventors. However, we do not observe the nature of their interactions. While availability of data to investigate these types of interactions is scarce, the need to understand the specific interaction channels that support flows of immigrant knowledge should be an important topic for future research. Also, with some exceptions (Choudhury & Kim, 2019) the influence of immigrant knowledge on individuals outside the ethnic community remains an under-researched phenomenon and should be prioritized on future research agendas. For example, our results show that the sourcing of immigrant knowledge could have important implications for the quantity and quality of the innovation output of non-members of the ethnic community. A deeper exploration of the implications of the intersection between ethnic community knowledge sourcing and the social realm would add to our understanding of innovation by providing practical insights for inventors and firm managers, and prescriptions for policy makers to maximize the benefits of this knowledge.

Acknowledgments This work was supported by the Independent Research Fund Denmark | Social Sciences.

Grant: "The role of diaspora investors in developing countries: A study of firm internationalization and inter-firm collaborations" (DFF—4182-00053).

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