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Working Paper 14-080

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Abstract

A longstanding literature holds that firms should hire and move talent from the geographic periphery to hubs as a means to *create value* from human capital. They do so, however, at the risk of losing the worker to rivals located in the same geographic hub, limiting their ability to *capture value* in this way. Our study explores both value creation and capture from hiring workers from the periphery and moving them either to headquarters or a peripheral location. We estimate the *human capital rents* accruing to the firm, i.e., the value created net of recruitment, training, and turnover costs. A unique dataset compiled from a large Indian technology firm allows us to exploit the randomized assignment of workers to headquarters and other peripheral locations to provide robust econometric estimates. We find that workers hired in small town locations and moved to headquarters exhibit higher turnover to competitors but also slightly improved performance, compared to being deployed in peripheral locations. In sum, back-of-the-envelope calculations suggest that net rents from human capital are similar whether new recruits from smaller towns are assigned to headquarters or peripheral locations. This suggests that moving workers hired from the periphery to production centers in peripheral locations might be an alternative to moving workers from the periphery to the hub. Fine-grained data of optional career development courses completed by workers shed light on the mechanisms. Our results contribute to the literatures on firms and migration, creating and capturing value from human capital, and worker turnover.

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1. Introduction

A firm's ability to create and capture value from human capital is a key source of competitive advantage (Campbell, Coff, and Kryscynski, 2012; Carnahan and Somaya, 2013). However, while the firm's resources are often concentrated at headquarters/a geographic hub (Bartlett, 1986; Glaeser 1997), high-quality talent is also to be found in peripheral locations such as smaller towns (Moretti, 2012).[2] A long standing literature dating back to Saxenian (2000) has argued that firms should hire talent in the periphery and move this talent to the hub as a means of creating value from the human capital of the migrant.[3] But this also implies a risk of the new hire being poached by competitors in the future. This has prompted some firms to set up offices in smaller towns (Wajcman, 2017), and has led to the emergence of firms such as MobSquad, which hires migrants but locates them in smaller towns such as Halifax and Calgary in Canada (Venugopal, 2020), presumably to prevent rivals from poaching talent. Similar concerns are pertinent to emerging markets like India where talent has been seen as the "most serious obstacle for growth" (Blom and Saeki, 2011) pushing firms to aggressively hire from smaller towns (Singh, 2018). However, firms have to not only find talent across geographies, but also decide where to locate talent. This question has become even more pertinent in a post COVID-19 world, where Indian IT giants such as TCS have been actively rethinking where to locate workers (Khetarpal, 2020).

Our paper seeks to answer the question: *For firms hiring workers from smaller towns, should they be located at the hub/headquarters or the periphery?* Research on worker migration has documented evidence of value *creation* by firms catalyzing the geographic migration of talent (Foley and Kerr, 2013; Wang, 2015; Hernandez and Kulchina, 2019; Choudhury and Kim, 2019). Yet a potential threat has been pointed out in research on strategic human capital: rival firms located in the same hub compete for talent (Mawdsley and Somaya, 2016; Carnahan, Kryscynski, and Olson, 2017). A firm incurs substantial costs in moving a new hire from a smaller town to the geographic hub, while the worker is free to move to a competitor, taking much of the firm's investments into their human and social capital along (Rogan, 2014) and limiting the focal firms' ability to capture the value

[2] As Swerts, Denis, and Mukhopadhyay (2018) reports, smaller towns (i.e. towns with fewer than 100,000 inhabitants) are home to one-third of the Indian urban population and its demographic growth. Additionally, Henderson, Shalizi and Venables (2001) document that Asian countries are less than 30% urbanized (compared to North America, which is 75% urbanized).
[3] For our paper, 'migrant' refers to the worker who is hired from the periphery, i.e., the smaller town, and moved to either the hub or a production center in a peripheral location. In other words, this study is focused on 'within-country migrants.'

created from the workers' geographic move. However, both literatures focus on either value creation or value capture from human capital, leaving open the question of how firms can resolve the trade-off in deciding whether to assign workers from smaller towns to headquarters or peripheral locations.[4]

Echoing recent calls to examine the *rents* from human capital, i.e., the value created net of the cost of human capital (Chadwick, 2017), we attempt to estimate such rents to answer our research question. We assume that the focal firm has multiple production centers in different geographies and hires talent from two sources: large cities and smaller towns. For both sets of workers, we explore the optimal geographic assignment for the firm, i.e., to headquarters or to a peripheral production center. Given that firms in India and other emerging markets have traditionally hired from large cities (Jensen, 2012), we examine talent allocation strategies for smaller town workers – relative to our baseline urban setting – by comparing rents from human capital when smaller town workers are posted to headquarters (in a major city) with rents when they are deployed in peripheral production centers. We also compare these to rents from workers hired from large cities.

While our research question is of interest to managers and to scholars in the strategic human capital literatures alike, in practice it is difficult to observe differences in value creation and capture from assigning smaller town workers to headquarters versus other locations. In conventional settings, the assignment of individuals to a production center may be correlated to observable and unobservable characteristics of the firm, the individual, and the production center. Hence, productivity estimates of small-town workers assigned to headquarters are likely to be biased upwards (downwards) depending on whether or not measures of worker ability are positively (negatively) correlated with the probability of being assigned to headquarters.

We address this concern by leveraging a natural experiment in a large Indian technology firm (hereafter INDTECH), which employs over 120,000 people worldwide and hires extensively from large cities and smaller towns across India. For entry-level workers, INDTECH hires talent from more than 250 colleges in India, many of them located in smaller towns. Crucial for our empirical design, INDTECH has a unique policy for

[4] While most Indian technology firms have their headquarters and major production centers located in large cities such as Bangalore, they have also built secondary knowledge production centers in the geographic periphery. Arora et al. (2001: 1272, Table 5) document that for the Indian software services industry, around 9% of NASSCOM firm locations are outside the large Indian cities.

assigning workers across its production centers. Every year, it recruits a new cohort of entry-level workers across the country, who, after a four-month induction training program, are randomly assigned to ten production centers using a computer application that is part of the firm's enterprise resource planning software. INDTECH randomizes worker assignment so that its end customers – mostly U.S.-based firms – are indifferent to the particular INDTECH center that executes their project, and to prevent sociolinguistic cliques from emerging in INDTECH's urban production centers. This randomized spatial allocation protocol allows us to circumvent econometric concerns in a traditional setting and directly compare the turnover and performance of small town workers assigned to headquarters in Bangalore to their city counterparts and to small town workers assigned to peripheral locations.

We find the following results. First, workers from smaller towns exhibit lower voluntary turnover compared to workers from large cities, regardless of placement location. However, comparing the voluntary turnover of smaller town workers across assignment locations, we find that Bangalore placement is associated with a significantly higher rate of turnover. Moreover, comparing the two most common reasons for worker departure – moving to competing firms and leaving for further study – we find that this effect is driven largely by small town workers' *higher* rates of turnover to *competing firms* when placed in Bangalore (13.8% compared to 5.9% for small town workers outside of Bangalore and 7.3% for large city recruits assigned to Bangalore), rather than the pursuit of further education (smaller town workers are *less* likely to pursue *higher education* regardless of assignment location and even less likely when placed in Bangalore). Second, despite this, workers from smaller towns tend to create disproportionately more value than those from large cities regardless of the location to which they are assigned, and especially when assigned to Bangalore. Marginal probabilities of the likelihood of attaining the highest performance rating suggest that while a Bangalore placement reduces performance for workers hired from large cities from 35.0% to 21.1%, the performance of workers from smaller towns remains constant, marginally rising from 40.0% to 40.1%. Combining these estimates, we calculate the likely net payoff – or rent from human capital – accruing to INDTECH from the different worker allocation decisions based on detailed supplementary evidence gathered during field interviews. Our back-of-the-envelope estimates suggest that human capital rents are similar from hiring and posting small town workers to Bangalore or a peripheral location. We also find that rents captured by INDTECH from smaller town workers always exceed rents captured from workers hired from large cities, irrespective of whether they are assigned to headquarters or other locations.

In addition, our research sheds light on the micro-foundations of value creation and capture from human capital. Leveraging internal data on voluntary training provided to interested workers at INDTECH, our analyses indicate that workers hired from smaller towns indeed appear to make more effort to invest in their professional development by taking more courses on average, and successfully completing a larger proportion of coursework, even when posted to Bangalore. Unreported results confirm that such activities contribute positively to their on-the-job performance at INDTECH. However, for some workers, additional training can become a source of turnover and thus prevent value capture. Workers from smaller towns posted to Bangalore are more likely to enroll in courses that equip them with skills that are equally valued by competitors, such as Business English; those outside of Bangalore focus on other types of courses that may offer less transferable skills.

Together, these results suggest that while hiring small town (compared to large city) workers is an optimal strategy for INDTECH, the firm captures similar rents from posting small town workers to headquarters or peripheral production centers. Crucially, this finding suggests that moving workers from the geographic periphery to hubs may not be the only option available to firms; moving smaller town workers to peripheral production centers might be an option that both scholars and managers should explore more.

Our results contribute to the literatures on value creation and value capture from human capital (Campbell, Coff, and Kryscynski, 2012; Carnahan and Somaya, 2013; Ganco, Ziedonis, and Agarwal, 2015; Chadwick, 2017); the organizations and strategy literature on worker turnover (Ton and Huckman, 2008; Carnahan, Agarwal and Campbell, 2012; Carnahan, Kryscynski, and Olson, 2017); the literature on the role of the headquarters in determining productivity outcomes of knowledge workers (Ghoshal and Nohria, 1989; Gupta and Govindarajan, 1991; Choudhury, 2017) and motivating further human capital accumulation (Gambardella and Giarratana, 2010); and the literature on the role of firms as catalysts of knowledge worker migration (Hernandez, 2014; Choudhury, 2015; Wang, 2015; Kulchina and Hernandez, 2019; Choudhury and Kim, 2019) not only *across countries*, but also *within countries* (Choudhury and Kwon, 2018).

The remainder of the paper is structured as follows. Section 2 outlines the theory that guides our analyses; Section 3 summarizes the empirical context, specifications, and data; Section 4 presents our identification strategy; Sections 5 and 6 our results and robustness tests; Section 7 our human capital rent calculations, and Section 8 the discussion and conclusion.

2. Theory

Our theoretical framework encompasses both value creation and value capture from human capital, with an emphasis on human capital rents, i.e., value creation net of the cost of human capital to the firm (Molloy and Barney, 2015; Chadwick, 2017). To paraphrase Chadwick (2017, 502), Barney (1991), Peteraf (1993), and other Resource-Based Theory (RBT) scholars have observed that resources such as human capital create rents when the value they generate… exceeds the firm's cost of acquiring and retaining those resources. Chadwick (2017) defines "rents from human capital" as the value created from human capital net of the costs of managing human capital, and suggests that firms may increase such rents by retaining workers longer, thus reducing the costs of repeatedly acquiring human capital.

However, hiring workers from smaller towns and moving them to headquarters (typically Bangalore in India, as documented by Parthasarathy, 2004) can increase the loss of such workers to competitors. This is especially true for workers hired from smaller towns, where few firms actively recruit. While workers from large cities are exposed to a wide range of other organizations and often self-select to join the focal firm as opposed to a competitor, for smaller town workers the firm might be the only option on graduating from college. This may result in a lower quality of initial matches for workers from smaller towns (Dauth et al., 2018) and a higher likelihood of subsequent separation, particularly for younger workers still determining their preferences (Wheeler, 2006; Bleakley and Lin, 2012; Andersson, and Thulin, 2013). As a result, once the small-town worker moves to headquarters, his/her 'matchmaking' opportunities dramatically improve and he/she may end up leaving to join a competitor (Saxenian, 1994; Fallick, Fleischmann, and Rebitzer, 2005).

Moreover, even if workers from small towns are not fully aware of the quality of their initial job match, the receipt of job offers from competitors may prompt them to re-think their current position. Building on Lee and Mitchell (1994) and Jovanovic (1979), Carnahan, Kryscynski, and Olson (2017) argue that worker turnover occurs when "mismatches become apparent to the workers and/or the firms" (Carnahan, Kryscynski, and Olson, 2017: 6), a learning process driven largely by the generation of new outside options.

