

Essays on Entrepreneurship and Human Capital in Knowledge-Intensive Industries

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Abstract

Managing human capital is one of the most critical activities for any organizations in knowledge-intensive industries. Increasingly, it requires detailed understandings on the interplay between individuals and environments as these individuals respond to various opportunities and challenges that arise outside the organizational boundary. My dissertation examines how individual innovators and knowledge workers from three different organizations respond to rapidly changing incentives, opportunities, and contexts. The first chapter focuses on user-innovators in an online community and how they respond to commercial opportunities by pursuing entrepreneurship. The second chapter studies knowledge workers in an IT company and investigates how distance from hometown affect their productivity and learning over time. The final chapter analyzes workers in a rental car company to understand how they allocate efforts in different tasks in response to increased career concerns from potential corporate restructuring.

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Introduction

My dissertation consists of three chapters each of which examines how individual innovators and knowledge workers from three different organizations respond to rapidly changing incentives, opportunities, and contexts. Chapter 1 studies user innovators in an online community setting. Communities are an important vehicle for innovation. Literature has theorized that community members freely disclose their ideas because positive incentives from free revealing outweigh expected returns from commercialization. Yet, limited empirical evidence exists on how complementors choose between value creation and capture. To fill the gap, I examine how bottlenecks, or easier access to complementary assets, affect value creation and capture by complementors. I collected individual-level data on contribution and commercialization from an online user innovation community in the video game industry. I estimated difference-in-differences specifications by leveraging an unanticipated, substantial price decrease of game engine, a critical complementary asset in game development. I present two main findings. First, easier access increases members' commercial intent, especially those with ex ante high-quality ideas. Second, easier access decreases members' contribution, indicating trade-offs between commercial opportunities and contribution. I discuss the implications to the strategy and innovation literature.

Chapter 2 is a joint work with Prithwiraj Choudhury. Companies often assign workers to far-flung locations to fill critical roles and to develop human capital. Yet little is known about how workers perform in assignments to locations far from their hometowns, which may subject them to reduced time allocation to family and increased psychic costs. By exploiting an Indian technology firm's policy of randomly assigning entry-level employees to eight widely scattered locations, we empirically assess how distance from hometown affects workers' performance.

Our results suggest that distance from hometown has a positive effect on worker performance in the short term and a negative effect over the longer term. Our subsequent analyses reveal the interactive field interviews, sub-sample analyses, and We offer evidence on a key mechanism: how employees allocate their time to work-related activities and to visiting distant family. To do so, we use field interviews, sub-sample analyses, and micro-data on the number of optional skill-development courses employees complete and on leave taken during the major Indian festival of Diwali. Consistent with our theories, we also find evidence of heterogenous effects based on the location of the production center and on gender.

In Chapter 3, I and my coauthor Jee-Eun Shin examine performance consequences due to unexpected career concerns – layoff risks due to institutional reasons. Exploiting a company-wide announcement of a merger decision by management as a trigger event for unexpected career concerns, we examine employee performance at a rental car company with stores across US airports before and after the merger announcement. First, we document positive incentive effects. Employee performance exhibits significant improvements subsequent to the merger announcement which suggests that unexpected career concerns trigger incentives to minimize potential layoff risks. Second, we document effort allocation effects depending on the extent of employee alignment (i.e. the extent by which employees are aligned with the overall company strategy). In particular, our findings suggest that in the presence of unexpected career concerns, employee alignment can mitigate myopic behaviors to fixate effort levels on relatively short-term performance measures at the expense of long-term performance measures. Our findings provide new evidence for the benefits of employee alignment as agile controls in mitigating career concern pressures during organizational change.

