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Return migration and geography of innovation in MNEs: a natural experiment of knowledge production by local workers reporting to return migrants

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Abstract

I study whether return migrants facilitate knowledge production by local employees working for them at geographically distant R&D locations. Using unique personnel and patenting data for 1315 employees at the Indian R&D center of a Fortune 500 technology firm, I exploit a natural experiment where the assignment of managers for newly hired college graduates is mandated by rigid HR rules and is uncorrelated to observable characteristics of the graduates. Given this assignment protocol, I find that local employees with returnee managers file disproportionately more US patents. I also find some evidence that return migrants act as a ‘bridge’ to transfer knowledge from the MNE headquarters to the local employees working for them.

Keywords: Return migration, knowledge production, multinational enterprise, internal labor markets

JEL Codes: F22, F23, O34, R12, J24

1. Introduction

There is an established literature that studies the geography of innovation of the multinational enterprise (MNE). Starting with Caves (1971), this literature has long posited that MNEs exist because of their ability to transfer and exploit knowledge more efficiently in the intrafirm context than through external market mechanisms. In the last few decades, the geography of innovation in the MNE has rapidly expanded. Since the mid-1990s, a large number of MNEs have set up R&D centers in China, India and other emerging markets. To quote Gereffi et al. (2008, 7), ‘China now boasts nearly 1000 multinational R&D centers...in India, an estimated 150 of US Fortune 500 firms had established R&D centers as of 2005.’

MNEs face an important constraint in expanding their geography of innovation — that of producing and transferring knowledge across borders. It has been 20 years since the classic study by Jaffe et al. (1993) on the localization of knowledge flows, as measured by patent citations. In the broader literature on spatial agglomeration, results from this study were interpreted as evidence that knowledge flowed more easily across spatially proximate — rather than spatially

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distant — agents.² The subsequent literature in economic geography (e.g., Boschma, 2005; Agrawal et al., 2006, etc.) examines the role of coinventor, ethnic, and social relationships in facilitating knowledge transfers. Agrawal et al. (2006) find that knowledge flows to an inventor's prior location are approximately 50% greater than if they had never lived there, and the researchers conclude that social relationships, not just physical proximity, are important for determining flow patterns.

Given these results, for the MNE, knowledge is likely to be localized within the larger, more established knowledge production centers, and the firm might face constraints in producing/transferring knowledge across borders at the newly set up emerging market R&D centers. However, there is a lack of empirical work on mechanisms that could help MNEs circumvent this constraint. As an example, there are no empirical studies that examine whether *transferring employees within the firm* helps MNEs achieve cross-border knowledge production at the newly set up emerging market R&D centers.

This paper attempts to bridge this gap in the literature and uses unique personnel data from a Fortune 500 MNE and a natural experiment to document evidence of disproportionate knowledge production by local employees reporting to return migrants at an emerging market R&D location. In doing so, this paper comes up with early insights related to the functioning of 'internal labor markets' of multinationals. Very few scholars have studied the functioning of MNEs' internal labor markets.³ One of the key papers in this literature, Baker et al. (1994), for example, studies a 'medium-sized US firm in a service industry.'

Related to the transfer of employees within the MNE is the broader literature on firms and migration and the phenomenon of return migration. The phenomenon of return migration has received renewed interest in the broader economics literature (e.g., Zucker and Darby, 2007). However, firms have been relatively absent from the literature on migration in general and return migration in particular.⁴ To quote Kerr et al. (2013, 1), 'from an academic perspective, there is very little tradition for considering firms in analyses of immigration. As one vivid example, the word 'firm' does not appear in the 51 pages of the classic survey of Borjas (1994) on the economics of immigration, and more recent surveys also tend to pay little attention to firms'.⁵ The authors also argue that 'this approach seems quite incomplete for skilled migration', given that firms play an active role in the migration of skilled workers. The current paper is one of the few empirical papers that studies *geographic migration of skilled employees within firm boundaries*.

In this paper, I use unique data for 1315 employees in a Fortune 500 multinational R&D center in India. Of the 1315 employees, 104 are return migrants, i.e., individuals who are ethnically Indian and have varying degrees of tenure at the US headquarters. I study the role of

² The authors conducted an experiment where citing-cited patents were coded to record whether or not the pair of patents was spatially co-located. The authors found that citing patents are three times more likely than control patents to come from the same state as the cited patents and up to six times as likely to come from the same metropolitan area.

³ Clemens (2013) is one of the few recent empirical papers that studies human capital mobility and innovation within MNEs.

⁴ There are a few case studies on return migrants affecting local knowledge production, including those in the Hsinchu Science Park in Taipei (Luo and Wang, 2004).

⁵ Other recent surveys on immigration include Kerr and Kerr (2011).

return migrants, as well as local employees with return migrant managers, in patent filing at the Indian R&D center. Here, I exploit the presence of a natural experiment. Existing human resources (HR) practices in the firm (explained in detail in Section 3.2) imply that whether or not a newly hired college graduate will be assigned a return migrant as a manager is uncorrelated to observable characteristics of the local employee. I exploit this to study whether local employees with return migrants as their managers file disproportionately higher numbers of patents than local employees with local managers. I additionally control for co-patenting between the local employee and manager and attempt to control for ‘status’ of the manager using his/her prior patent grants. I also account for heterogeneity in the local employee population by accounting for the tenure and the organizational group in which the local employees work.

In summary, I have three major findings. First, return migrants have higher prior patent grants and file more patents compared to local hires, though this result is driven by return migrants with high organizational tenures. Second, local employees who have return migrants as their managers file more patents; the odds ratio is 6.2 for newly hired college graduates and 2.4 for all local employees who report to return migrants. This result exploits the natural experiment and is arguably my most robust result. Third, I find some evidence that patents filed by local employees with return migrant managers exhibit higher self-backward citation rates compared to patents filed by local employees with local managers. The final result is suggestive of the fact that return migrants may act as a ‘bridge’ for transferring knowledge from the MNE headquarters to the local employees who work for them.⁶ These results comprise a step forward in thinking about the expanding geography of innovation in the MNE and return migration. The rest of this paper is organized as follows: Section 2 summarizes the prior literature and presents an explanatory framework; Section 3 reviews the data and the variables; Section 4 presents the results; and Section 5 concludes the paper. References, tables and figures are at the end.

2. Knowledge production by local employees with return migrant managers

My research question is whether return migrants facilitate knowledge production by local employees working for them. If I find support for this proposition, a possible mechanism is that return migrants act as a ‘bridge’ to transfer knowledge from the MNE headquarters to the local employees working for them. In Section 2.3, I present an explanatory framework related to my research question. I also summarize alternative mechanisms that could explain why the proposition might hold. Prior to that, I summarize the literature upon which my explanatory framework is built.

2.1 Proximity, social ties, and knowledge transfer

⁶ There could be at least four mechanisms driving the main finding that local employees with return migrant managers file more patents than local employees with local managers: (i) selection into treatment based on observable and/or unobservable characteristics; (ii) co-patenting between the returnee manager and local employee; (iii) status effects of having a returnee manager; and (iv) returnee managers acting as a ‘bridge’ for knowledge transfer from the headquarters to the local employees. Section 3.2 explains my identification strategy in detail.