Finally, to the extent that firms incur high costs to recruit and relocate workers from small towns to headquarters in anticipation of superior performance, such workers may be especially be likely to solicit external job offers. For instance, Lee et al. (2008) build on March and Simon (1958) to theorize worker turnover using the lens of "inducement-contribution utility balance that is, in turn, a function of two major distinct but related motivational forces: (1) the perceived desirability, and (2) the perceived ease of movement out of the organization," (Lee et al., 2008: 651). As a result, workers who exhibit superior performance may perceive themselves to have ease of movement out of the organization (a pull factor) and re-evaluate their perceived match with the focal organization if a competing job offer is received. In summary, faced with a competing offer, workers from smaller towns might experience both a greater perceived mismatch with the focal firm and a greater pull towards competitors, prompting a greater likelihood of turnover.

To mitigate this possibility, an alternative talent allocation strategy might be to hire small town workers but assign them to production centers on the periphery where the potential for poaching is lower. As a 2014 World Bank report pointed out, several Indian states have facilitated the set-up of "industrial parks," even in remote regions, enabling this managerial choice (Saleman and Jordan, 2014).[5]

However, the possibility of turnover and implications for value capture from human capital thereof is arguably not the only consideration for firms when deciding where to locate talent. Urging scholars to heed the importance of value creation from human capital, Chadwick (2017: 503) suggests that firms could raise rents by increasing the value created from human capital, in particular through "a training program or by creating complementarities" with other firm resources. Dating back to Bartlett (1986), headquarters have been described

[5] As an example, while most Indian technology firms have their headquarters and major production center located in large cities such as Bangalore, they also have secondary knowledge production centers in the geographic periphery. Arora et al. (2001: 1272, Table 5) document that for the Indian software services industry, around 9% of NASSCOM firm locations are outside the large Indian cities.

as a "centralized hub" for organizational resources. Subsequent literature has established the pivotal role of the headquarters in accumulating and allocating organizational resources (Ghoshal and Nohria, 1989; Ghoshal and Bartlett, 1990; Gupta and Govindarajan, 1991; Dacin et al., 1999; Andersson, Forsgren, and Holm, 2002; Björkman, Barner-Rasmussen, and Li, 2004; Nell and Ambos, 2013). Moreover, knowledge workers in non-headquarters locations face significant constraints on securing resources and/or knowledge that resides at headquarters (Choudhury, 2015, 2017; Monteiro, Arvidsson, and Birkinshaw, 2008). Studies of worker migration have documented evidence of value *creation* from human capital when firms catalyze the geographic migration of talent (Foley and Kerr, 2013; Hernandez, 2014; Choudhury, 2015; Wang, 2015; Hernandez and Kulchina, 2019; Choudhury and Kim, 2019). This implies that talent hired from smaller towns might be more productive and create more value when assigned to headquarters, which are often located in a large city.[6]

Together, these arguments suggest that value creation from human capital is plausibly greater when workers hired from smaller towns are assigned to headquarters (e.g., in Bangalore[7]) than to production centers on the periphery. It is also plausible that they exhibit disproportionately higher turnover when assigned to headquarters, raising the cost of human capital for the firm. Less clear is whether firms generate greater rents (i.e., value creation net of human capital costs stemming from turnover) by assigning smaller town talent to headquarters or the periphery. In other words, we are unable to arrive at a theoretical prior for our research question, i.e., conditional on hiring talent from smaller towns, should firms assign such talent to headquarters or to production centers on the geographic periphery? For this reason, we rely on robust econometric analysis to reveal an empirical pattern.

3. Data

[6] If the headquarters is located in a "knowledge hub", i.e., a large city with a high concentration of knowledge and ideas (Marshall, 1890; Jacobs, 1968; Lucas, 1988; Jaffe, Trajtenberg, and Henderson, 1991; Glaeser, 1997; Moretti, 2004; Ellison, Glaeser, and Kerr, 2007; Combes, Duranton, and Gobillon, 2008), the mere exposure to and interaction with individuals with knowledge that is superior or complementary to the focal worker may raise their productivity and in turn generate value for the firm. Building on Jacobs (1968), Glaeser (1997: 2) describes such large cities as "intellectual furnaces where new ideas are formed." Alcácer and Chung (2007) document how technologically advanced firms locate in regions with high concentration in academic knowledge. Saxenian (1994) uses the example of Silicon Valley to argue that the spatial agglomeration of knowledge helps human capital augmentation of knowledge workers located in this region.

[7] As in the case of India, where most technology firms are headquartered in Bangalore, for the remainder of the paper we will assume that the headquarters location of the focal firm is within a large city, and that this location is subject to the learning, knowledge spillovers, and human capital augmentation effects outlined in the spatial agglomeration literature.

Our empirical setting is one of India's largest IT firms (INDTECH). The firm has more than 120,000 workers spread over 10 production centers in India, and its customers span the globe. After entry-level workers are recruited, they undergo two random assignments. First, they are randomly assigned to one of three "technological areas" – ".NET," Java, or Mainframe – that represent INDTECH's core business. Based on this assignment, they then receive four months of related induction training.[8] Worker training is staggered and can begin at any point from May to December of each year. Second, once workers have completed training, they are randomly assigned to a production center. Each of the 10 production centers at INDTECH works on projects related to all three technological areas (".NET," Java, Mainframe); thus, entry-level INDTECH workers can be assigned to any production center.

INDTECH's decision to assign a new hire to one of the three technological areas is uncorrelated with observable characteristics of the individual. To avoid bias caused by diverse temporal trends affecting the technologies in which workers are trained, we restricted our data collection exercise to workers trained in a single area – ".NET". This minimizes any bias resulting from differences in worker performance due to short-term demand or supply trends in each of the technology areas. We collected unique data for all entry-level, fresh college graduates recruited in 2007 who had no prior full-time employment experience. The workers in our sample came from more than 250 colleges across India. In total, we collected data on 1,665 undergraduates hired and assigned to the .NET technology area in 2007.[9] INDTECH hires about 10,000 undergraduates every year. Since we focused only on workers trained in .NET, we collected data on about 17% of the total entry of undergraduates in 2007.

INDTECH trains new workers assigned to a particular technological area in batches of typically around 80-120 workers each, though exact numbers vary. The company has a corporate training center in the southern Indian city of Mysore with a 337-acre campus, 400 instructors, and 200 classrooms. According to our field interviews, INDTECH spends around $3,500 per worker to train new college graduates for four months on

[8]. The .NET Framework (pronounced dot net) is a software framework developed by Microsoft that runs primarily on Microsoft Windows. It includes a large library and provides language interoperability (each language can use code written in other languages) across several programming languages (http://en.wikipedia.org/wiki/.NET_Framework).

[9] Technically, INDTECH hired 1,696 undergraduates in 2007 that were assigned to .NET. However, 34 of them dropped out during initial training and were never assigned to any production center. We therefore lack all post-hire variables for these workers and drop them from the sample.

computer science topics, such as relational databases, client-server concepts, and programming languages. In addition, as described earlier, the post-training assignment of workers to a production center is not correlated to observable worker characteristics.

We were interested in examining how turnover and performance of workers from smaller towns and large cities vary with their locational assignment. As a result, we constructed two independent variables of interest. Our first independent variable of interest was whether or not the worker hailed from a smaller town (*From smaller town*). To construct this variable, we obtained detailed worker resumes, which included the name and location of workers' primary schools, high schools, and undergraduate colleges. The INDTECH data for this was available for 93% of the 2007 batch. In the next step, we classified Indian cities and towns based on the classification system outlined by the Sixth Pay Commission report of the Government of India.[10] The classification system divides India's cities and towns into three categories, with the largest six metropolitan areas of Delhi, Mumbai, Bangalore, Chennai, Kolkata, and Hyderabad classified into the first category, the next largest cities in the second category, and the smallest towns in the third.[11]

Given this data, we code *From smaller town* as 1 if the following three conditions are met: the worker attended (1) primary school in a location outside the largest six metros; (2) high school in a location outside the largest six metros; and (3) college in a location outside the largest six metros. Assuming that being from a smaller town is correlated to *ex post* higher productivity, this turns out to be the most conservative way of coding the variable *From Smaller Town*. In this definition, workers who went to primary and high school in a smaller town but attended college in one of the largest six metros are coded as 0. Thus, although these workers might have consequently moved to college in one of the six largest metros, they are still coded as part of the control group. In the robustness section, we relax this assumption and our results continue to hold.

Our second independent variable of interest was whether or not the worker was assigned to INDTECH's headquarters in the technological and resource hub of Bangalore (*Placed in Bangalore*). We

[10] The government issued a circular on August 29, 2008 to formalize this classification system, and all Indian state-owned entities and government departments use this classification system to establish the cost of living for employees.
[11] Details of this categorization of Indian cities and towns are available at:
http://www.referencer.in/PayCommission/Reports/OM_Allowances.pdf

constructed this variable by assigning each worker a value of 1 if the worker was randomly assigned to Bangalore using their computer-generated talent allocation protocol and the value of 0 if the worker was randomly assigned to one of the remaining eight production centers.[12]

We then created three sets of dependent variables of interest to capture three broad constructs: worker voluntary turnover, worker performance, and worker human capital accumulation. Our first set of dependent variables aimed to capture workers' turnover choices. For each worker that departs INDTECH, the company records their reasons for departure. We used these data to first code the variable *Quit by Choice*, which takes the value of 1 if the worker quit of their own (rather than the company's) volition, and 0 otherwise. Delving further into the reasons for voluntary departure, we distinguished between *Quit for Further Study* which takes the value of 1 if the worker quit to pursue further study and 0 otherwise, and *Moved to a Competitor* which takes the value of 1 if the worker quit to move to a competing firm and 0 otherwise.

Our second set of dependent variables aimed to capture each worker's on-the-job performance in his/her first year in the role. We measured their performance in two ways. First, we created the variable *Performance,* which captures worker productivity. At the end of every year, all INDTECH workers that worked on a coding/testing project for at least nine months in the calendar year receive a performance rating. For new hires, workers' training schedule affected whether they satisfied the "nine-month rule." For instance, in the 2007 sample, workers who started their training after September 2007 would not finish until early 2008. Most of those workers were not assigned to a project prior to March 2008, making them ineligible to receive a 2008 performance rating. This mitigated the concern that INDTECH's decision to deploy a worker to a project depended exclusively on superior ability, based on observable and/or unobservable characteristics.[13] For the 2007 sample, we collected performance data for all workers (n=511) who met these criteria and received a performance rating at the end of 2008.

[12] While INDTECH has a total of 10 production centers in India, the time window of our data and focus on employees working on the .NET Framework only covers nine production centers.

[13] We also empirically validate that controlling for the training batch, logical and verbal scores, gender, and smaller town origin were not significant predictors of receiving a performance rating in 2008; only CGPA training was a positive predictor of receiving a performance rating in 2008, so we include this control in all further specifications.

Field interviews with the head of talent development at INDTECH, a senior manager in HR, and several workers in the sample also indicate that the performance ratings for entry-level undergraduates are based on objective measures. These include quality of coding and/or testing (measured using "mistakes" in the code that are recorded by automated software) and timeliness and completeness in coding/testing and documentation (also measured using automated software). Each worker's manager gives an initial performance rating based on the objective criteria, and then managers from Human Resources check the rating against the underlying scores (i.e., scores of coding error rates, coding completeness) to correct any erroneous scores. To quote a senior human resources manager, *"for the first three years, performance evaluation is strictly based on objective metrics."*

In addition, we created a second measure of on-the-job performance, *Dismissed*. This variable takes the value of 1 if INDTECH dismissed the focal worker from his/her job within the first three years of their employment and 0 otherwise. Dismissals were driven almost entirely by low performance. For instance, no workers receiving at least the middle performance rating were dismissed, but 70% of those receiving the lowest performance rating were dismissed. Overall, across the full sample of 1,665 workers, 5.3% were dismissed.

Finally, our third set of dependent variables aims to capture workers' human capital accumulation efforts. These measures leverage INDTECH's generous policy to fund further education for their workers. In particular, INDTECH offers each of its entry-level workers nearly unlimited access to a set of in-house and externally provided online courses. Workers can enroll in these courses in their spare time free of charge and take as many courses as they wish. While enrollment is entirely optional and not reflected in workers' performance ratings, INDTECH tracks workers' enrollments and pass rates in these courses. We obtained additional data on these enrollments and pass rates for each worker in our database. These data are at the worker-course level, and indicate the course name, level (if multiple course levels are available), and whether the worker passed the course. In the event of failing, workers were allowed to retake the course until they passed.