Chapter 1. From Complementors to Competitors: How Tools of Production Affect Value Appropriation by User Innovators

1.1. Introduction

How do individuals create and capture from their innovations? History often describes individuals' transition into entrepreneurship for commercialization as a critical driver of creative destruction and economic growth (Schumpeter, 1943). Yet, for most innovators transition into entrepreneurship and competing in product markets may not be such a straightforward choice (Audia and Rider 2005) because of the difficulty of the access to complementary assets for commercialization (Gans and Stern 2003, Teece 1986). These individuals choose alternative value appropriation strategies initially, such as collaborating with other organizations, but may switch to commercialization as their value appropriation strategy once certain environmental changes lower the barrier to access complementary assets. In other words, innovators may traverse between cooperation and competition to appropriate value in response to changes in external environments.

User innovation provides an interesting setting to consider individual innovators' choice of value appropriation strategies (Hippel 1988). User innovators are defined as end-users who come up with novel ideas to fill the functional gap between their needs and existing product offerings that they consume (Hippel 1994). Interestingly, the literature describes two divergent value appropriation strategies from which user innovators capture value (Gambardella et al. 2017). On the one hand, user innovators may choose to follow “user complementors” mode by

disclosing their complementary innovation to be combined with existing products and assets. User innovators may capture some created value if the collaboration is via formal mechanisms (Chatterji and Fabrizio 2012); however, it is also possible they behave as “unpaid complementors” if the collaborative relationship is rather informal and loose within ecosystems (Boudreau and Jeppesen 2015, Harhoff et al. 2003). On the other hand, other user innovators choose to become entrepreneurs and compete with other firms by commercializing their innovation into standalone products in the market (Shah et al. 2012). Despite this stark difference in terms of implications to industry, at present we have relatively little empirical evidence about what factors shape user innovators’ choice of value appropriation strategies. Particularly, we do not know whether user innovators following different value appropriation strategies are inherently different in a static sense, or simply the results of adopting to different environments in a dynamic sense. Recent studies have provided some conceptual frameworks and qualitative evidence to address the gap (Baldwin and Hippel 2011, Baldwin et al. 2006, Shah and Tripsas 2007, 2016), we still lack comprehensive understandings on how different user innovators adopt divergent value appropriation strategies. Understanding this tension is also critical because the sustainability of some innovation strategies depends on continued participation of user as complementors (Altman and Tushman 2017).

In this paper, I provide a framework and evidence that is consistent with the latter view. Specifically, I evaluate the argument that a certain environmental characteristic, particularly the availability to critical production tools, affects user innovators’ choice of value appropriation strategies. To observe the dynamics, I start with user complements, or user innovators who disclose their innovation so that other firms or consumers in the same ecosystem use it in combination with the original product and service for enhanced performance (Gambardella et al.

2017). Building on the literature on bottlenecks (Baldwin 2018, Jacobides et al. 2018) and tools for research and experimentation (Murray et al. 2016, Scotchmer 1991), I argue that user complementors can be competitors in the product market space once tools provide viable alternative technical solutions to the focal ecosystem's bottleneck. I also examine how changes in user innovators' value appropriation strategies in turn influences value creation by a core firm within ecosystems. Moreover, I argue that not all complementors respond equally because prior experience within ecosystems serves as an opportunity to reduce market uncertainty for certain user complementors. Together, I describe a understudied process in which complementors become competitors, with implications to value dynamics between firms and individual innovators such as user innovators (Jacobides and Tae 2015).

I study user complementors in the PC video game industry to provide empirical evidence. Several features of the PC video game industry make it particularly well-suited to examine the research question. First, there are sizable active user complementors, or "modders," who modify existing games to create new contents with novel characters, items, and maps and freely share the innovation outcome to the communities (Boudreau and Jeppesen 2015, Jeppesen 2004). Interestingly, anecdotal evidence suggests that some of these user complementors choose commercialization path and release their innovation into product market as standalone game products, indicating that these users complementors are indeed exposed to multiple value appropriation strategies as described before. Second, because user complementors rely heavily on online communities for the dissemination and commercialization of their innovations, I am able to obtain fine-grained dataset capturing unpaid contribution and commercialization as alternative value appropriation strategies. Finally, its modular structure (Baldwin and Clark 2000) allows us to identify technical and strategic bottleneck in the game development process:

game engine module. From a product design perspective, a video game can be seen as a piece of software following modular architecture. Put simply, it consists of 1) core engine layer that defines a basic principle of the game, and 2) game code layer that constitutes additional creative contents. User innovators recreate existing games by modifying game code layer to introduce new characters or items to the existing games, but they cannot create independent, standalone game from the innovation as developing core engine layer is much more complex and costlier.