The literature in economic geography has long documented a relation between proximity and knowledge transfer (Jaffe et al., 1993). Boschma (2005) outlines how cognitive, organizational, social, institutional, and geographic proximity is related to learning and knowledge transfer. Geographic proximity and co-location facilitates knowledge transfer by strengthening other dimensions of proximity. There are several empirical papers that demonstrate the importance of coinventor, social, ethnic, and other ties in transferring knowledge. In her study of Chinese and Indian engineers and entrepreneurs in Silicon Valley, Saxenian (1999) outlines the role of trust and reciprocity in transferring knowledge among members of the ethnic community. Agrawal et al. (2008, 258) conclude that ‘spatial and social proximity are substitutes in their influence on access to knowledge’. Breschi and Lissoni (2009) use European patent data and find that at the MSA level, 17% of citations are localized, compared to 11% of controls. However, once they removed patent pairs linked by mobile inventors and patent pairs linked by the coinvention network, the localization effect weakens even further — at the MSA level, 11.8% of the citations were localized, compared to 9.9% for controls. In a recent paper, Crescenzi et al. (2013) find that physical proximity is an important influence on collaboration, but is mediated by organizational and ethnic factors. In a recent working paper, Franzoni et al. (2012) employ a survey of 16 country panels and find that mobile academics perform better than those who have not experienced any mobility.

There is also a broader literature in economics that has explored a knowledge worker’s network position and knowledge transfer. In a theoretical treatment of this subject, Cowan and Jonard (2004) find that the steady state level of average knowledge in a network is maximal when the network structure exhibits ‘small world’ properties, i.e., when most of the connections between agents are ‘local’, but roughly 10% of the connections between agents are ‘long distance’. Fleming et al. (2007) use patent collaboration data to examine this and find evidence that larger connected components correlate with increased innovation.

2.2 Return migrants and cross-border knowledge production/transfer

In the context of MNEs, return migrants, especially return migrants who occupy managerial positions, occupy a unique position within a firm’s social network. On the one hand, they have preexisting inventor, ethnic and social ties back to the headquarters and, on the other hand, they also have local employees working for them in the home country. Given the prior literature on proximity, social ties and knowledge transfer, it is plausible that local employees working for return migrants leverage their proximity to return migrants and the preexisting ties of their return migrant managers in their own knowledge production process.

The literature on return migration has received renewed interest in recent years. Borjas and Bratsberg (1996) and Dustmann et al. (2011) point out that the percentage of migrants who return to their home countries within 10-20 years is 25% to 30% of the initial group.⁷ In addition to rates of return migration, recent research has also studied the quality of return migrants. As

⁷ Using US census data, Mayr and Peri (2008) find that for both Eastern European and Asian immigrants, return migration rates for individuals who entered the US while they were very young is from 15% to 25%.

Zucker and Darby (2007) and Biondo et al. (2012) summarize, return migration is often concentrated among the most successful and highly educated of the migrants. Dustmann and Weiss (2007) use UK data to show that the propensity of migrants to return to their home countries is much stronger for highly skilled workers.⁸

There is also an emerging literature on knowledge transfer by return migrants to their home countries. An important contribution here is by Saxenian (2006), who coined the term ‘new Argonauts’ for return migrants. As Saxenian outlines, similar to the Greeks who sailed with Jason in search of the Golden Fleece, the new Argonauts, i.e., foreign-born, technically skilled entrepreneurs who travel back and forth between Silicon Valley and their home countries, identify market opportunities in their home countries, locate foreign partners and manage cross-border business operations. There are other recent empirical studies on how return migrants and other foreign experts help firms in their home countries. Giannetti et al. (2012) study policies introduced by Chinese provinces to attract return migrants and find that hiring directors with foreign experience leads to higher firm valuation, productivity and profitability. Other related papers are Malchow-Møller et al. (2011) and Markusen and Trofimenko (2009). However, there are no prior empirical studies on how *within* MNEs, return migrant managers facilitate knowledge production by local employees. This is the gap I seek to fill.

There is a related literature focused on the role of diaspora in facilitating international knowledge transfer. Kerr (2008) notes that knowledge diffusion occurs at an uneven rate across countries and suggests that ethnic scientific networks are important for short-term technology transfer from the US.⁹ In a study of the Indian software industry, Nanda and Khanna (2010) find that diaspora networks may serve as substitutes for local institutions in helping entrepreneurs outside the software hubs access knowledge. A related paper is by Foley and Kerr (2013), who study the impact ethnic inventors have on the global activities of US firms. The authors find that a 10 percentage point increase in the share of innovation by individuals of a particular ethnicity is associated with a 1 percentage point increase in the share of multinational affiliate activity in countries related to that ethnicity. Related to this, Agrawal et al. (2011) find that inventors based in India who work for MNEs disproportionately cite the Indian diaspora than do those who are employed by the same firm but are based at facilities in other countries. Docquier and Rapoport (2012) provide a useful overview of this literature.

2.3 Framework for generic MNE: knowledge transfer from returnee managers to local employees

⁸ On the negative side, Gaulé (2011) finds that the most successful scientists are less likely to return. In a similar vein, Biondo et al. (2012) find that academic scientists from Italy exhibited a very low propensity to return to their home country. There are other questions that the recent literature on return migration has explored. As an example, McCann et al. (2010) develop a theory of the optimal structure of visits back home by international migrants. Migrants compare the costs of travel and the opportunity costs of time with the psychological costs associated with separation.

⁹ To study how ethnic scientific communities facilitate international knowledge transfers, Kerr (2008) uses patent citations as a measure of technology transfer and employs a name-matching algorithm to establish ethnicities

I now present a highly stylized explanatory framework for a generic MNE that transfers return migrants from the headquarters to an emerging market knowledge production center.

I assume two types of employees working at the emerging market knowledge production center of the MNE — return migrants or returnees (R) and local employees (L). Each local employee has a manager, and the manager could be a return migrant (M_R) or the manager could be a local employee him/herself (M_L). The outcome variable I am interested in is knowledge creation by local employees, measured by local employees' patent filings. The treatment here is the pairing of L to either M_R or M_L .

In this paper, I posit that local employees with returnee managers file more patents than local employees with local managers. In other words, I posit that patenting is higher for L who have M_R as managers compared to L who have M_L as managers. Compared to local managers (M_L), returnee managers (M_R) might be higher ability and/or might have stronger preexisting coinventor, ethnic and social ties back to the MNE headquarters. Compared to local managers (M_L), returnee managers (M_R) might also act as a 'bridge' for transferring knowledge to employees working for them. This might support my main proposition. However, compared to local managers (M_L), returnee managers (M_R) could have weaker local ties within the emerging market center. This might go against my main proposition. It is important to point out that prior research (e.g., Singh, 2005) has also shown that a firm is a coordinating mechanism and knowledge transfer might be easier within firm boundaries compared to outside firm boundaries. Given this, what I study is the 'additional' effect of having a return migrant as a manager versus having a local employee as a manager.

If I find support for my main proposition, there could be several mechanisms that explain the result, i.e., why local employees with returnee managers file more patents than local employees with local managers. First, there could be selection into treatment based on observable and/or unobservable characteristics of the local employee. In other words, there could be systematic differences in observable and/or unobservable characteristics of local employees with returnee managers and local employees with local managers. Here, I borrow insights from a recent theoretical paper in economics that models positive assortative matching, whereby more knowledgeable local employees team with more knowledgeable managers (Dasgupta, 2012).¹⁰ The author develops a general equilibrium model to understand how the entry of an MNE in a southern country affects host country workers through on-the-job training from managers and knowledge transfer. The author models an MNE as an international production team. In a two-country model, the northern country has more knowledgeable agents compared to the southern country. The model assumes that managers and workers get together in firms to produce knowledge. Following integration, or the creation of the international production team, northern managers try to leverage their superior knowledge with respect to southern workers. However, some of the best southern workers in the model learn from some of the best northern managers. In other words, complementarity between the workers' and managers' knowledge in production

¹⁰ Prior work in economics also provides evidence that MNEs undertake substantial efforts in the education of local workers and that MNEs offer more training to workers than do local firms (e.g., Fosfuri et al., 2001).

and learning technologies leads to positive assortative matching, whereby more knowledgeable workers team with more knowledgeable managers.