Using these data, we created four variables. The first, *Number of Courses Taken*, captures the total number of courses each worker enrolled in. The second, *Percent of Courses Passed*, captures the percentage of courses the worker passed, conditional on taking at least one course. For the third and fourth variables, we further distinguished between course types. INDTECH offers its workers a broad range of courses, from technology-specific courses such as ".NET Foundation Certification" to industry-specific courses such as "Introduction to Aerospace Industry". We focused on one course type: "Business Language (English)". English courses were both among the most popular (the third most popular after .NET and the IQ Foundation Certification programs), and the most widely applicable in the workers' daily work both within and outside of INDTECH, should the worker later move to a competitor later. Across our sample, 13.9% of workers took at least one English course during their first year of work. Based on these data, we coded our third variable, *Number of English Courses*, as the total number of English courses a worker took in their first year. Finally, INDTECH offered English courses at 10 different levels of difficulty, with 10 being the most advanced. We therefore coded our fourth variable, *Highest Level of English Courses* taken, as the maximum level of English that the worker took, varying between 1 and 10.

To help rule out alternative explanations, we added a battery of controls. First, we added controls for workers' pre-entry performance on a standardized recruitment test administered by INDTECH. This test had two components – verbal and logical – and we recorded the scores separately for each, as *Verbal Score* and *Logical Score*. Second, we also controlled for cumulative grade point average, *CGPA Training*, which captures worker performance during the four-month induction training and is expected to be positively correlated to subsequent performance within the firm. Finally, we controlled for worker gender (*Male*) and dummies for the production centers to which workers were assigned.

Table 1 summarizes descriptive statistics of the personnel and performance data for the entire sample and two sub-samples by worker origin and production center placement. Columns (1)-(3) compare the personnel and performance data for workers from smaller towns with workers from large cities. The results reported in Column (3), Panel B indicate that workers from smaller towns perform better on the logical component of the recruitment test (difference = -1.038; p<0.01). Panel C indicates a statistically significant difference in performance ratings for smaller town and large city workers (difference = -0.168; p <0.01). Panel D indicates statistically significant differences in the number of and pass rates for courses taken by workers from smaller towns relative to those from large cities (difference = -0.775; $p<0.01$ and = -4.403; $p<0.001$, respectively). Panel E also indicates a lower and statistically significant difference in voluntary attrition rates overall and in attrition to further study for smaller town and large city workers (difference = 0.117; $p<0.001$ and = 0.105; $p<0.001$, respectively). Columns (4)-(6) compare the personnel and performance data for workers placed in Bangalore versus other production centers. The descriptive statistics reported in Column (6), Panels A and B show that workers placed in Bangalore do not differ significantly from those placed outside of Bangalore on pre-entry characteristics, further validating the random assignment protocol at INDTECH. Post-entry, Panels D and E indicate that workers placed in Bangalore take fewer courses (difference = 0.315; $p<0.05$) and are more likely to quit by choice (difference = -0.050; $p<0.05$). However, while suggestive, these results are based on pairwise comparisons, omitting a battery of controls for pre-entry worker characteristics and location fixed effects. We turn to examine the effects of Bangalore placement and small-town origin with controls next.

[Insert Table 1 Here]

4. Identification Strategy

As described in the introduction, our identification strategy exploits a random computer-generated talent allocation protocol at INDTECH. After four months of induction training, the firm randomly assigns workers to its 10 production centers across the country, including its headquarters in Bangalore. Appendix A outlines the steps followed by the assignment algorithm. This policy ensures that the assignment of a worker to a particular location within the firm does not correlate with measures of observed ability, such as test scores at the end of induction training and implies that the production center fixed effects are arguably uncorrelated with the variable *From Smaller Town* or other observable characteristics of the worker. However, to verify this assumption, we also run a model predicting assignment to Bangalore based on pre-hire worker characteristics, discussed below and presented in Table 5.

INDTECH's primary motivation for this talent allocation policy is to ensure that INDTECH's end customers are indifferent to the location of the production center that executes their projects. Their secondary motivation is to prevent the emergence of regional and/or ethnic cliques at the production centers. To quote the head of talent development at INDTECH, *"We do not want all Tamils to join the Chennai center or all Punjabis to* *join Chandigarh and start conversing in their regional language rather than in English. If that happens, both our clients and workers from other parts of the country are affected."*

Using this identification strategy, we construct three sets of models. First, to examine how the voluntary turnover of smaller town workers will vary with the assignment to the headquarters located in a knowledge hub, compared to when they are assigned to a non-headquarters location, we run the following specification:

$$(1)\quad Quit_i = \beta_0 + \beta_1 From\ Smaller\ Town_i + \beta_2 Placed\ in\ Bangalore_i + \beta_3 From\ Smaller\ Town_i * Placed\ in\ Bangalore_i + \sum_{j=1}^{J} \beta_j I_{ji} + \epsilon_i$$

where *i* refers to each individual, and I_{ji} is a vector of *J* individual-level control variables. We measure $Quit_i$ with three separate dependent variables: *Quit by Choice,* a dummy variable indicating that the worker exited the firm by 2011 of their own volition; *Moved to Competitor,* a dummy variable indicating that the worker moved to a competing firm by 2011; and *Quit for Further Study,* a dummy variable indicating that the worker exited the firm by 2011 to pursue further study. Since all three variables are binary, we implement these specifications using logit estimators and robust standard errors clustered at the location of the production center. Finally, to ensure that our results are not driven by unobservable biases in the sorting of workers to production centers, we also replicate all our results with placement location fixed effects using conditional logit estimators grouped at the production center. The results remain unchanged.

Second, to examine how the performance of smaller town workers varies with the assignment to the headquarters located in a knowledge hub, compared to when they are assigned to a non-headquarters location, we run the following specification:

$$(2)\quad Performance_i = \beta_0 + \beta_1 From\ Smaller\ Town_i + \beta_2 Placed\ in\ Bangalore_i + \beta_3 From\ Smaller\ Town_i * Placed\ in\ Bangalore_i + \sum_{j=1}^{J} \beta_j I_{ji} + \epsilon_i,$$

where *i* refers to each individual and I_{ji} is a vector of *J* control variables. We measure $Performance_i$ in two ways: either using *Performance* ratings at the end of 2008 or the indicator variable *Dismissed*. Given that *Performance* is measured in normalized bands, we implement these specifications using an ordered logit model. The specifications with *Dismissed* as the dependent variable are implemented using logit models. In both models, we cluster the standard errors by the location of the production center to which the worker is assigned. Finally, as in specification (1), we also replicate our estimations with placement location fixed effects using the Blow-Up-and-Cluster estimator for ordered logit fixed effects developed by Baetschmann, Staub, and Winkelmann (2015) (for details of the estimation procedure please see the Results section) and the conditional logit estimator grouped at the placement location. The results remain unchanged.

Third, in addition to exploring the raw variation in turnover and performance, we are interested in examining the mechanisms underlying our propositions. Specifically, we aim to test the differences in human capital accumulation efforts between workers from smaller towns and large cities once they are assigned to the headquarters in Bangalore. To estimate how smaller town origin impacts worker's *i* human capital accumulation, we run the following specification:

$$(3)\quad Courses\ taken_i = \beta_0 + \beta_1 From\ Smaller\ Town_i + \beta_2 Placed\ in\ Bangalore_i + \beta_3 From\ Smaller\ Town_i * Placed\ in\ Bangalore_i + \sum_{j=1}^{J} \beta_j I_{ji} + \epsilon_i$$

where i refers to each individual and I_{ji} is a vector of J control variables. We measure *Courses taken* using the four distinct variables described above: *Number of Courses Taken, Percent of Courses Passed, Number of English Courses Taken* and *Highest Level of English Courses Taken*. We then explore each worker's propensity to take such additional coursework based on their placement in Bangalore and a battery of controls. For regressions on the *Number of Courses Taken* and the *Number of English Courses Taken*, since these are count variables, we estimate the models using Poisson estimators with robust standard errors clustered at the production center. For models with the dependent variable of *Percent of Courses Passed*, we use OLS with errors clustered at the production center level. Since the *Highest Level of English Courses Taken* is an ordered categorical variable taking values between 1 and 10, we implement this specification with an ordered logit and errors clustered at the production center level. Finally, we replicate all analyses with production center fixed effects and our results remain unchanged.

In all three specifications described above, we control for Recruitment Test Scores *(Logical Score* and *Verbal Score)*, the cumulative grade point average at the end of training (*CGPA Training*), gender (*Male)*, and where indicated in the tables, also the fixed effects for the production center to which the worker is assigned.

5. Results

Worker Origin, Placement in Bangalore and Turnover

We begin our analyses by graphically exploring raw tabulations of worker turnover and performance. Figure 1 depicts overall rates of voluntary turnover by worker origin and placement location. We see that workers placed in Bangalore exhibit higher rates of turnover regardless of their origin. Moreover, workers from smaller towns exhibit a larger and statistically significant (at the 5% level) jump in their propensity to voluntarily leave INDTECH when placed in Bangalore than workers from large cities for whom the difference in attrition across production centers is not significant (p-value = 0.329). However, we also see that workers from smaller towns exhibit lower and statistically significant (at the 5% level) rates of voluntary turnover regardless of placement location.

[Insert Figure 1 Here]

Table 2 reports the results from our tests of specification (1) above. To recap, we test whether workers from smaller towns are more or less likely to exhibit voluntary turnover on average, and by assignment location. Column (1) shows that workers from smaller towns are less likely than workers from large cities to quit INDTECH voluntarily regardless of their placement location (at an average marginal rate of 29.5%, relative to 40.9% for workers from large cities). Column (1) further shows that both workers from smaller towns and workers from large cities are, on average, more likely to quit of their own volition when placed in Bangalore. However, Column (2) shows that this effect is mostly driven by workers from smaller towns, whose departure rates are significantly higher in Bangalore than other locations. Average marginal effects indicate that workers from smaller towns placed in Bangalore depart at a rate of 36.0%, while their counterparts outside of Bangalore depart at a rate of 27.9%, a difference of 8.1 percentage points. In contrast, workers from large cities are not significantly more likely to depart INDTECH when assigned to Bangalore (p-value = 0.285) and average marginal effects indicate an increase in departure rates of only 2.9 percentage points when in Bangalore (43.2%, relative to 40.3% outside of Bangalore). We conclude from these results that a Bangalore assignment does increase the probability of turnover quite substantially for smaller town workers; however, workers from smaller towns continue to exhibit less turnover than workers from large cities overall. Our results continue to hold even when we add placement location fixed effects that help control for any other unobserved location-specific variation that may bias our results. To do this, we re-estimate specification (1) using conditional logit models grouped at the production location level. These results, in Column (3), show that the conclusions in Column (2) continue to hold, even with fixed effects.

We dig deeper into the variation in turnover to better understand how worker origin and placement location affects firms' human capital rents. Columns (4)-(9) examine differential effects by worker destination, separately estimating the likelihoods of turnover to competitors and further study, the two most common reasons workers leave INDTECH: i.e., joining a competitor or leaving to pursue further education. We present each set of results in turn below.

Columns (4)-(6) present the results for turnover to competitors. While the direct effect of being a smaller town worker is not significant, the interaction effect between smaller town origin and placement in Bangalore is positive and significant, indicating that the difference in turnover risk to competing firms between workers from smaller towns and large cities grows significantly when smaller town workers are placed in Bangalore, even when we add placement location fixed effects. Average marginal effects based on the specification in Column (5) suggest that while workers from smaller towns placed outside of Bangalore are nearly as likely to move to competitors (5.9%) as workers from large cities regardless of placement (between 6.7% and 7.3%), workers from smaller towns placed in Bangalore are nearly twice as likely to move to a competing firm (13.8%).

At the same time, however, workers from smaller towns are significantly less likely to experience turnover to pursue further education. These results, reported in Columns (7)-(9), indicate that workers from smaller towns are disproportionately less likely to pursue further studies and are even less likely to do so when placed in Bangalore, even with location fixed effects. A plausible explanation for these results is that workers from smaller towns may be more resource constrained and unable to easily pursue graduate studies. In addition, it is possible that smaller town workers placed in Bangalore view further studies as having an excessively high opportunity cost, given the availability of alternative employment opportunities. Together, the two opposing trends in the destination of worker turnover shed light on the likely effects of overall turnover on INDTECH.

All results reported in Table 2 are further robust to estimating all models using OLS with production center fixed effects and errors clustered at the production center, to re-running all models with bootstrapped and clustered standard errors, and to using paired bootstrap-t clustered errors robust to a small number of clusters described in the Robustness section and presented in Table 6.

[Insert Table 2 Here]

Worker Origin, Placement in Bangalore, and Performance

Figure 2 outlines productivity (i.e., 2008 performance ratings) for workers hired from smaller towns and large cities for the 2007 batch by production center placement. We run distributional tests to compare the short-term performance for smaller town and large city workers using the two-sample Wilcoxon rank-sum (Mann-Whitney) test and reject the null hypothesis that the performance data for the two groups follow the same distribution. We also run the same distributional tests to compare the short-term performance of workers across production locations (in Bangalore versus outside of Bangalore) and fail to reject the null hypothesis that the performance data for the two groups follow the same distribution.

[Insert Figure 2 Here]

Table 3 presents our results for specification (2) relating worker *Performance* and chances of *Dismissal* to their origin and whether their placement location is in or outside of Bangalore. Note that while the full sample contains 1,665 workers, the sample size in the regression analyses in Columns (1)-(3) in Table 3 is much smaller due to the "nine-month work rule" described in the Data section above. In addition, the reported observations in the table are split into two categories: (1) 'actual' and (2) 'used for BUC'. Actual observations refer to the number of available observations for all variables in the model. 'Used for BUC' refers to the Blow-Up-and-Cluster (BUC) procedure developed by Baetschmann, Staub, and Winkelmann (2015). This estimation helps overcome the limitations of ordered logit models that preclude us from adding fixed effects directly as a set of dummies, and allows us to consistently estimate ordered logit models with production center fixed effects (for other recent applications of the BUC procedure, see also Wang and Jensen (2019) and Tilcsik (2014)). The procedure leverages the consistency of conditional logit estimation by dichotomizing the dependent variable K-1 times at each available cut-off (where K refers to the number of categories in the dependent variable) and estimating all the dichotomizations jointly with conditional logits, grouped at the level of the fixed effect. As a result, the number of observations used in Columns (3) exceeds those available in the raw data by about two-fold, or the number of cut-offs in the dependent variable.

We begin by examining in Columns (1) and (2) the differential effects of Bangalore placement on the performance of workers from smaller towns and large cities. As Column (1) shows, workers from smaller towns show stronger performance regardless of placement location. Average marginal effects based on Column (1) show that workers from smaller towns have a 40.2% likelihood of receiving the highest performance rating, relative to workers from large cities, who receive the same rating with a 31.8% probability. However, the difference in their performance relative to their large city counterparts grows especially large when they are posted to Bangalore. Average marginal effects for Column (2) show that while the likelihood of attaining the highest performance rating for workers from smaller towns stays almost identical, at 40.1%, workers from large cities posted to Bangalore receive the highest performance rating only 21.1% of the time. Finally, the interaction effect of Bangalore placement and worker origin remains positive and significant even when we include placement location fixed effects in Column (3).

Columns (4)-(6) report our results on dismissal. Here we see no statistically significant differences in the likelihood of dismissal by worker origin and placement location, suggesting that outperformance of workers from smaller towns in Columns (1)-(3) is not driven by higher risk-taking on the job.

All reported results are robust to bootstrapped and clustered standard errors at the production center, to re-running all analyses with an OLS model with production center fixed effects and wild bootstrapped and clustered standard errors. The results in Columns (1)-(3) are also robust to re-coding *Performance* as a binary variable, taking the value of 1 if *Performance* takes the highest value of 3 and 0 otherwise, and re-running the analyses with either a conditional logit or an OLS estimation. These results are omitted for the sake of brevity and available from the authors upon request. Finally, we replicate all our analyses also with pairs-cluster-robust standard errors that are robust to estimations with few clusters (Cameron, Gelbach, and Miller, 2008; Andrew, 2015), described in the Robustness section.

In sum, our results suggest that workers from smaller towns are both more likely to outperform their counterparts outside of Bangalore (and also outperform large city workers placed in Bangalore) and more likely to experience turnover to join a competitor, when posted to Bangalore.

[Insert Table 3 Here]

Evidence of Mechanisms and Human Capital Accumulation

To examine a plausible mechanism driving our results, we leverage INDTECH's provision of further education courses and implement specification (3) to examine whether workers from smaller towns are more likely to enroll in additional coursework that augments their human capital in ways that may both aid their value creation and value capture potential at INDTECH. Table 4 reports our results.

Columns (1)-(3) examine the number of courses that workers from smaller towns enroll in when placed in Bangalore versus in other production centers. Using the Poisson estimator, we find robust evidence that workers from smaller towns enroll in a significantly larger number of additional courses than workers from large cities regardless of placement location (about 22.9% more, or about four fifths of an extra class). Moreover, while the interaction with Bangalore reduces this effect, it does not fully negate it, decreasing it by less than half the magnitude (by 10.8%), suggesting that workers from smaller towns posted to Bangalore still enroll in a larger number of courses than workers from large cities regardless of their placement.

Columns (4)-(6) repeat the analyses for the percent of courses the workers enroll in and "pass" (the terminology used by INDTECH to indicate that the worker has successfully completed the course and earned the requisite credits to do so). We find that workers from smaller towns pass a slightly higher percentage of their courses – about 2.5% more – on average. Moreover, workers posted to Bangalore pass an additional 2.5% more of their courses than their counterparts placed elsewhere. All results in Columns (1)-(6) are further robust to the inclusion of placement location fixed effects. Together with the above results on the number of courses taken, these results suggest that workers from smaller towns tend to invest more heavily in their skill development and accumulate more human capital in their time at INDTECH. In further unreported results, we also verify how enrollment in these courses positively and significantly correlates with worker performance ratings, suggesting that these investments help workers from smaller towns generate more value while at INDTECH.

However, do smaller town workers' efforts to invest in their human capital also help explain their higher chances of mobility to competitors when they are assigned to Bangalore? To investigate this, we examine the propensity of workers from smaller towns to take courses that help build their general human capital that is easily transferable across firm boundaries – namely courses in Business English. Discussions with workers and HR managers at INDTECH indicate that investments in functional courses (such as in Banking or Telecommunications) might be less transferrable to competitors as technology firms located in Bangalore exhibit heterogeneity in the clients and projects they perform for clients. However, English language courses are highly transferable and sought after, especially in the IT sector geared towards serving international customers. To conduct this test, we re-estimate specification (3) for the total number of English courses taken and their level. Using Poisson estimation, Columns (7)-(9) show that workers from smaller towns do not take more English courses when posted to peripheral locations but do take more English courses (about 75% more) when posted to Bangalore, suggesting that they may be expecting to move to competing firms in the future. Finally, Columns (10)-(12) show that conditional on taking at least one English course, workers from smaller towns do not enroll in a higher level of English courses on average, but are about twice as likely to take English to a maximum level of above two (out of a total of ten, with the tenth being the highest level) than workers from large cities posted to Bangalore. They are also less likely to only take English to the first, most basic level, with workers from smaller towns doing so at an average marginal rate of 47.6%, while workers from large cities doing so at an average marginal rate of 68.2%. All results are further robust to the inclusion of placement location fixed effects.

In summary, the results in this section provide suggestive evidence that workers from smaller towns are more likely to invest in their professional development not only to aid their success and value-creation potential within INDTECH, but also to improve their external employment opportunities when in Bangalore, which may contribute to their ability to capture value.

[Insert Table 4 Here]

6. Robustness Checks

One of our most important robustness checks aims to validate the talent allocation protocol (i.e., validating that INDTECH's decision to assign a worker to a particular production center is not correlated with observable worker-level characteristics, including prior performance during recruitment and training). As shown in Table 5, we found that the decision to allocate a worker to its headquarters in Bangalore after induction training was *not* correlated with observable worker-level characteristics such as being *From a Smaller Town*. Likewise, the decision to assign a worker to Bangalore was neither correlated with observable measures of prior performance (such as CGPA at the end of training or standardized test scores at the recruitment stage) nor with gender. These findings validate the random talent allocation policy underlying our study.

[Insert Table 5 Here]

In addition to the robustness tests listed in the results section, we specifically address the potential problem of our relatively small number of clusters (the number of INDTECH placement locations) in Tables 2 and 3 by re-running these results with an OLS model with placement location fixed effects and standard errors estimated using the paired bootstrap-t clustered estimator with 1000 reps. As described in Cameron, Gelbach, and Miller (2008), this estimator is specifically designed to address the small number of clusters problem. As the results in Panel A of Table 6 indicate, our qualitative conclusions in Table 2 continue to hold. As before, the results in Column (2) show that while the overall voluntary turnover for workers from smaller towns is higher when placed in Bangalore than when placed outside of Bangalore, the coefficient sizes suggest that on average, workers from smaller towns tend to turn over less often voluntarily. Moreover, smaller town workers continue to be significantly more likely to move to competitors when placed in Bangalore, relative to their counterparts outside of Bangalore and relative to large city workers in Bangalore. Control variables also continue to have the same signs and similar levels of significance. Similarly, as the results in Panel B of Table 6 show, our qualitative conclusions in Table 3 also continue to hold. The interaction on coming from a smaller town and being placed in Bangalore has a statistically significant and positive effect on Performance, but there is no effect on the probability of being dismissed. Control variables also continue to have the same signs and similar levels of significance.

[Insert Table 6 Here]

Finally, in additional robustness checks (omitted to conserve space) we also relaxed the definition of the *From Smaller Town* variable. In the base case, we had taken the most limiting definition of the variable, coding the variable as 1 only if there was no missing data for the school, high school, and college location and if all three of these locations were smaller towns. In robustness checks, we relaxed this limitation of missing data and counted a worker's origin as *From Smaller Town* if the location of at least one of his or her observed educational institutions – school, high school or college – was in a smaller town. Our results remained robust, with the exception of Column (6) in Table 3, where we find that with the relaxed assumption, the logit (but not the OLS with location fixed effects) estimator shows that workers posted to Bangalore coming from a smaller town are slightly more likely to be fired. However, we believe that this is consistent with there being slightly greater variance in performance among workers we code as coming from smaller towns once we enlarge the definition of smaller town.

7. Human Capital Rents by Worker Origin and Placement Location

Finally, we attempt to estimate the net payoff or *rents* stemming from different configurations of human capital. Following Chadwick (2017), we depict the associated firm rents graphically in Figure 3 to show INDTECH's 'rent rectangles' from human capital and describe the procedure for their calculation here. We base our calculations on detailed additional evidence gathered during field interviews.

In the first step, we estimate the "revenues" generated by different types of workers. To do so, we begin by estimating the dollar value of productivity gains associated with hiring a worker from a smaller town and also of placing this individual in the company headquarters. We based this analysis on 2008 performance data for the 2007 batch of workers. We used the predicted probabilities of achieving the highest performance rating in 2008 for small town versus large city workers. Average marginal effects based on Column (1) in Table 3 indicate that small town workers receive the highest performance rating at a rate of 40.2%, while workers hired from large cities do so at a rate of 31.8%. Our interviews suggest that compared to those who achieve the highest performance rating in 2008, other workers needed 35% more man-days to correct coding/testing/documentation errors. This is based on rough calculations with INDTECH HR managers on error rates and lost man-days due to coding/testing/documentation errors, and implies that workers achieving the top performance rating can complete the same amount of work as those receiving lower performance ratings in just under three quarters (0.741) the amount of time as lower-performing workers.

To arrive at a dollar-value estimate of the total value generated by each type of worker, however, we need an estimate of each worker's contribution to firm revenues. While direct measures of the revenue contributions of workers in our sample are not available, we are able to obtain an estimate of the average revenues that a worker at INDTECH generates using publicly available data on INDTECH's total firm revenues and dividing these by the total number of workers. This calculation yields an average revenue of about $50,000 per worker. While this figure ignores the substantial variation across worker and job types, note that our calculations of the relative rents from different types of workers are not sensitive (in relative rank) to the absolute value of average revenues chosen.