A second mechanism to explain why local employees with returnee managers might file more patents than local employees with local managers might be related to coinventing. There is a vast literature on the importance of teamwork in inventive activities. Jones (2009) demonstrates that for patented inventions, the rising ‘burden of knowledge’ has led to increasing ‘cost of breadth’ and has resulted in increased specialization and teamwork. If returnee managers file more patents and these patents are co-patented with local employees who work for them, then local employees with returnee managers might file more patents than local employees with local managers.

A third mechanism might be related to the ‘status’ effect of having a returnee manager. Returnee managers might have more leverage with the MNE headquarters when it comes to getting funding for their own inventive projects and/or the inventive projects of local employees working for them.

Finally, returnee managers could facilitate knowledge transfer from the headquarters to the local employees who work for them. Given the proximity and knowledge transfer literature summarized earlier, and given the special position held by returnee managers in the social network of an MNE (i.e., they have both preexisting social ties to the headquarters and they also have local employees working for them), it is plausible that returnee managers act as a ‘bridge’ to transfer knowledge from the MNE headquarters to the local employees working for them. This knowledge transfer might lead to higher patenting by local employees with returnee managers compared to local employees with local managers. Section 3.2 outlines my identification strategy in detail and summarizes how I test for the four mechanisms summarized above.

3. Data and methods

3.1 Empirical setting

My empirical setting relates to a single firm — the Indian R&D center of ‘TechMNE’. This firm is a Fortune 500 technology company that started its Indian R&D center in the late 1990s. The center was incubated by a group of 12 return migrants from the US headquarters, and it steadily grew to more than 1300 employees over the next decade. I collected cross-sectional data related to personnel records, patenting, and social ties for all 1315 employees on the payroll of the Indian R&D center of TechMNE as of December 2007. In line with several prior studies in the innovation literature, I use patenting as the measure of knowledge production. All patents filed in my empirical context are US patents.

I have an advantage in using patenting as my measure of knowledge production. Since all the patent counts in this case are for the same firm, several sources of firm-level heterogeneity, such as R&D efficiency, patent propensity, etc., are held constant. However, given that I study a single firm setting, the external validity of my results might be limited.

In addition to collecting data for all 1315 employees on the payroll in 2007, I conducted 45 interviews with a sample of employees over a period of three months. These interviews were only to augment the personnel data collection process, and the primary motive of the interviews was to generate insights related to the empirical strategy and identification strategy. I conducted interviews with 20 of the 39 senior managers at TechMNE's India R&D center with tenures of more than 10 years and with a sample of 25 mid- and entry-level employees. This is in the established tradition in the economics literature of empirical work within a single firm (e.g., Baker et al., 1994). Ichniowski and Shaw (2006) use the term 'insider econometrics' to describe this body of work, and they describe insider econometrics as productivity studies that combine extensive fieldwork to assemble useful organization-level datasets with rigorous econometric hypothesis testing of the effects of organization-specific determinants of productivity.

3.2 Identification strategy

To recap, my main proposition is that local employees with returnee managers file more patents than local employees with local managers. If I find support for this proposition, as summarized in Section 2.3, there could be at least four mechanisms driving it: (i) selection into treatment based on observable and/or unobservable characteristics; (ii) co-patenting between the returnee manager and local employee; (iii) status effects of having a returnee manager; and (iv) returnee managers acting as a 'bridge' for knowledge transfer from the headquarters to the local employees. The interviews I conducted at TechMNE's Indian R&D center led to several insights relevant to my identification strategy.

First, during my field interviews, I identified that the HR policies dictating the allocation of managers (either a return migrant or a local manager) to 'new college hires' recruited by the firm in India presented a natural experiment and helped me control for the possibility of treatment based on observables, as suggested by Dasgupta (2012). These 'new college hires' were employees who had completed four-year undergraduate programs in engineering and had been hired by the firm directly from college. The HR policies related to the assignment of managers for local employees who are 'new college hires' imply that the allocation of managers is uncorrelated with observable characteristics of the new college hires. There are three important considerations driving this natural experiment: (i) the recruitment of a limited number of new college hires who all have very high grades and come from only the top colleges; (ii) the assignment of managers happening prior to socialization opportunities between new college hires and prospective managers; and (iii) the assignment of managers being done by HR staff members located in different cities than the managers.

TechMNE started recruiting new college hires only in 2003 and has hired 57 new college hires on average in the subsequent four years. This is in contrast to Indian IT service firms who recruit hundreds, if not thousands, of new college hires every year. The limited number of new college hires has allowed TechMNE to visit only the 'Top 25–30 colleges of India' and select the 'best of talent'. In fact, TechMNE has also been rated by a reputed industry survey as the most preferred employer amongst engineering graduates for four years in a row. As a result,

TechMNE has had the bargaining power to recruit only the very best candidates from these colleges, and the new college hires selected by TechMNE are relatively homogeneous in their academic grades and other pre-recruitment academic indicators. In addition, at the time of being assigned a manager, new recruits do not have any firm-specific skills that make them attractive to any particular project manager.

Interviews with HR personnel indicated that for bureaucratic reasons, the assignment of managers to new college hires happens prior to induction training and prior to any real opportunities for the new college hires and prospective managers to socialize and get to know each other. In fact, this assignment takes place prior to the new college hires starting work at the R&D center and typically happens in the summer break prior to the induction training program. In summary, the calendar of events is the following: the new college hires are recruited through campus interviews in the fall of year 't-1' or the spring of year 't'; the assignment of manager takes places in the summer break prior to the induction training program; and the induction training program commences in the fall of year 't'.

Finally, the assignment of manager is done by the HR staff in the TechMNE Indian headquarters of Delhi, while the prospective managers are all located in the R&D center in Hyderabad. Interviews conducted with the HR staff based on Delhi generated several insights. Around April, TechMNE managers submitted their 'manpower requirements' for their Fall projects. As part of their manpower requirement submissions, TechMNC managers provide details on how many additional college hires and how many additional experienced hires they require. However, final employment letters for the college hires are usually finalized and mailed out at the end of April, indicating that TechMNC managers do not have access to observables for the incoming batch of college hires while making their manpower requirement estimates. Interviews also confirmed that at the end of recruitment, the administration of employment letters and employment contracts is done entirely by the HR staff. Interviews with HR staff also indicate that in July/August, the HR staff 'run down the list of open positions (indicated by the manpower requirements submitted in April) and assign local employees to different managers'. In other words, the only thing the HR staff considers in making the decision is which projects need people at the time. Interviews with HR staff explicitly confirmed that they 'do not consider college, grades or other characteristics of college hires while assigning them to managers'. An HR staff member also stated that 'it is very unusual for TechMNC managers to call us up and lobby for a particular new college hire; they hardly know these guys. However, this practice is more common for experienced hires. Managers might call us up and lobby for an experienced hire who has the skills they are looking for'.

To econometrically establish the randomness of the assignment of either a return migrant or a local manager to each of these new college hires, I collected data on pre-treatment indicators for the new college hires, e.g., whether the new college hire studied at any of the elite Indian Institute of Technology colleges (IITs) or at other engineering colleges. I also collected data to establish whether the new college hire had ethnic or social ties with the future manager. In summary, I find that these pre-treatment indicators do not systematically predict assignment of a

new college hire to a return migrant or a local manager. Details on this test can be found in the section on robustness checks.

If I find support for my main proposition (i.e., local employees with returnee managers file more patents than local employees with local managers), the second mechanism that could lead to this result is co-patenting between the returnee manager and the local employee. To check this, I investigated whether or not local employees and their managers were listed as inventors on the same patent. Out of the total 137 patents filed by the TechMNE India R&D center during the period of my study, 59 patents had more than one inventor, and out of these 59 patents, only one patent had both a local employee and his/her manager listed as inventors. In other words, I can rule out coinventing as a mechanism driving my results. A related possibility is that local employees with returnee managers file ‘global collaborative patents’. In a recent paper, Kerr and Kerr (2014) define global collaborative patents as patents where at least one inventor is located outside of the United States and at least one inventor is located within the United States. The authors find that 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 United States. In my sample, I find that only four of the 59 patents with more than one inventor have a United States inventor listed as co-patentee. Three of these patents exclusively have returnees listed as the local employees, while one of these patents has a local employee with a returnee manager listed as a co-patentee. None of these four patents have a local employee with a local manager listed as a co-patentee.