Combining the relative performance differences across workers and the average revenue contributions by all workers at INDTECH, we arrive at the following formula to calculate the total productivity of each worker type:

*Probability of Achieving Top Performance Rating * Extra Productivity of Top Performers * $50,000 + (1 – Probability of Achieving Top Performance Rating) * $50,000*

Applying this formula to workers hired from smaller towns, we calculate that their total value generated for INDTECH amounts to $57,035 (0.402*1.35*50,000+0.598*50,000) and the total value generated by workers from large cities amounts to $55,565. However, since we know that the *average* employee at INDTECH generates about $50,000 in value, we rescale these figures to preserve this average, and arrive at the final value generated by smaller town workers of $50,647 and large city workers of $49,342.

However, these figures are the averages for workers hired from smaller towns and large cities regardless of placement location. If these workers are instead posted to headquarters in Bangalore, the relative performance differences grow between large city and smaller town workers, to 21.1% and 40.1% chances of receiving the top performance rating, respectively. Therefore, the relative re-scaled productivities of employees from smaller towns and large cities become $50,628 and $47,676, respectively.

In the second step, we estimate the costs of recruiting workers of different types. INDTECH's entry-level salaries are about $8,000 per year (at 2013 U.S. Dollar to Rupee exchange rates) regardless of placement and worker productivity. Therefore, workers from smaller towns and large cities all receive the same salary of $8,000. However, recruiting workers from smaller towns requires additional expenditures. Based on our discussions with INDTECH's recruiting managers, we estimate that there is a $21 incremental cost of hiring a remote worker. This is based on several criteria: incremental travel costs for INDTECH executives involved in hiring from smaller towns, the additional search costs associated with trips to screen colleges and students from smaller town, and the larger number of candidates who need to be interviewed in smaller towns compared to large cities.

In addition, differences in attrition rates across different types of workers and placement locations create significant differences in the cost of training, turnover, and replacement. Specifically, INDTECH spends about $3,500 on training each newly hired worker in the four-month training program. Since all hires regardless of origin go through this training, the figure only enters our calculations through attrition rates. To the extent that workers from smaller towns are less likely to exit the firm voluntarily, as shown in Table 2, Columns (1) and (2), the average annual costs of re-training new hires should fall with the addition of workers from smaller towns. Average marginal analyses indicate that workers from smaller towns exit INDTECH at an average rate of 9.8% per year relative to workers from large cities, who do so at a rate of 13.6% per year.[14] This difference is reduced but remains large even when both types of workers are posted to Bangalore (12.0% annual attrition rate for workers from smaller towns and 14.3% annual attrition rate for workers from large cities). Multiplying these figures by the training ($3,500) and recruitment ($21) costs of smaller town workers yields a total recruitment, training, and replacement cost of $345 for workers from smaller towns and $476 for workers from large cities, regardless of placement location. When posted to Bangalore, these figures grow to $423 and $501 for smaller town and large city workers, respectively.

[14] Note that the attrition results in Table 2 are based on worker attrition after three years at INDTECH from the date of entry. We annualize these figures by assuming a constant rate of attrition each year, using the size of the entry cohort as the base with respect to which we calculate rates of departure. The annualized rates are therefore a third of the total rates for the three years for each group.

In sum, the expected costs of employing workers from smaller towns regardless of location amount to $8,345 ($8,000 in salary and $345 in recruitment, training, and replacement costs) and employing workers from large cities amounts to $8,476. In Bangalore, the respective estimated costs are $8,423 and $8,501 for smaller town and large city workers.

Bringing together the estimates of revenue and costs for each worker type, we arrive at our back-of-the-envelope estimates for human capital rents captured by INDTECH each year from workers in our sample. These are depicted as the 'rent rectangles' in Figure 3, and show that workers from smaller towns placed outside of Bangalore generate the greatest amount of rents ($42,284), followed closely by workers from smaller towns placed in Bangalore ($42,206). The lowest rents derive from workers from large cities posted to Bangalore, whose higher rates of attrition and lower productivity generate only $39,174 in rents, a difference of $3,032 compared to workers from smaller towns posted to Bangalore, which amounts to nearly 38% of the workers' annual salary of $8,000.

However, given our data constraints, these calculations provide only *a very rough estimate* of the net payoff associated with hiring from smaller towns and have at least two important limitations. First, we do not have an estimate of sunk costs of investments that INDTECH made related to hiring from smaller towns. Neither do we have an estimate of operating costs per worker, related to real estate, utilities, etc. Second, we cannot distinguish between the costs of losing workers to voluntary turnover for pursuing higher studies versus turnover to competing firms. The latter may have important observed and unobserved costs that affect the trade-off as estimated. For instance, additional (unreported) results indicate that top-performing workers from smaller towns are even more likely to leave to join competing firms and less likely to leave to take up further education when posted to Bangalore, compared to elsewhere, and compared to their large city counterparts, suggesting that such turnover may be even more costly than estimated in Figure 3. However, while our data limit more accurate calculations, we hope that our approach will spur future research on the role of worker characteristics, not only in value creation and capture, respectively, but also in net rent generation for firms, since the latter is likely to be the true underlying driver of recruitment decisions.

8. Discussion

Firms in emerging markets such as India face a dual problem: finding talent in smaller towns, and where to subsequently locate new talent: at firm headquarters or in peripheral production centers. Hiring talent from the geographic periphery and moving it to the hub may optimize value creation, but as Campbell, Coff, and Kryscynski (2012: 377) observe (emphasis added by authors), "human capital can be at the core of a resource-based advantage if it is valuable, rare *and can be kept from rivals*." Moving talented small town new-hires to headquarters may increase turnover, i.e., losses to competitors, and hence limit value capture by the employer. Our study explores this trade-off by exploiting a natural experiment within a large Indian technology firm to establish robust econometric evidence. Our results suggest that rents from human capital are *comparable* whether smaller town recruits are assigned to peripheral centers or to headquarters, and that smaller town talent generates greater human capital rents than workers hired from large cities across all production centers.

Shedding light on the underlying mechanisms driving these results, we show how workers from smaller towns strategically invest more in professional development through further training while at INDTECH than their large city counterparts. However, when posted to Bangalore, their choices of training favor knowledge and skills that are transferable, such as Business English, suggesting that their job mobility (loss to competitors) may, in part, be driven by their preparation for and openness to outside employment opportunities.

Our study has several limitations. Following the tradition of insider econometrics in personnel economics (Baker, Gibbs, and Holmstrom, 1994; Bartel, Ichniowski, and Shaw, 2004; Bandiera, Barankay, and Rasul, 2005), our data is collected from a single firm; future research should corroborate our central findings in other settings. Also, although we interpret our results using a human capital augmentation lens and provide some evidence using the courses that workers enroll in, we cannot test for or rule out alternative and complementary mechanisms such as effort or motivation. In prior literature, Chiswick (1978) found that migrants hired from the geographic periphery were often more highly motivated than residents; Carliner (1980) noted that migrants chose to work longer and harder than non-migrants; Bailey (2005) also explored whether immigrant workers adapted better to uncertainty. Any of these mechanisms might be at play here and in other settings. Another limitation is that, in equilibrium, the gains from moving smaller town workers to the large city headquarters may disappear as firms set up production centers in smaller towns over time and/or production centers in non-headquarters locations scale up. Here again, we borrow from the long-standing wisdom in the within-country migration literature, positing that *"neither migration, nor any equilibrating force is strong enough to eliminate imbalances instantaneously"* (Yap, 1976: 122).

Despite these limitations, our study contributes to several literatures relevant for scholars of organization and strategic human capital, notably the nascent literature on the role of firms in migration, dating back to Kerr, Kerr, and Lincoln, (2015), who lamented, "Firms are mostly absent from the literature on the impact of immigration…this approach seems quite incomplete for skilled migration given that firms play an active role in the migration of skilled workers, in the context of U.S. and other countries."[15] Our contribution is to examine both the role of firms in catalyzing *within-country migration* of knowledge workers in emerging markets[16] and estimate the *net rents* of assigning talent hired from the periphery to either the hub or periphery. While prior literature on firms and migration has stressed the potential value creation of moving human capital from the geographic periphery to hubs, our study documents the importance of considering both value creation and value capture to the firm. Our study suggests that hiring talent in the periphery and moving it to a peripheral production center might be an alternative to moving the same talent to the hub.

Our work also contributes to the literature on strategic human capital (Campbell, Coff, and Kryscynski, 2012; Carnahan and Somaya, 2013; Ganco, Ziedonis, and Agarwal, 2015; Molloy and Barney, 2015; Chadwick, 2017), notably by documenting how location, i.e., of the recruitment and the production center, are *both* relevant in determining value creation, particularly from small town recruits. Despite the information technology sector in India citing the lack of skills as the "most serious obstacle for growth" (Blom and Saeki, 2011), most firms focus their hiring efforts on the seven largest cities (Jensen, 2012), making the smaller town worker a "valuable, yet scarce" source of human capital in the labor markets of cities such as Bangalore. Chadwick (2017) argues

[15] Subsequently, in the context of migration across national borders, this literature has examined the relationship between immigrants and the foreign expansion of organizations from their home countries (Hernandez, 2014), demonstrated the role of firms in interorganizational knowledge transfer (Wang, 2015) and intrafirm knowledge transfer (Choudhury, 2015) through return migration, studied the role of multinational firms in fostering ethnic innovation (Foley and Kerr, 2013) and knowledge recombination (Choudhury and Kim, 2019) and has examined how subsidiaries of multinationals rely on resources from the migrant community (Hernandez and Kulchina, 2019).

[16] While within-country migration has been long studied in economics (Harris and Todaro, 1970; Young 2013; Bryan, Chowdhury, and Mobarak, 2014; Bazzi et al., 2016; Munshi and Rosenzweig, 2016), to the best of our knowledge, this is the one of first empirical studies of whether catalyzing within-country migration creates value for firms.

that the dilemma for firms seeking rents from inherently scarce human capital is that the latter is portable – from one firm to another. Molloy and Barney (2015: 311) further argue that in "competitive labor markets" where a "large number of individuals and firms are interested in trading around human capital and…where individuals and firms have the same accurate expectations about the value that human capital can generate," value is captured by the individual, not the employer. While our results validate the notion of loss to competitors made by Chadwick (2017), we highlight heterogeneity around the geographical location: this effect is only salient when smaller town workers are assigned to large city headquarters. Speaking to the assertions of Molloy and Barney (2015), we demonstrate that smaller town workers generate value for the firm when assigned to non-headquarters locations; in fact, even when they are assigned to headquarters, they generate net value to the firm, despite higher turnover rates. Taking a more nuanced view on the capturing of value (or not) from the *general* human capital of the scarce worker, our results suggest different human capital augmentation strategies for workers based on their location. To recap, while all smaller town workers are likely to take a greater number of training courses, those assigned to headquarters are more likely to take courses related to Business English.

Our results also speak to the literature in strategy and organizations on worker turnover (Ton and Huckman, 2008; Carnahan, Agarwal, and Campbell, 2012; Carnahan, Kryscynski, and Olson, 2017) and link to the literature on human capital (notably Becker, 1964; Campbell, Coff, and Kryscynski, 2012; Molloy and Barney, 2015) by demonstrating variation in selection of training courses between smaller town workers who manifest voluntary turnover to competitors and workers who do not. Future work could track longer term performance effects for the source firm (e.g., Campbell, Coff, and Kryscynski, 2012), alumni effects (Carnahan and Somaya, 2013) and whether the focal firm can implement management practices to reduce turnover of valuable human capital employed at headquarters (Carnahan, Kryscynski, and Olson, 2017). Finally, our results speak to the literature on the role of headquarters in determining productivity outcomes of knowledge workers (Ghoshal and Nohria, 1989; Ghoshal and Bartlett, 1990; Gupta and Govindarajan, 1991; Choudhury, 2017).