If I find support for my main proposition, the third mechanism that could lead to this result is status effects of having a returnee manager. Having a returnee manager might enable a local employee to leverage the headquarters when it comes to getting his/her inventive projects funded. To partly control for the status of the returnee manager, I control for prior patent grants of the returnee manager. Arguably, returnee managers with more prior patent grants might have higher status. However, given that I do not have data on which local employees applied for funding and either got the funds or got rejected, I cannot completely rule out this mechanism.¹¹ This is an important limitation of my study.

Finally, if I find support for my main proposition, a fourth mechanism that could be driving my result is that returnee managers act as a ‘bridge’ for knowledge transfer from headquarters to the local employees. In other words, local employees with returnee managers leverage the preexisting social, ethnic inventor ties of their managers to access knowledge that

¹¹ Patent filing is a budget-constrained process at TechMNE. Though the patent filing cost is relatively moderate, there is a significant investment of inventor man-hours in the pre-patenting stage when a patentable idea is being developed by the employee. First, local employees in the Indian R&D center need to ‘pay off’ their regular project team to be able to work on a patentable idea, and they require funding from a global product manager at TechMNE’s US headquarters to fund their man-hours spent working on patentable ideas. Second, at TechMNE, monetary resources needed for patenting are centralized in the headquarters. Funds for patenting and supporting the pre-patent stage development of an idea are exclusively controlled by the US-based product managers of this firm. These product managers are not engineers or scientists, but are mostly MBAs responsible for providing strategic direction to product development teams. The product managers review patentable ideas from around the world and decide to fund ideas that fit with their ‘strategic priorities’ for the product. The US-based product managers have the freedom to invest in patentable ideas from within their own product team, as well as in ideas suggested by employees from other product teams. In 2010, in about 55% of the cases, funding for an idea came from an organizational group outside the product group to which the local employee belonged.

resides at the firm headquarters. To test this mechanism, I conduct an analysis of patent ‘self-backward citations’. If returnee managers act as a bridge for knowledge transfer from the headquarters to local employees, then patents filed by local employees with returnee managers are likely to have more self-backward citations (i.e., citations to prior patents filed by inventors working at the TechMNE headquarters) compared to patents filed by local employees with local managers. Section 4.3 explains this analysis in detail.

3.3 Dependent variable

For my main regression analysis, as the dependent variable, I use a count of patents filed (*number_patents_filed_i*) and whether or not the employee has filed at least one patent (*has_filed_patent_i*). Patent filings were for years 2004-2007 and were all filed when the employees were working in the Indian R&D center of the focal firm.

An alternative dependent variable is the count of patents granted (*number_patents_granted_i*). Patents granted were for years 1994-2007, when the employees were working at either the US or Indian R&D center of TechMNE. Interviews with TechMNE lawyers indicated that the USPTO patent granting process took 4-5 years. This implies that the prior patent grants referred to patents filed in the year 2002 or earlier, while the employee was still on the payroll of TechMNE, working at either the US or Indian R&D center of TechMNE.

3.4 Independent variables, control variables and specification

The main independent variables of interest are a dummy variable for whether or not the employee is a return migrant (*is_returnee_i*) and a dummy variable for whether or not the local employee has a return migrant manager (*manager_is_returnee_i*).

Given that I am dealing with count data, in the base case, I use insights from Hausman et al. (1984) and Wooldridge (1999) to run a Poisson model adjusted for quasi-maximum likelihood estimation and robust standard errors. In dealing with count data like patents, Azoulay, Zivin and Wang (2008) summarize the advantages of choosing a Poisson model adjusted for QML standard errors: because the Poisson model is in the linear exponential family, the coefficient estimates remain consistent as long as the mean of the dependent variable is correctly specified. QML (‘robust’) standard errors are consistent even if the underlying data-generating process is not Poisson. In the base case, I run a Poisson model adjusted for quasi-maximum likelihood estimation and robust standard errors. This model has several advantages. To implement the quasi-maximum likelihood Poisson model, I use the generalized linear model with Poisson family and use the iterative reweighted least square option.

The main control variables (Z_i) include tenure and organizational group of the employee, prior patent grants of the manager and social ties between the employee and the manager. In Section 3.5, I describe the data collection process and provide details on how the control variables were coded.

To test for whether or not returnees and/or local employees reporting to returnee managers engage in disproportionately more patenting, I run the following specification:

$$E(Y_i|X_i) \sim \exp(\beta_1 R_i + \beta_2 T_i R_i + Z_i \gamma)$$

Here, Y_i indicates the count dependent variables (either patents filed or patents granted) and R_i is the main independent variable of interest.

When I compare patenting of local employees with returnee managers to patenting by local employees with local managers, R_i indicates that the local employee has a returnee manager (*manager_is_returnee_i*) and T_i indicates the tenure of the manager. When I compare patenting of returnees to patenting by local employees, R_i indicates that the employee is a returnee (*is_returnee_i*) and T_i indicates the tenure of the employee.

3.5 Preparing the dataset

As part of my fieldwork within TechMNE, I collected data on personnel records, patenting records, past educational records, social ties and other variables for all employees who were on the payroll as of December 2007. This yielded a cross-sectional dataset of 1315 employees. The data was made available from multiple sources and needed considerable cleaning and coding.

The main dependent variables relate to patent filing and prior patents granted to employees. This data was collected from the firm's patent lawyers. The main independent variables relate to whether or not the local employee has a returnee manager (*manager_is_returnee_i*) and whether or not the employee is a returnee (*is_returnee_i*). These variables were coded using personnel data collected from HR.

As summarized earlier, the first set of control variables relates to the tenure and organizational group of the employee. For tenure, I have six dummy variables corresponding to the following categories: less than 1 year, 1-2 years, 2-4 years, 4-6 years, 6-10 years and more than 10 years. I also have six dummy variables corresponding to the various organizational groups at TechMNE. These organizational groups were 'Client', 'Server and Tools', 'MBD' (Business Division), 'Entertainment Devices', 'OSB' (Online Services Business) and 'Corporate'. Controlling for organizational group helps me control for the possibility that certain groups have a higher propensity to patent compared to others, have a higher staffing need or have a higher proportion of high ability senior employees. In robustness checks, I also control for the job title of the local employee. For job titles, I have the following five categories: software development, program management, SDET (software development engineer involved in testing), other IT and business.

To control for status and productivity effects of the manager, I also control for prior patent grants of the manager. Prior patent grants of the manager were defined as 'patents granted to manager between years 1994-2007, when the manager was working at either the US or Indian R&D centers of TechMNE'. As indicated earlier, interviews with TechMNE lawyers indicated that the USPTO examination took an average of 4-5 years. This implies that the prior patent grants referred to patents that the manager worked on in the year 2002 or earlier, while still on the payroll of TechMNE. In addition, I control for the effect of social ties between the employee and his/her manager. Such ties could be of various types, and I control for the following social ties: college ties, ethnic ties, home state ties and ties related to common social interests. To

identify these ties for each employee, I collected information on their membership within ‘virtual communities’.

Employees at TechMNE could voluntarily join a wide variety of intraorganizational online communities. Employees use these online communities to post information on the topic or activity of interest and to plan events. My interviews indicated that employees did not necessarily need to have expertise or experience in the topic or activity of the community to become members; indeed, employees often joined a particular community in order to learn more about its topic or activity. Thus, belonging to an online technical or social community at TechMNE was an expression of active interest in that community, rather than an indication of knowledge in its area. The members of a community received regular e-mail updates about the topics and activities of that community; they could find out more by clicking on links that would take them to the community’s Web page. My interviews also indicated that there was a cost to belonging to a community in which an employee no longer had an interest — in the form of unwanted e-mails and solicitations for participation in the community. As a result, employees usually cancelled their memberships in communities in which they were no longer interested. Employees of TechMNE’s India R&D center had access to 12,680 virtual communities. I manually coded each community as a ‘technical community’ (n=9456), a ‘social community’ (n=653), an ‘HR community’ (n=917) or an ‘IT help desk community’ (n=1654), based on the name and description of each group. As an example, a community was coded as an ‘IT help desk community’ if employees joined the community to request access to a particular server or piece of code, to report problems with their computers, etc. A community was coded as an ‘HR community’ if the community related to information on recruiting, HR policies, credit card applications, travel logistics, cost centers, building access permissions, car pools, etc.

Using the name and description of each social group, I also classified the 653 social communities into the following categories: college alumni communities, ethnic communities, home state communities and social interest communities. As an example, for one particular college in India, the Birla Institute of Technology and Science (BITS) at Pilani, there were four social communities — ‘Alumni of BITS, Pilani in Hyderabad’, ‘Alumni of BITS, Pilani’, ‘Alumni of Birla Institute of Technology and Science, Pilani’ and ‘Alumni of Birla Institute of Technology and Science, Pilani in Hyderabad’. An alumnus of this college could be a member of one, two, three or four of these communities. I coded an employee as an alumnus of BITS Pilani as long as he/she was a member of at least one of these four communities. An example of a social interest community related to playing cricket: the cricket team communities were linked to cricket teams in TechMNE’s intrafirm league. My coding was independently verified by two senior managers at TechMNE, and any discrepancies were resolved.

In the next step, I identified communities to which all 1315 employees belonged. Data is available for 1279 of the 1315 employees, and this yields 152,101 employee-virtual community rows. In the final step, for each manager-local employee pair, I identified social ties between local employees and their managers and created dummy variables to indicate common ethnic ties (*manager_shares_ethnicity*), college ties (*manager_shares_college*), home state ties

(*manager_shares_homestate*) and common social interests (*mgr_shares_social_interest*). I also formed a composite index with equal weights for these individual ties (*manager_shares_soc_reln_index*).

4. Results

4.1 Summary trends

Tables 1a and 1b summarize employment and patenting records as well as data on social ties between local employees and their managers. Table 1b further summarizes patent filing and patent grants for the four relevant subsamples of employees — (i) local employees with returnee managers; (ii) local employees with local managers; (iii) managers who are local employees; and (iv) managers who are returnees. Table 1b indicates that local employees with returnee managers have both higher patent grants and higher patent filings compared to local employees with local managers. The table also indicates that managers have higher patenting compared to employees; this could be related to the longer tenure of managers in the organization.

[TABLES 1a AND 1b ABOUT HERE]

Figure 1 outlines the trend of return migrants, local employees with returnee managers and local employees with local managers as a fraction of total employees over the period 1997-2007 (Panel A). Figure 1 also outlines the trend of the patent grants to return migrants, local employees with returnee managers and local employees with local managers over 2001-2006 (Panel B). Given that the Indian R&D center of TechMNC started operations in the late 1990s and given that it takes a minimum of 4 years for a U.S. patent to be granted, for the summary trends analysis I only considered patent grants starting 2001. In other words, for the summary trends analysis, I only considered U.S. patent grants for patents filed after the Indian R&D center started operations. As Panel A indicates, the fraction of return migrants in the total composition of employees declines over time. Local employees with local managers started out as the smallest group when this R&D center was incubated. Over time, however, this group emerged as the single-largest group of employees. Panel B indicates that local employees with returnee managers have a disproportionate share of patents grants. From 2001 to 2006, local employees with returnee managers were granted 51% of the patents on average, though they comprised only 26% of the total employee base on average.

[FIGURE 1 ABOUT HERE]

Figure 2 plots the fraction of employees who file at least one patent, and I consider the effect of the main independent variable in question — whether the local employee has a return migrant or local manager. For local employees who have return migrant managers, the fraction of employees who file a patent is around 0.15. For local employees who have local managers, the fraction of patenting is much lower, around 0.05.

[FIGURE 2 ABOUT HERE]

4.2 Patenting by return migrants and by local employees with returnee managers

Next, I conduct econometric analyses using cross-sectional data to test for whether return migrants exhibit higher patenting compared to local employees and, more importantly, whether or not local employees with returnee managers exhibit higher patenting than local employees with local managers.

I first test for whether return migrants have higher prior patent grants and higher patent filings compared to local employees and whether this relation is mediated by heterogeneity in the returnee pool, as an example measured using tenure. Results are presented in Tables 2 and 3. Table 2 shows that return migrants are more likely to have higher patent grants compared to local employees. Column 4 in Table 2 indicates that this effect is driven by return migrants with tenures of greater than 10 years in the firm. Similarly, Table 3 indicates that return migrants are likely to file more patents than local employees. Column 3 in Table 3 indicates that this effect is driven by return migrants with tenures of greater than 10 years in the firm. This could be related to either the underlying quality of return migrants with lesser tenures or to the time needed to adjust to the Indian R&D center.

[TABLES 2 AND 3 ABOUT HERE]

Next, I conduct econometric analyses to test whether local employees with returnee managers exhibit higher rates of patent filing compared to local employees with local managers. In doing so, I exploit the natural experiment of manager assignment for new college hires. Results are presented in Tables 4 and 5. In summary, I find evidence that local employees with returnee managers file more patents than local employees with local managers. In Tables 4 and 5, I test for whether reporting to a return migrant leads to a higher number of patents filed (*number_patents_filed*). Table 4 considers local employees who are new college hires, represents results from the natural experiment and indicates strong support for my main proposition that local employees with returnee managers file more patents than local employees with local managers. I also compute an odds ratio using '*has filed patent*' as the dependent variable, as well as a Logit specification, and I find that the odds ratio of filing at least one patent is 6.2 for new college hires.

Table 5 considers all local employees. Columns 3 and 4 in Table 5 also indicate that the positive effect on patenting of having a return migrant manager is mostly driven by return migrant managers who have relatively high tenures. The interaction effects are positive and statistically significant for manager tenure of 6-10 years and greater than 10 years; I also find a weaker positive effect for manager tenure of 1-2 years. In other words, (i) patenting is higher for local employees who have a returnee manager, where the returnee manager has a tenure of more than 6 years (given that the interaction effects are positive and statistically significant for manager tenure of 6-10 years and greater than 10 years); (ii) patenting is higher for local employees who have returnee managers, where the returnee manager has a tenure of 1-2 years, though this is a weaker effect.¹²

¹² My interviews indicate a possible explanation for this finding – returnee managers with relatively high tenures have wider oversight to a large number of innovative projects back in the U.S. headquarters and could act as a bridge in transferring

In addition, only for the fresh college hires regression (Table 4) does prior patent grants by the manager have a negative effect on patent filing by the local employee. Given that prior patent grants of managers is plausibly correlated with status of manager, this partly helps me control for the possibility that the status of the returnee manager drives patent filing by local employees with a returnee manager. However, this effect is not significant in Table 5. I also compute an odds ratio using '*has filed patent*' as the dependent variable, as well as a Logit specification, and I find that the odds ratio of filing at least one patent is 2.4 for all local employees who report to return migrants.

[TABLES 4 AND 5 ABOUT HERE]

4.3 Patent self-backward citations analysis

Here, I test for whether patents filed by local employees with returnee managers have higher self-backward citation rates compared to patents filed by local employees with local managers. If I find support for this, it would suggest that returnee managers possibly act as a bridge to transfer knowledge from the MNE headquarters to the local employees.