In examining the question of human capital allocation across production centers, our results contribute to the literatures on agglomeration economies, knowledge spillovers, and organizational and subsidiary location choices (Jaffe, Trajtenberg, and Henderson, 1993; Chung and Alcácer, 2002; Monteiro, 2015). This literature acknowledges the potential risks of locating in economic hubs for firms with scarce and valuable knowledge that can be accessed and imitated by competitors (Shaver and Flyer, 2000; Alcácer and Chung, 2014; Mariotti, Mosconi, and Piscitello, 2019). However, prior literature has not focused on the topic of protecting valuable human capital, hired from the periphery, in the hubs. In particular, the results here suggest that multi-unit firms may be able to directly shape and benefit from agglomeration economies in knowledge hubs by strategically allocating their top human capital away from large city hubs to avoid poaching by rivals, while retaining a presence in such hubs to continue 'listening in' (Monteiro, 2015) on the activities of their competitors and benefiting from potential knowledge spillovers.

In addition to the future research directions outlined earlier, an important extension of this research agenda would be to study heterogeneity in firm policy relative to hiring and managing smaller town workers in emerging markets such as India. As prior literature on the dynamics of inter-organizational careers, notably Bidwell and Briscoe (2010), has argued, workers are more likely to work for larger firms that provide more training early in their careers and move to smaller organizations that reward their skills later in their careers. It is possible that the smaller town workers in our sample assigned to Bangalore exhibit a similar pattern. Whether there exists a separating equilibrium where some firms (like INDTECH) hire smaller town workers and facilitate migration of smaller town workers to knowledge hubs and other firms (e.g., smaller technology start-ups also located in the knowledge hub) *do not* hire directly from smaller towns, but instead hire smaller town workers once they have moved to the hub, remains to be explained.

Our findings have important managerial implications for firms hiring talent from the geographic periphery, both in within-country and cross-border settings. While firms such as MobSquad (profiled earlier) have proactively followed a strategy of locating migrant talent in peripheral production centers to protect the workers from being hired by larger competitors, analysis of our setting suggests that net rents from human capital are similar whether talent hired from the periphery is posted to headquarters or to peripheral production centers. Additional research is needed in alternative settings to advance our understanding of this domain, and should take account of the fixed cost and operating costs of building production centers in a hub or at a peripheral location. This is especially true post COVID-19, when talent might be less geographically mobile and when workers might exhibit greater preferences of being closer to their hometowns. In a post-COVOD-19 era, large IT companies such as TCS (which employs greater than 400,000 workers) have embarked on an aggressive remote work strategy and thinking through whether to allow remote workers to live in smaller towns and work for the company virtually (Khetarpal, 2020). Our results speak to the choices that firms such as TCS have to make in deciding where to locate talent.

Future work should also explore similar questions relative to hiring and locating talent from smaller towns, in the context of developed countries. In an influential article, Schleicher (2017) documents a fall in interstate geographic mobility in the United States over decades. In a recent working paper, Austin, Glaeser, and Summers (2019) argue that divisions in employment across space have led to social problems in the American heartland. Clearly, it would be worth investigating (based on net rents from human capital) whether firms in the U.S. are better off moving talent from smaller towns to hubs such as Silicon Valley or building/scaling up production in the periphery.

In conclusion, this study, based on unique data, a natural experiment, and a stylized approach to estimating rents from human capital, provides causal evidence to help evaluate choices of where to assign talent hired from the periphery: at the hub or the periphery. It advances literatures on firms and migration, creating and capturing value from human capital, worker turnover, and the role of headquarters in the productivity of knowledge workers. Our insights have managerial relevance in managing talent from the periphery and thinking about the geography of work for employees in a post COVID-19 world. We also illustrate a framework that considers both value creation and value capture from human capital in making strategic human capital decisions.

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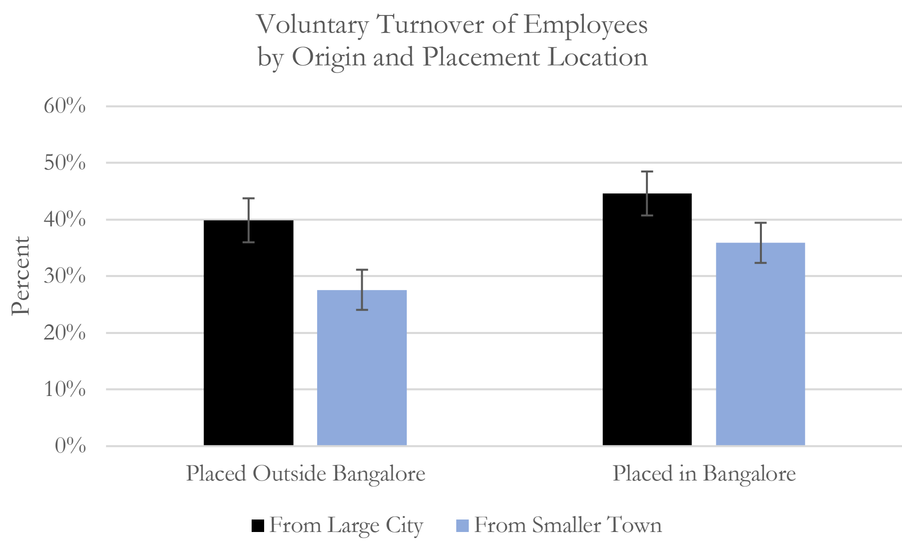
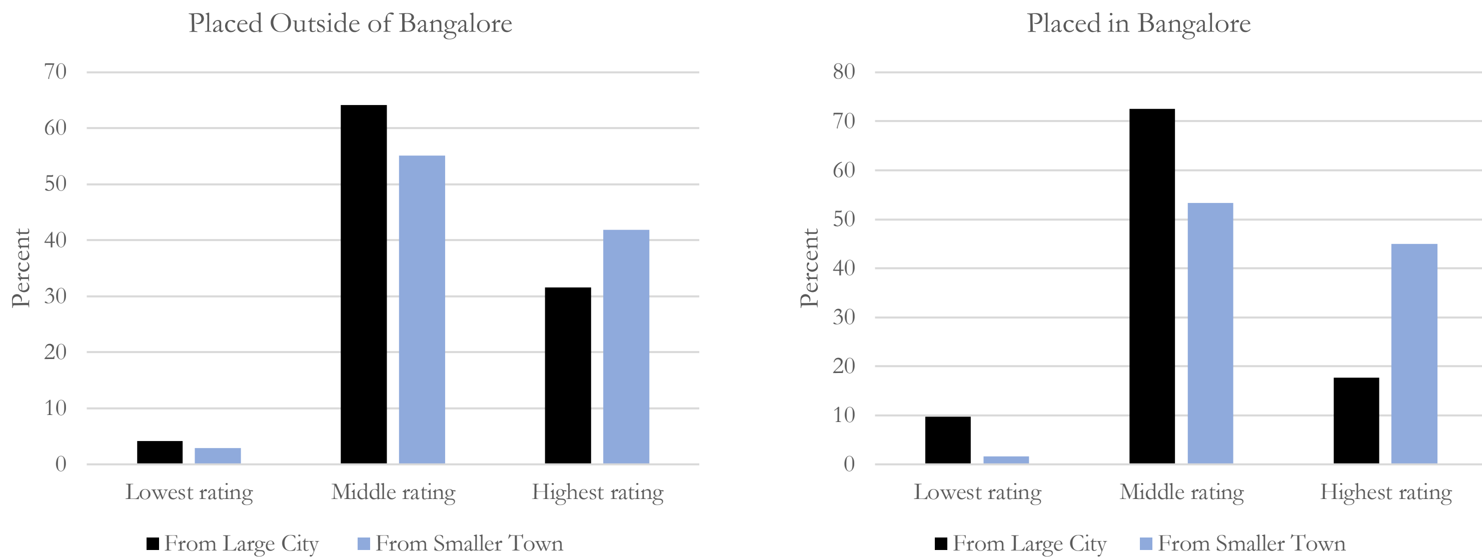
Figure 1
Turnover Rates of Employees by Origin and Placement Location



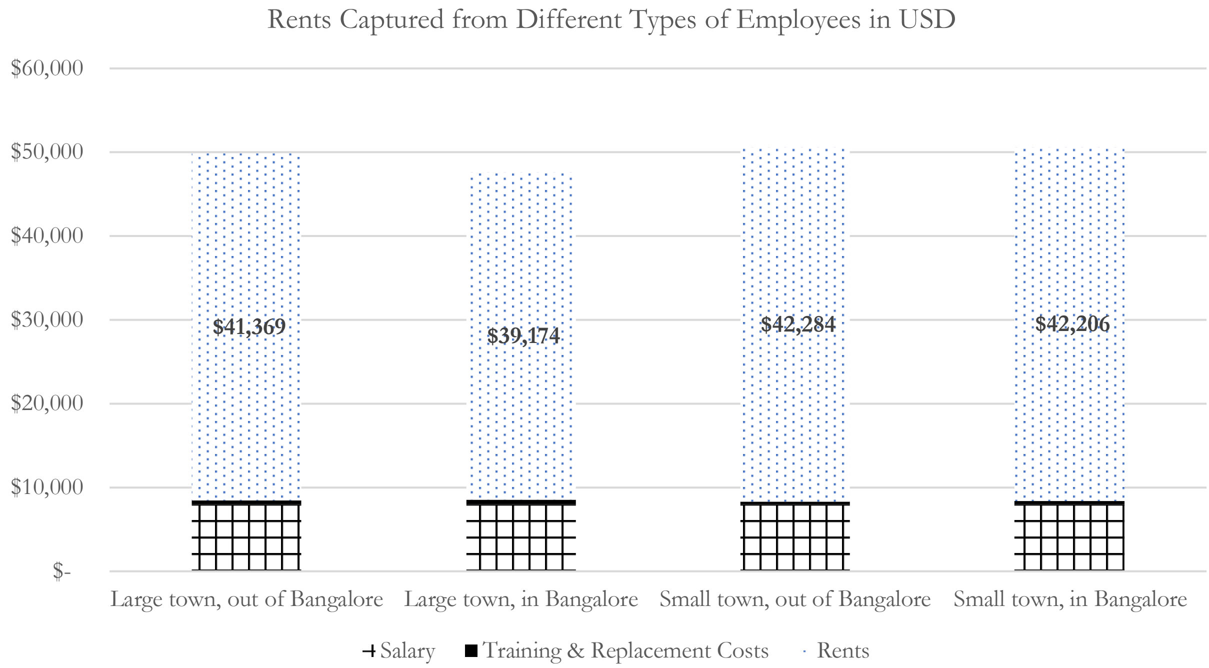
NOTE. — This graphic plots the rates of turnover (three years after entry for the 2007 batch) for smaller town employees and employees from large cities, split by production center location in the raw data. We see that employees placed in Bangalore exhibit higher rates of turnover regardless of their origin. Moreover, employees from smaller towns exhibit a larger and statistically significant at the 5% level jump in their propensity to voluntarily leave INDTECH when placed in Bangalore than employees from large cities for whom the increase is not significant at the 5% level (p-value = 0.329). However, we also see that in both locations, workers from smaller towns exhibit lower and statistically significant at the 5% level rates of voluntary turnover than workers from large cities.

Figure 2
Distribution of Performance in 2008 by Employee Origin & Production Center Placement



NOTE. — This graphic plots the distributions of performance at the end of 2008 for the 2007 batch and compares performance for the smaller town employees to employees from large cities by production center location. Interviews with managers at INDTECH indicate that performance at the end of 2008 for the 2007 batch is measured using two dimensions – error rate in coding/testing and completeness in coding/testing and documentation – and is distributed across three possible discrete ratings. The performance ratings show that while employees from smaller towns are less likely to receive the middle performance rating regardless of their placement location, they are more likely to receive the highest performance rating and less likely to receive the lowest performance rating in both locations. Moreover, the differences in these two likelihoods are larger for employees placed in Bangalore than those placed outside of Bangalore. We also run separate distributional tests using the two-sample Wilcoxon rank-sum (Mann-Whitney) test to compare the raw short-term performance for large city and smaller town employees, and the short-term performance of Bangalore and non-Bangalore placements. We reject the null hypothesis that the raw performance data for employees from smaller towns and large cities (tier 1 and tier 2/tier 3) follow the same distribution. However, we fail to reject the null that the performance data for employees placed in Bangalore versus outside of Bangalore follow the same distribution in the raw data.