To conduct this analysis, I first match the filed patents (hand-collected data) with subsequent granted patents (publicly available USPTO data). In my dataset for the focal firm, patents filed belong to years 2004-2007, and I match the filed patents with a dataset of USPTO patent grants as of 2014. I use a string of the name of the assignee firm, names of the inventors and the filing date to match the filed patents with subsequently granted patents. Based on this methodology, I was able to conclusively match 65 out of the 137 filed patents to subsequently granted patents. I am then able to compare backward citation counts for patents filed by local employees with returnee managers to patents filed by local employees with local managers.

The results are reported in Table 6 and indicate that patents filed by local employees with returnee managers have almost twice the number of self-backward citations (i.e., citations to prior patents filed by inventors at the TechMNE headquarters) compared to patents filed by local employees with local managers; the difference of means is also statistically significant. However, there is no statistically significant difference in the means of total backward citations to prior patents or total backward citations to non-patent prior art for these two groups of employees. These results are indicative of selective knowledge transfer from the TechMNE headquarters to local employees with returnee managers. However, my estimates are plausibly upward biased given the small sample size of matched patents and the fact that I run only a difference-in-means analysis.

[TABLE 6 ABOUT HERE]

ideas from this wide array of headquarter projects to local employees working for them. On the other hand, returnee managers with tenures of 1-2 years have deeper exposure to a few innovative projects back in the U.S. headquarters and could act as a bridge in transferring ideas from these specific headquarters projects to local employees working for them. However, returnee managers with tenures of 4-6 years may lack both deep exposure to specific headquarters-based projects and might also lack a wide oversight to a large number of headquarters-based projects to be helpful to local employees working for them.

4.4 Robustness checks

Next, I subject my results to a battery of robustness checks. I first check for the validity of the natural experiment and whether the assignment of return migrant versus local manager to new college hires is, indeed, plausibly random. I test whether manager assignment can be predicted using pre-treatment variables like educational institution and ethnic/college links between new college hires and prospective managers. To do this, I create a pre-treatment variable to account for whether the new college hire went to the elite Indian Institute of Technologies (IITs) versus other national- and state-level engineering colleges in India. I also create other pre-treatment variables to account for ethnic and social ties between the new college hire and the prospective manager. Given that all these pre-treatment variables should create a systematic bias toward being allocated a return migrant manager, I test for whether such a systematic bias exists. None of the pre-treatment variables suggest any systematic bias in manager assignment; this validates the plausible randomness of manager allocation for new college hires.

Then, I repeat the regressions of Table 5 for various subsamples of the population and get the following results: the effect of having a return migrant manager on higher patent filings is positive and significant for groups that are more involved in knowledge production (e.g., developers); however, there is no effect for groups that are not directly involved in knowledge production (e.g., testers).

Next, I test for whether local managers with strong headquarters ties have the same effect on their local employees who work for them as do return migrant managers. To test this, I replicate Tables 4 and 5 using the mirror image of the variable *manager_is_returnee_i*. Given that travel to the headquarters seems to be a valid mechanism for building social relationships at the headquarters, I also interact the mirror image variable with the number of trips made by the manager to the headquarters. I find that having a local manager has a negative effect on patent filings, but if the local manager travels to the headquarters, there is a compensating positive effect on patenting, though it is not statistically significant. This result is also robust to controlling for the employee's own travel to the headquarters. In summary, local managers who build their social relationships by traveling to the headquarters might start looking like return migrants managers.¹³

I also test the return migrant manager effect using alternate specifications and alternative dependent variables. First, I replicate Tables 2-5 using a negative binomial specification as well as a Poisson with robust standard errors, and I get robust results. As a robustness check, I also use a propensity scores-based matching analysis to analyze the effect of having a return migrant manager on patent filings. Results (available from the author) indicate that the average treatment effect of having a return migrant manager on patent filings is positive and statistically significant. I estimate the propensity scores using several pre-treatment covariates, including organizational group, functional area, job title and return migrant status, and I run several

¹³ Detailed analyses available from the author.

matching algorithms, including n-nearest neighbor, radius, kernel and local linear matching.¹⁴ As a robustness check, I also use a different set of dependent variables not related to patenting. Given the virtual communities data described earlier, I count the number of online knowledge communities for each employee. I find that having a return migrant manager leads to a positive and statistically significant effect on the number of online knowledge groups to which an employee belongs.

However, when I conduct a falsification test and conduct the same analyses using the number of IT administration groups an employee belongs to, I do not get this effect. The argument here is that the number of knowledge groups should be an indicator of knowledge production and knowledge transfer efforts of an employee; however, the number of IT admin groups should not be directly related to knowledge production and knowledge transfer efforts of an employee. In the former case, having a return migrant manager has a positive effect (just like patents); in the latter case, having a return migrant manager does not have a positive effect. Also, instead of using manager patent grants as a control variable, I use manager patent filings as a control variable, and the results remain consistent. Finally, instead of using multiple measures of ethnic, social, college and home state ties between managers and local employees, I use the composite index of social ties, and the results remain consistent.

5. Discussion

The current study is one of the first empirical studies of skilled migration *within* the multinational enterprise and informs the literature on return migration and the literature on the geography of innovation of MNEs. It also contributes to the broader literature on ‘proximities’ in economic geography by studying how employee transfers within the firm facilitate knowledge production/transfer at geographically distant R&D centers.

In summary, I have three major findings: (i) return migrants with high organizational tenure drive patenting activity in the Indian R&D center of this MNE; (ii) local employees with returnee managers file more patents than local employees with local managers (this result exploits a natural experiment driven by rigid HR rules); and (iii) patents filed by local employees with return migrant managers exhibit higher self-backward citation rates compared to patents filed by local employees with local managers. This result suggests that return migrants might act as a ‘bridge’ for transferring knowledge from the headquarters to local employees.

Arguably, my most robust finding relates to patent filing by local employees with returnee managers. To try and account for endogeneity and selection concerns in which local employees get a return migrant as a manager, I use my knowledge of HR practices gathered through interviews and exploit the natural experiment of assigning managers to new college hires. My results could be interpreted as evidence of on-the-job learning of knowledge production skills for local employees with returnee managers. My interviews with local employees with returnee managers also indicate that return migrant managers ‘connect local

¹⁴ I also account for the bias correction issue documented by Abadie and Imbens (2006). This approach is codified by Abadie et al. (2004), and the relevant Stata command is *nnmatch*.

employees with ideas in the US headquarters’ and additionally ‘help local employees grasp the patenting process at the US headquarters’.

This study has several limitations. The natural experiment does not control for endogeneity in the quality of the return migrants; it is possible that the return migrants are higher ability individuals, and all I can do to account for this is to account for the heterogeneity in the return migrant population by tenure and organizational group. Though I tried to carefully observe and document the HR processes related to manager assignment for new college hires, I cannot completely rule out treatment based on unobservables. Also, though I control for prior patent grants by the manager to control for ‘status’ of the manager, I do not have data on which local employees applied for funding and either got the funds or got rejected and, as a result, I cannot completely rule out the possibility that local employees with returnee managers have disproportionate access to funding. Additionally, my evidence for returnee managers acting as a bridge for knowledge transfer is based on a relatively small sample of matched patents, and the results could be upward biased. Further, given that I study a single firm setting, more analysis is needed before the results can be generalized to a broader set of MNEs across a broader set of geographic locations. Also, future work should consider other plausible measures of knowledge production beyond patents. Future work needs to explore how return migrants are different from other kinds of migrants and other ways in which return migrants make unique contributions to cross-border knowledge production (e.g., by engaging with local research labs in emerging markets).

However, my results make several contributions. To the best of my knowledge, this is the first empirical study of return migration within firm boundaries, and it provides evidence that return migrants play an important role in knowledge production and knowledge transfer at newly established MNE R&D centers. My findings also provide deeper insights on the role of return migrants in the context of the MNE. First, as the longitudinal analysis presented earlier suggests, the contribution of return migrants in building innovation capabilities at the subsidiary may be time sensitive in nature — over time, the fraction of return migrants declines as a percentage of total employees, and their contributions to subsidiary patenting decline, too. Second, return migrants play a direct role in subsidiary patenting, but they also play an indirect role through the local employees who work for them. Third, I provide evidence on the heterogeneity of the return migrant population and highlight the fact that not all return migrants are equally likely to influence knowledge production at the subsidiary. For the larger sample, only the return migrants who have long prior tenures at the MNE have a direct effect on patenting at the subsidiary and on local employees who work for them.

I also make several contributions to the literature on the geography of innovation for firms. I provide econometric evidence that the transfer of employees within the firm helps knowledge production in newly established R&D centers. I also provide robust econometric evidence that transferring employees from the larger established R&D centers to the newly established R&D centers of the firm leads to on-the-job learning by local employees reporting to the ‘migrants’. These results are relevant for MNEs as well as for single-country firms with

multiple knowledge production centers. Finally, my results also inform the nascent literature on internal labor markets of multinationals. So far, the internal labor markets literature has not paid much attention to multinationals. As a result, the literature has not addressed several questions that relate to career paths of MNE employees. For instance, the literature has so far thought of career paths as vertical movements (mostly upward) in a stable hierarchy. However, it is not known, for instance, how moving between multinational affiliates (e.g., from the headquarters to the subsidiary) affects career outcomes and knowledge production outcomes. My results comprise a step forward in understanding the internal labor markets of MNEs, though significantly more work is needed in this area.

The results of the current study are relevant for managers of MNE R&D centers around the world, especially in emerging markets. With the notable exception of Zhao (2006), there are very few examples of empirical work on the underlying mechanisms that enable MNEs to produce knowledge in emerging markets. Given the large number of Fortune 500 MNE R&D centers in countries such as China and India and given the large fraction of such centers managed by return migrants, the results are directly relevant to the setting up and managing of current and future MNE R&D centers.

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Table 1a. Summary statistics of patenting and personnel records

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>number_patents_granted</i>	1315	0.12	1.15	0	29
<i>number_patents_filed</i>	1315	0.20	0.93	0	21
<i>has_been_granted_patent</i>	1315	0.03	0.17	0	1
<i>has_filed_patent</i>	1315	0.10	0.29	0	1
<i>is_returnee</i>	1315	0.08	0.27	0	1
<i>manager is returnee</i>	1118	0.33	0.47	0	1
<i>returnee_tenure_at_subsidiary(years)</i>	104	2.44	2.05	0	10
<i>recruited_as_college_graduate</i>	1315	0.18	0.38	0	1
<i>fraction tenure < 1yr</i>	1202	0.25	0.43	0	1
<i>fraction tenure = 1-2 years</i>	1202	0.34	0.47	0	1
<i>fraction tenure = 2-4 years</i>	1202	0.28	0.45	0	1
<i>fraction tenure = 4-6 years</i>	1202	0.04	0.20	0	1
<i>fraction tenure = 6-10 years</i>	1202	0.06	0.24	0	1
<i>fraction tenure > 10 years</i>	1202	0.03	0.18	0	1
<i>fraction jobtitle = business</i>	1315	0.01	0.11	0	1
<i>fraction jobtitle = other IT</i>	1315	0.05	0.22	0	1
<i>fraction jobtitle = software</i>	1315	0.41	0.49	0	1
<i>fraction jobtitle = program mgmt</i>	1315	0.11	0.31	0	1
<i>fraction jobtitle = testing</i>	1315	0.33	0.47	0	1
<i>fraction org grp1</i>	1202	0.28	0.45	0	1
<i>fraction org grp2</i>	1202	0.06	0.23	0	1
<i>fraction org grp3</i>	1202	0.07	0.25	0	1
<i>fraction org grp4</i>	1202	0.15	0.35	0	1
<i>fraction org grp5</i>	1202	0.08	0.26	0	1
<i>fraction org grp6</i>	1202	0.37	0.48	0	1
<i>mgr_shares_college</i>	1078	0.01	0.12	0	1
<i>mgr_shares_ethnicity</i>	1078	0.01	0.12	0	1
<i>mgr_shares_hometown</i>	1078	0.003	0.06	0	1

Note: This data was collected from multiple sources within TechMNE. Tenure, job title and organizational group data was collected from personnel records; return migrant status and return migrant relocation date was collected from HR; patent grants and patent filing was collected from the patent lawyers at this firm. To identify social ties, for each employee, information on their membership within ‘virtual communities’ was collected. Employees of TechMNE’s India R&D center have membership in 12,680 virtual communities, and these were physically coded as ‘social’ (653 communities), ‘knowledge’ (9456 communities), etc. Using the name and description of each social group, the 653 social groups were classified into the following categories: college ties, ethnic ties and home state ties. In the next step, for all 1315 employees, the groups they belong to were identified. Data is available for 1279 out of the 1315 employees, and this yields 152,101 employee-virtual community rows. In the final step, for each manager-local employee pair, social ties related to common ethnicity, college and hometown were identified.

Table 1b. Summary statistics of patenting by type of employee

	Obs	Mean	Std. Dev.	Min	Max
Number of patents granted					
<i>local employees with returnee managers</i>	319	0.06	0.42	0	5
<i>local employees with local managers</i>	722	0.01	0.14	0	3
<i>local employees who are managers</i>	140	0.07	0.43	0	4
<i>return migrants who are managers</i>	61	1.23	4.31	0	29
Number of patents filed					
<i>local employees with returnee managers</i>	319	0.30	0.90	0	6
<i>local employees with local managers</i>	722	0.09	0.49	0	6
<i>local employees who are managers</i>	140	0.59	2.05	0	21
<i>return migrants who are managers</i>	61	0.74	1.54	0	7
Has filed at least one patent					
<i>local employees with returnee managers</i>	319	0.15	0.36	0	1
<i>local employees with local managers</i>	722	0.05	0.23	0	1
<i>local employees who are managers</i>	140	0.21	0.41	0	1
<i>return migrants who are managers</i>	61	0.33	0.47	0	1

Note: This table compares patent grants and patent filing for local employees with returnee managers and local employees with local managers. The table also summarizes patent grants and patent filings for both returnee and local managers. The personnel data identifies the manager for 1041 out of the total 1211 local employees. The summary statistics indicate that local employees with returnee managers have both higher patent grants and higher patent filings versus local employees with local managers. The table also indicates that managers have higher patenting compared to employees; this could be related to the higher tenure of managers in the organization. Patent filings were for years 2004-2007 and were all filed when the employees were working in the Indian R&D center of the focal firm. Patents granted were for years 1994-2007, when the employees were working at either the US or Indian R&D center of TechMNE. Interviews with TechMNE lawyers indicated that the USPTO examination took an average of 4-5 years. This implies that the prior patent grants referred to patents that the employee(s) worked on in year 2002 or earlier, while still on the payroll of TechMNE.

Table 2. Return migrants and prior patent grants

	Dependent Variable = Number of patents granted			
	(1)	(2)	(3)	(4)
is_returnee	4.06*** (0.44)	3.84*** (0.43)	0.88* (0.49)	-
tenure between 6 and 10 years	-	-	2.37*** (0.65)	2.82*** (0.66)
tenure more than 10 years	-	-	4.55*** (0.65)	3.83*** (0.87)
is_returnee * (tenure_less_than6yrs)	-	-	-	1.59 (1.09)
is_returnee * (tenure_6-10yrs)	-	-	-	0.26 (0.66)
is_returnee * (tenure_more_than10yrs)	-	-	-	1.71** (0.79)
Dummies for org groups	No	Yes	Yes	Yes
N	1315	1202	1202	1202
R2	0.08	0.12	0.30	0.30

Note: This table reports the results of a quasi-maximum likelihood (QML) Poisson regression where the dependent variable is prior patent grants and the independent variable of interest is 'is_returnee'. A generalized linear model with Poisson family and the iterative reweighted least square option is used to implement the QML Poisson specification. Patents granted were for years 1994-2007, when the employees were working at either the US or Indian R&D center of TechMNE. Interviews with TechMNE lawyers indicated that the USPTO patent granting process took 4-5 years. This implies that the prior patent grants referred to patents filed in the year 2002 or earlier, while the employee was still on the payroll of TechMNE. For columns 3 and 4, the tenure dummies are consolidated into three categories to achieve a uniform distribution of individuals across the three tenure categories. These categories are 'tenure less than 6 years' comprising 30 returnees, 'tenure between 6 and 10 years' comprising 30 returnees and 'tenure greater than 10 years' comprising 37 returnees. Tenure data is available for 97 out of the 104 returnees. *Denotes significance at the 10% level; **Denotes significance at the 5% level; ***Denotes significance at the 1% level.