Figure 3
'Rent Rectangles': INDTECH's Value Creation and Appropriation by Employee Origin and Placement Location (in US dollars)



NOTE. — We estimate these 'rent rectangles' by relying on our calculations in Section 7, Human Capital Rents by Employee Origin and Placement Location. We first estimate the total value created by different types of workers, which we infer from our performance regressions in Table 3, extensive interviews with managers at INDTECH, and publicly available data on average revenues for INDTECH employees, which we estimate to be about $50,000 by dividing INDTECH's revenues by the total number of employees (however the logic is independent of the exact figures used). For example, to calculate the total value created by workers from smaller towns when they are placed in Bangalore, we multiply their likelihood of achieving the highest performance rating (0.401) by the expected additional productivity of workers receiving such ratings (extra 35%) and the average productivity of workers at INDTECH ($50,000), and add it to their likelihood of not achieving the top performance rating (1-0.401) multiplied by their expected average productivity ($50,000). We then re-scale these values by a factor of 0.888 to make sure that the average performance of all employees at INDTECH is still $50,000. These calculations yield total value created by workers from smaller towns placed in Bangalore of $50,628. Next, we subtract the annual wages paid to all employees of $8,000 and the different attrition and retraining costs of different types of workers based on our estimations from Table 2 and additional figures of training and recruitment costs obtained from INDTECH. While average training costs are the same for all workers ($3,500), attrition rates vary and recruiting workers from smaller towns incurs an additional cost of $21. Subtracting each worker type's average productivity from their wages and training and replacement costs, we arrive at the net revenues captured by INDTECH from each worker type – the dollar-values depicted in bold in the figure. As the dollar-value estimates in the figure show, because employees from smaller towns tend to be both slightly more productive than their large city counterparts and less mobile, on net, they create more value for INDTECH than their large city counterparts. However, their higher rates of turnover in Bangalore mean that the net value for INDTECH is slightly higher for employees from smaller towns placed outside of Bangalore than in Bangalore.

Table 1
Summary Statistics: Comparison of Employees by Origin and Placement Location

	Summary Statistics for Full Sample					Summary Statistics by Origin			Summary Statistics by Placement Location		
	Observations	Mean	St. dev.	Min	Max	(1) From Smaller Town = 0	(2) From Smaller Town = 1	(3) Difference	(4) Placed in Bangalore = 0	(5) Placed in Bangalore = 1	(6) Difference
Panel A: Employee characteristics											
From smaller town	1,254	0.506	0.500	0	1	0.000	1.000	-1.000	0.514	0.474	0.041
Placed in Bangalore	1,665	0.205	0.404	0	1	0.210	0.184	0.026	0.000	1.000	-1.000
Male	1,665	0.656	0.475	0	1	0.656	0.649	0.007	0.662	0.630	0.032
Panel B: Recruitment and training scores											
Recruitment test score logical	1,605	4.940	3.352	-4	9	4.607	5.645	-1.038***	4.958	4.869	0.089
Recruitment test score verbal	1,605	4.295	3.983	-8	16	4.539	4.249	0.29	4.249	4.474	-0.225
CGPA training	1,665	4.516	0.370	2.8	5	4.506	4.517	-0.012	4.512	4.533	-0.021
Panel C: Performance											
Performance in 2008	676	2.293	0.544	1	3	2.231	2.399	-0.168***	2.308	2.240	0.068
Dismissed	1,665	0.053	0.224	0	1	0.052	0.047	0.004	0.057	0.035	0.022
Panel D: Human capital accumulation											
Number of courses taken	1,665	3.330	3.113	0	12	2.997	3.772	-0.775***	3.394	3.079	0.315*
Percent of courses passed	940	80.741	18.641	0	100	77.931	82.335	-4.403***	80.325	82.459	-2.134
Number of English courses taken	940	0.147	0.377	0	3	0.163	0.136	0.027	0.156	0.109	0.047
Highest level of English courses taken	131	1.779	1.541	1	10	1.646	1.685	-0.039	1.802	1.650	0.152
Panel E: Employee turnover											
Quit by choice	1,665	0.356	0.479	0	1	0.409	0.291	0.117***	0.346	0.396	-0.050*
Moved to competitor	1,665	0.077	0.267	0	1	0.068	0.077	-0.009	0.074	0.091	-0.017
Quit for further study	1,665	0.166	0.372	0	1	0.220	0.115	0.105***	0.161	0.185	-0.024

+p<0.1; *p<.05; **p<.01; ***p<.001

NOTE. — Table 1 contains summary statistics for the entire sample and the two sub-samples, by employee origin and production center placement. The variable *From smaller town* is coded as 1 if the individual went to primary school, high school, and college in a non-tier 1 town in India. We classify Indian towns based on the tier system outlined by the Pay Commission report of the Government of India (details at: www.referencer.in/PayCommission/Reports/OM_Allowances.pdf). *Placed in Bangalore* takes the value of 1 if after training the employee was placed in the company headquarters in Bangalore using the firm's propietary random assignment protocol. The *logical* and *verbal recruittment test scores* are from the standardized multiple choice recruitment tests; the standardized tests include negative penalties for wrong answers. *CGPA training* is the cumulative grade point average at the end of the training. *Performance* is only available for workers who have been with the firm for at least nine months prior to the evaluation period and all employees are from the 2007 intake. All other variables are defined in the Data section. Columns (1)-(3) compare the averages across all our variables for workers from smaller towns and large cities. In Panel B we find that workers from smaller towns score significantly higher on logical test scores taken before their entry into INDTECH. In Panel C we find that workers from smaller towns perform better once on the job. In Panels D and E we find that workers form smaller towns take a larger number of courses overall, pass these courses at higher rates, quit their employer less often overall and quit less often to pursue further study. Columns (4)-(6) compare the averages across all our variables for workers placed in Bangalore and other production centers. In Panel B we find no statistically significant differences for employees placed in and out of Bangalore, validating the firm's random assignment protocol. In Panel D we find that workers placed in Bangalore take fewer additional courses on average, and in Panel E we find that workers placed in Bangalore are more likely to quit voluntarily, but there are no significant differences in their propensity to pursue further study or move to competitors.

Table 2
Employee Turnover

VARIABLES	(1) Quit Logit	(2) Quit Logit	(3) Quit Conditional Logit	(4) Quit to Competitor Logit	(5) Quit to Competitor Logit	(6) Quit to Competitor Conditional Logit	(7) Quit for Further Study Logit	(8) Quit for Further Study Logit	(9) Quit for Further Study Conditional Logit
From Smaller Town	-0.523***	-0.579***	-0.629***	0.093	-0.137	-0.073	-0.721***	-0.617***	-0.716***
	(0.080)	(0.087)	(0.107)	(0.240)	(0.229)	(0.217)	(0.122)	(0.090)	(0.094)
Placed in Bangalore	0.242*	0.120		0.560***	0.098		-0.022	0.167	
	(0.123)	(0.112)		(0.111)	(0.073)		(0.170)	(0.158)	
From Smaller Town * Bangalore		0.270**	0.310**		0.846***	0.777***		-0.572***	-0.475***
		(0.105)	(0.119)		(0.230)	(0.225)		(0.082)	(0.071)
Logical Score	-0.005	-0.005	-0.002	-0.006	-0.006	-0.009	0.001	0.001	0.006
	(0.023)	(0.023)	(0.023)	(0.055)	(0.055)	(0.054)	(0.021)	(0.020)	(0.021)
Verbal Score	0.040**	0.041**	0.037**	-0.052*	-0.047+	-0.048+	0.085***	0.084***	0.080***
	(0.013)	(0.013)	(0.013)	(0.026)	(0.026)	(0.026)	(0.015)	(0.016)	(0.015)
CGPA Training	0.998***	0.995***	0.933***	0.790	0.783	0.803	1.100**	1.107**	1.007**
	(0.256)	(0.256)	(0.253)	(0.578)	(0.577)	(0.584)	(0.397)	(0.395)	(0.357)
Male	-0.124	-0.119	-0.170	0.346	0.361	0.342	0.204*	0.195+	0.135
	(0.104)	(0.106)	(0.118)	(0.220)	(0.229)	(0.243)	(0.100)	(0.099)	(0.107)
Constant	-5.008***	-4.980***		-6.345*	-6.228*		-6.842***	-6.901***	
	(1.076)	(1.065)		(2.911)	(2.830)		(1.708)	(1.696)	
Observations	1,208	1,208	1,208	1,208	1,208	1,177	1,208	1,208	1,208
Location FE	No	No	Yes	No	No	Yes	No	No	Yes

Standard errors in parentheses are clustered at the production center level.
+p<0.1; *p<.05; **p<.01; ***p<.001

NOTE. — This table examines how turnover is related to employee origin and placement by implementing specification (1) using logit estimation without production center fixed effects and conditional logit grouped at the production center level, and robust standard errors clustered at the production center level. The results in models (1)-(3) indicate that employees from smaller towns are, on average, less likely to leave INDTECH by choice than their large city counterparts, even when placed in Bangalore, though the interaction effects in Columns (2) and (3) suggest that departure hazard diminishes for workers from smaller towns placed in Bangalore. However, these patterns mask two distinct relationships. On the one hand, employees from smaller towns appear more likely to move to a competing firm when placed in INDTECH's headquarters in Bangalore. Average marginal effects based on Column (5) indicate they are about twice as likely (at a rate of 13.8%) to move to a competitor than either workers from smaller towns outside of Bangalore (a rate of 5.9%) or workers from larger cities in any location (a rate of about 7% for each sub-group). On the other hand, Column (7) indicates that employees from smaller towns are less likely to pursue further education, especially when placed in Bangalore (Column (8)), and the effects remain even after we add production center fixed effects. Average marginal effects based on logit estimations in Column (8) indicate that workers from smaller towns are almost 30% less likely to pursue higher studies when in Bangalore (at a rate of 9.1%), relative to employees from smaller towns outside of Bangalore (at a rate of 12.9%), while workers from large cities pursue higher study at a rate of about 21% outside of Bangalore and 24% in Bangalore. These results are robust to re-running the model with bootstrapped and clustered standard errors and with using OLS with production center fixed effects and bootstrapped and clustered standard errors.

Table 3
Employee Performance

VARIABLES	(1) **Performance** Ordered Logit	(2) **Performance** Ordered Logit	(3) **Performance** BUC Ordered Logit	(4) **Dismissed** Logit	(5) **Dismissed** Logit	(6) **Dismissed** Conditional Logit
From Smaller Town	0.411*	0.239+	0.276	-0.038	-0.051	0.048
	(0.172)	(0.125)	(0.182)	(0.343)	(0.382)	(0.402)
Placed in Bangalore	-0.365***	-0.763***		-0.893***	-0.945***	
	(0.103)	(0.133)		(0.179)	(0.212)	
From Smaller Town * Bangalore		0.769***	0.794***		0.113	0.007
		(0.137)	(0.179)		(0.373)	(0.390)
Logical Score	0.078**	0.081**	0.082**	-0.070*	-0.070*	-0.084**
	(0.024)	(0.025)	(0.026)	(0.034)	(0.034)	(0.032)
Verbal Score	0.006	0.009	0.008	-0.011	-0.011	-0.013
	(0.013)	(0.012)	(0.014)	(0.038)	(0.038)	(0.038)
CGPA Training	2.095***	2.075***	2.087***	-4.608***	-4.607***	-4.461***
	(0.258)	(0.256)	(0.230)	(0.379)	(0.381)	(0.385)
Male	0.206	0.221	0.145	0.255	0.256	0.243
	(0.216)	(0.214)	(0.216)	(0.180)	(0.178)	(0.160)
Constant				16.867***	16.868***	
				(1.557)	(1.559)	
Observations (actual)	511	511	511	1,208	1,208	1,157
Observations (used for BUC)			1,014			
Location FE	No	No	Yes	No	No	Yes

Standard errors in parentheses are clustered at the production center level.
+p<0.1; *p<.05; **p<.01; ***p<.001

NOTE. — This table examines how employee performance is related to employee origin and placement by implementing specification (2). Columns (1)-(3) in this table use the ordered logit without location fixed effects and the blow-up-and-cluster (BUC) estimators with location fixed effects (as described in Baetschmann, Staub, and Winkelmann (2015)), and errors clustered at the production center. Columns (4)-(6) implement logit without production center fixed effects and the conditional logit estimators grouped at the production center level, with errors clustered at the production center. The results in Column (1) indicate that there is a positive and statistically significant relationship between being from a smaller town and *ex post* productivity measured using performance rating scores, regardless of placement location. The results in column (2) further indicate that this positive effect is largely driven by employees from smaller towns placed at the firm's headquarters in Bangalore. Finally, Column (3) shows that the results are not driven by differential placement rates of workers from smaller towns into Bangalore – the interaction effect survives even when we control for production center fixed effects. Columns (4) and (5) further indicate that these results are not driven by higher risk-taking of employees from smaller towns that could lead to dismissal. In fact, there is no statistically significant difference in dismissal rates between workers from smaller towns and workers from large cities, even when they are placed in Bangalore, and the coefficients drop even more once we control for production center fixed effects in Column (6). Further, average marginal effects based on Column (2) indicate that employees from smaller towns placed in Bangalore have a 40.1% likelihood of receiving the highest performance rating, while employees from a large city placed in Bangalore have a 21.1% chance of receiving the highest rating. In contrast, the likelihood of being dismissed (Column (5)) is nearly indistinguishable across the two groups, at about 3.4% for an employee from a smaller town placed in Bangalore, and about 3.3% for an employee from a large city placed in Bangalore. These results are robust to re-running the model with bootstrapped and clustered standard errors and with using OLS with production center fixed effects and bootstrapped and clustered standard errors. All results are further robust to controlling for test scores at the end of training, standardized recruitment test scores, and gender. Among the control variables, as expected, CGPA at the end of training and logical test scores during recruitment are highly correlated to performance and the likelihood of dismissal.

Table 4
Individual-Level Drivers of Value Creation

VARIABLES	(1) **Number of Courses** Poisson	(2) **Number of Courses** Poisson	(3) **Number of Courses** Poisson with FE	(4) **% Courses Passed** OLS	(5) **% Courses Passed** OLS	(6) **% Courses Passed** OLS with FE	(7) **Number of English Courses** Poisson	(8) **Number of English Courses** Poisson	(9) **Number of English Courses** Poisson with FE	(10) **Level of English Courses** Ordered Logit	(11) **Level of English Courses** Ordered Logit	(12) **Level of English Courses** BUC Ordered Logit
From Smaller Town	0.204***	0.223***	0.226***	3.435*	3.182+	2.005+	-0.159	-0.246+	-0.228	-0.065	-0.240	-0.259
	(0.046)	(0.050)	(0.058)	(1.136)	(1.419)	(1.063)	(0.146)	(0.134)	(0.151)	(0.333)	(0.370)	(0.313)
Placed in Bangalore	-0.078	-0.024		1.735	1.041		-0.268**	-0.579***		0.125	-0.566	
	(0.051)	(0.050)		(1.457)	(2.126)		(0.098)	(0.096)		(0.426)	(0.602)	
From Smaller Town * Bangalore		-0.102*	-0.103+		1.328	2.498+		0.580***	0.562***		1.146*	1.662***
		(0.048)	(0.054)		(1.656)	(1.306)		(0.135)	(0.150)		(0.505)	(0.447)
Logical Score	0.011	0.011	0.010	-0.308	-0.308	-0.284	0.005	0.004	0.003	-0.030	-0.032	-0.079
	(0.010)	(0.010)	(0.009)	(0.367)	(0.367)	(0.366)	(0.033)	(0.033)	(0.030)	(0.042)	(0.040)	(0.068)
Verbal Score	-0.024***	-0.024***	-0.023***	0.277*	0.285*	0.287+	-0.031	-0.028	-0.029	0.119+	0.118+	0.164*
	(0.006)	(0.006)	(0.005)	(0.098)	(0.104)	(0.130)	(0.020)	(0.020)	(0.019)	(0.061)	(0.061)	(0.078)
CGPA Training	0.172	0.173	0.192	16.866**	16.849**	16.613**	-0.285	-0.292	-0.314	-0.765	-0.825	-1.942*
	(0.150)	(0.149)	(0.137)	(3.726)	(3.741)	(3.663)	(0.254)	(0.252)	(0.225)	(0.984)	(0.983)	(0.886)
Male	0.056	0.055	0.069+	-4.097+	-4.080+	-4.239*	0.071	0.076	0.075	-0.304	-0.217	-0.921+
	(0.036)	(0.036)	(0.038)	(1.885)	(1.886)	(1.789)	(0.226)	(0.227)	(0.213)	(0.514)	(0.516)	(0.492)
Constant	0.350	0.339		4.901	5.077		-0.469	-0.404				
	(0.634)	(0.625)		(17.620)	(17.769)		(1.124)	(1.091)				
Observations	1,208	1,208	1,208	687	687	687	687	687	687	96	96	96
Observations (BUC)												334
Location FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
R-squared				0.099	0.100	0.122						

Standard errors in parentheses are clustered at the production center level except for Poisson with fixed effects which presents robust standard errors.
+p<0.1; *p<.05; **p<.01; ***p<.001

NOTE. — This table examines the relationship between employee origin, placement location, and human capital accumulation. All columns implement specification (3), with Columns (1)-(3) and (7)-(9) using Poisson estimation with and without production center fixed effects and robust standard errors, Columns (4)-(6) implementing OLS with and without production center fixed effects and standard errors clustered at the production center, and Columns (10)-(12) using ordered logit and the blow-up-and-cluster (BUC) (Baetschmann, Staub, and Winkelmann, 2015) ordered logit with production center fixed effects and standard errors clustered at the production center. Column (1) indicates that there is a positive and statistically significant relationship between being from a smaller town and the propensity to take on additional coursework at INDTECH. Column (2) further indicates that employees placed in Bangalore who are also from smaller towns take about 10% fewer courses on average, relative to their counterparts outside of Bangalore, but still significantly more than their large city counterparts in and out of Bangalore. Column (3) further shows that all results survive even once we control for placement location fixed effects. Columns (4)-(5) indicate that employees from smaller towns pass a higher fraction of the courses they take regardless of placement location, and Column (6) shows that they may be even more likely to pass their coursework when they are placed in Bangalore. The results in Column (7) indicate that there is no relationship between being from a smaller town and the propensity to take English courses at INDTECH on average. However, workers from smaller towns placed in Bangalore are more likely to take English courses than either their counterparts outside Bangalore or large city employees in Bangalore, based on estimates in Columns (8)-(9). They also take the courses to a higher level. Columns (10)-(12) show that employees placed in Bangalore take English to a significantly higher level. Marginal effects indicate that, on average, these employees are roughly twice as likely to take English at every level above the first (lowest) level, and are roughly 15% less likely (at a rate of 47.6%) to take English at the lowest level, compared with their counterparts from large cities placed in Bangalore (at a rate of 68.2%). All results are robust to controlling for test scores at the end of training, standardized recruitment test scores, gender, and production center fixed effects. All results are further robust to running an OLS model with production center fixed effects and bootstrapped and clustered standard errors at the production center.

Table 5
Validity of the Random Assignment

VARIABLES	(1) **Assigned to Bangalore** Logit	(2) **Assigned to Bangalore** Logit	(3) **Assigned to Bangalore** Logit	(4) **Assigned to Bangalore** Logit	(5) **Assigned to Bangalore** Logit	(6) **Assigned to Bangalore** Logit
From Smaller Town	-0.163	-0.132	-0.147	-0.167	-0.164	-0.119
	(0.343)	(0.347)	(0.346)	(0.342)	(0.348)	(0.351)
Logical Score		-0.019				-0.029
		(0.019)				(0.018)
Verbal Score			0.017			0.022
			(0.025)			(0.025)
CGPA Training				0.301		0.226
				(0.268)		(0.270)
Male					-0.179	-0.218
					(0.176)	(0.185)
Constant	-1.325***	-1.228***	-1.392***	-2.685*	-1.209***	-2.168+
	(0.221)	(0.267)	(0.247)	(1.226)	(0.259)	(1.298)
Observations	1,254	1,208	1,208	1,254	1,254	1,208

Standard errors in parentheses are clustered at the production center level.
+p<0.1; *p<.05; **p<.01; ***p<.001

NOTE. — All models use the logit estimator. Robust standard errors in parentheses are clustered at the placement location level. This table reports results to validate the talent allocation protocol (i.e., validating that the production center assignment is not correlated with observable employee-level characteristics, including prior performance during recruitment and training). Results across all models indicate that the decision to allocate an employee to the largest and most important production center (located in Bangalore) following induction training is not correlated with observable employee-level characteristics such as being from a smaller town or observable measures of prior performance (such as CGPA at the end of training or standardized test scores at the recruitment stage). The decision to allocate an employee to Bangalore is also not correlated with other observable individual characteristics such as gender. This validates the talent allocation policy underlying our study.

Table 6
Robustness Tests for Tables 2 and 3

Panel A: Robustness Test for Table 2

	(1) **Quit by Choice** OLS with FE	(2) **Quit by Choice** OLS with FE	(3) **Moved to Competitor** OLS with FE	(4) **Moved to Competitor** OLS with FE	(5) **Quit for Further Study** OLS with FE	(6) **Quit for Further Study** OLS with FE
From Smaller Town	-0.121***	-0.134*	0.010	-0.005	-0.106*	-0.095*
	(0.000)	(0.010)	(0.580)	(0.710)	(0.010)	(0.010)
From Smaller Town * Bangalore		0.061+		0.072***		-0.055***
		(0.080)		(0.000)		(0.000)
Logical Score	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(0.900)	(0.900)	(0.890)	(0.890)	(1.000)	(0.990)
Verbal Score	0.008*	0.009*	-0.003+	-0.003	0.012***	0.012***
	(0.040)	(0.040)	(0.080)	(0.130)	(0.000)	(0.000)
CGPA Training	0.183*	0.182*	0.045	0.044	0.112*	0.112*
	(0.030)	(0.040)	(0.270)	(0.260)	(0.040)	(0.040)
Male	-0.037	-0.036	0.020	0.021	0.019	0.018
	(0.340)	(0.360)	(0.330)	(0.340)	(0.170)	(0.180)
Observations	1,208	1,208	1,208	1,208	1,208	1,208
R-squared	0.066	0.066	0.017	0.020	0.069	0.070
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Robustness Test for Table 3

	(1) **Performance** OLS with FE	(2) **Performance** OLS with FE	(3) **Performance** OLS with FE	(4) **Dismissed** OLS with FE	(5) **Dismissed** OLS with FE	(6) **Dismissed** OLS with FE
From Smaller Town	0.168	0.115	0.071	-0.004	0.007	0.005
	(0.130)	(0.120)	(0.200)	(0.810)	(0.600)	(0.750)
From Smaller Town * Bangalore			0.170*			0.009
			(0.010)			(0.370)
Logical Score		0.018**	0.018**		-0.003	-0.003
		(0.030)	(0.030)		(0.250)	(0.250)
Verbal Score		0.001	0.002		0.001	0.001
		(0.780)	(0.660)		(0.390)	(0.380)
CGPA Training		0.501***	0.495***		-0.293**	-0.293**
		(0.000)	(0.000)		(0.020)	(0.020)
Male		0.036	0.037		0.012	0.012
		(0.510)	(0.490)		(0.230)	(0.210)
Observations	540	511	511	1,254	1,208	1,208
R-squared	0.024	0.144	0.148	0.000	0.260	0.260
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses are paired bootstrap-t clustered at the production center level.
+p<0.1; *p<.05; **p<.01; ***p<.001

NOTE. — These models replicate the analyses in Tables 2 and 3 with the OLS estimator with fixed effects and paired bootstrap-t clustered standard errors with 1,000 replications, a procedure that is robust to small numbers of clusters (Cameron, Gelbach, and Miller, 2008). The table reports coefficients and p-values in parentheses. As the results indicate, our qualitative conclusions in Tables 2 and 3 continue to hold. We find in Column (2) of Panel A that while the voluntary turnover for workers from smaller towns is higher when they are placed in Bangalore than when they are placed outside of Bangalore, the coefficient sizes suggest that on average, employees from smaller towns tend to turn over less often voluntarily. Columns (4) and (6) further confirm that workers from smaller towns are more likely to depart INDTECH for competing firms and less likely to pursue further education when placed in Bangalore, confirming our findings in Table 2. In Column (3) of Panel B, we confirm the findings in Table 3: the interaction on *From Smaller Town* and *Bangalore* has a statistically significant and positive effect on Performance, but there is no effect on the probability of being Dismissed. Control variables also continue to have the same signs and similar levels of significance.