Table 3. Return migrants and patent filing

Dependent variable = Number of patents filed			
	(1)	(2)	(3)
is_returnee	1.32*** (0.27)	1.13*** (0.29)	-
tenure between 6 and 10 years	-	-	2.06*** (0.39)
tenure more than 10 years	-	-	-14.48*** (0.84)
is_returnee * (tenure_less_than6yrs)	-	-	-0.21 (0.68)
is_returnee * (tenure_6-10yrs)	-	-	-0.55 (0.55)
is_returnee * (tenure_more_than10yrs)	-	-	16.25*** (0.88)
Dummies for org groups	No	Yes	Yes
N	1315	1202	1202
R ²	0.02	0.04	0.16

Note: This table reports the results of a quasi-maximum likelihood (QML) Poisson regression where the dependent variable is the number of U.S. patents filed for years 2004-2007 and the independent variable of interest is 'is_returnee'. A generalized linear model with Poisson family and the iterative reweighted least square option is used to implement the QML Poisson specification. For column 3, the tenure dummies are consolidated into three categories to achieve a uniform distribution of individuals across the three tenure categories. These categories are 'tenure less than 6 years' comprising 30 returnees, 'tenure between 6 and 10 years' comprising 30 returnees and 'tenure greater than 10 years' comprising 37 returnees. Tenure data is available for 97 out of the 104 returnees. *Denotes significance at the 10% level; **Denotes significance at the 5% level; ***Denotes significance at the 1% level.

Table 4. Patenting by local employees with returnee managers: results of natural experiment of new college hires

	Dependent variable = Number of patents filed				
	(1)	(2)	(3)	(4)	(5)
manager is returnee	2.30*** (0.81)	2.02** (0.79)	1.85** (0.73)	1.83** (0.71)	1.82*** (0.69)
prior patent grants of manager	-	-	-	-	-10.92*** (0.49)
Dummies for tenure	No	Yes	Yes	Yes	Yes
Dummies for org groups	No	No	Yes	Yes	Yes
Dummies for ties with manager	No	No	No	Yes	Yes
N	225	225	225	215	215
R ²	0.03	0.37	0.42	0.42	0.43

Note: This table reports the results of a quasi-maximum likelihood (QML) Poisson regression where the dependent variable is the number of U.S. patents filed for years 2004-2007 and the independent variable of interest is ‘manager is returnee’. A generalized linear model with Poisson family and the iterative reweighted least square option is used to implement the QML Poisson specification. The sample includes only local employees who are new college hires and the analysis exploits the natural experiment based on rigid HR rules (described in Section 3.2). Controls include prior patenting by the manager, ethnic and college ties between the manager and the employee and the employee’s tenure and organizational group.*Denotes significance at the 10% level; **Denotes significance at the 5% level; ***Denotes significance at the 1% level.

Table 5. Patenting by local employees with returnee managers controlling for tenure of manager

	Dependent variable = Number of patents filed			
	(1)	(2)	(3)	(4)
manager is returnee	0.65** (0.28)	0.72** (0.28)	-	-
manager is returnee * (tenure of manager < 1 year)	-	-	1.08 (0.76)	1.06 (0.76)
manager is returnee * (tenure of manager between 1 and 2 years)	-	-	1.56* (0.86)	1.64* (0.86)
manager is returnee * (tenure of manager between 2 and 4 years)	-	-	-0.93 (0.97)	-0.88 (0.98)
manager is returnee * (tenure of manager between 4 and 6 years)	-	-	0.39 (0.47)	0.43 (0.48)
manager is returnee * (tenure of manager between 6 and 10 years)	-	-	0.74** (0.33)	0.71** (0.33)
manager is returnee * (tenure of manager > 10 years)	-	-	0.70** (0.35)	0.84** (0.37)
prior patent grants of manager	-	-0.03 (0.03)	-	-0.04 (0.03)
Dummies for tenure	Yes	Yes	Yes	Yes
Dummies for org groups	Yes	Yes	Yes	Yes
Dummies for ties with manager	Yes	Yes	Yes	Yes
N	1045	1045	1045	1045
R ²	0.13	0.14	0.13	0.15

Note: This table reports the results of a quasi-maximum likelihood (QML) Poisson regression where the dependent variable is the number of U.S. patents filed for years 2004-2007 and the independent variable of interest is ‘manager is returnee’. A generalized linear model with Poisson family and the iterative reweighted least square option is used to implement the QML Poisson specification. The sample includes all local employees, i.e. both new college hires and experienced hires. Controls include prior patenting by the manager, ethnic and college ties between the manager and the employee and the employee’s tenure and organizational group. Columns 3 and 4 additionally includes a control related to tenure of the returnee *Denotes significance at the 10% level; **Denotes significance at the 5% level; ***Denotes significance at the 1% level.

Table 6. Patent citations analysis

	Patents of local employees with returnee managers (N=33)	Patents of local employees with local managers (N=32)	Difference in means
Self-backward citations (i.e., citations to prior patents filed by inventors working at the TechMNE headquarters)	1.9	1.0	0.85*
Total backward citations (patent)	16.0	12.2	3.9
Total backward citations (non-patent)	3.9	2.8	1.1

Note: This table presents results comparing self-backward citation rates of patents filed by local employees with returnee managers, compared to patents filed by local employees with local managers. Patents filed belong to years 2004-2007, and were matched against a dataset of USPTO patent grants as of 2014. A string comprising the name of the assignee firm, names of the inventors and the filing date was used to match the filed patents with subsequently granted patents. Based on this methodology, 65 out of the 137 filed patents were conclusively matched to subsequently granted patents. The first row indicates that patents filed by local employees with returnee managers have almost twice the number of self-backward citations (i.e., citations to prior patents filed by inventors at the TechMNE headquarters) compared to patents filed by local employees with local managers; this difference of means is also statistically significant. However, the second and third rows indicate that there is no statistically significant difference in the means of total backward citations to prior patents or total backward citations to non-patent prior art for these two groups of employees. *Denotes significance at the 10% level; **Denotes significance at the 5% level; ***Denotes significance at the 1% level.

Panel A. Fraction of (i) return migrants, (ii) local employees with returnee managers and (iii) local employees with local managers in total number of employees.

Panel B. Patent grants over time for (i) return migrants, (ii) local employees with returnee managers and (iii) local employees with local managers.

Figure 1. Fraction of return migrants and local employees with a returnee manager in total number of employees (Panel A) and patent grants by return migrants, local employees with returnee managers and local employees with local managers (Panel B). Given that the Indian R&D center of TechMNC started operations in the late 1990s and given that it takes a minimum of 4 years for a U.S. patent to be granted, the summary trends analysis only considers patent grants starting 2001.

Note: This graphic shows the fraction of employees who file at least one patent. Among local employees who have return migrant managers, the fraction of employees who file at least one patent is around 0.15. Among local employees who have local managers, the fraction of employees who file at least one patent is around 0.05.

Figure 2. Patent filing by local employees with returnee managers compared to patent filing by local employees with local managers.