For identification, I exploit a substantial, and arguably exogenous reduction in access costs to game engine module and use a difference-in-difference strategy. Licensing game engine modules used to be prohibitively costly for most individual innovators. Since late 2009, however, starting with Unreal 3, some major game engine developers have changed their business model and provide the subscription-based option that is much more favorable to independent (indie) developers. Under the new business model, an individual (indie) developer usually does not have to pay a significant upfront cost to license game engine software, which essentially provides a viable alternative to game engine module inside the incumbent firms' game modules. I use a difference-in-differences strategy by using the first of such business model change by Unreal 3 in November 2009. Specifically, I compare 155 user complementors whose innovation and skills are compatible with Unreal 3 Engine to other user complementors without compatible skills to Unreal 3 Engine. By comparing these two groups of innovators in terms of commercialization and contribution, I am able to study how commercialization opportunities triggered by lowered development costs affect user complementors' choice of value appropriation strategies.

I present two main findings. First, I find that a 10 percent increase in the number of commercialization activities when the costs of accessing production tools necessary to commercialize new technologies decrease. Yet, the increase does not come uniformly; rather, it

is user complementors who have received strong market quality signal that respond to democratized access to production tools. This implies that user complementors' value appropriation strategies are determined from a nuanced interplay between accumulated human capital as complementors and external environments. Second, I find that when facing reduced development costs, the affected innovators decrease contribution efforts by 12 percent, indicating the trade-offs between commercial opportunities provided by easier access to complementary assets and contribution. The decrease is mostly from contribution to their existing projects. While it is difficult to measure directly, this implies that incumbent firms' ability to benefit from user complementors is reduced.

The findings here are closely related to several recent papers on community-based innovators and entrepreneurship. First, a few recent papers look at how macro-level factors such as competition from commercial platforms and economic downturn affect the motivation of members to knowledge-creating communities (Kummer et al. 2015, Nagaraj and Piezunka 2017). This paper similarly investigates how an environmental factor in terms of the availability of tools affect the behavior of user innovators active on communities. However, the focus here is more related to external commercialization opportunities, and also measure the behavior of user innovators not only in terms of contribution (community participation) but also in terms of commercialization as value appropriation strategy. Second, Boudreau (2018) describes how substantially low entry costs unleash the massive number of entries by amateur developers to the digital platform. He also documents that most new entrants do not perform well except a few outliers. However, while Boudreau (2018) focuses on the entry patterns and performance for developers without strong profit motives, this paper describes how profit motives affect user complementors whose prior knowledge-sharing activities were not seemingly motivated from

profit motives. Furthermore, this paper suggests that even among new entrants responding to low-cost entry opportunities, there is significant heterogeneity in human capital, prior experience and the quality of idea.

More broadly, this paper contributes to several streams of strategy and innovation literatures. First, it contributes to the knowledge-based entrepreneurship literature, and particularly on when and how users and other community-based innovators pursue commercialization as their value capture strategy (Agarwal and Shah 2014). Building on the user innovation (Hippel 2016), technology commercialization (Gans and Stern 2003, Teece 1986), and ecosystems literature (Baldwin 2018, Kapoor 2018), I hypothesize and empirically test the hypothesis that these innovators adjust their value appropriation strategies when certain critical tools of production provide viable alternatives to existing technological and strategic bottlenecks. In particular, I argue that some complementors change their roles from collaborators with core firms within ecosystem to competitors. within a given value chain to competitors to the offer. Second, it adds to the value-based strategy (Brandenburger and Stuart 2005) and ecosystems literatures by demonstrating how complementors affect the value created and captured by core firms within ecosystems. Many prior works in this space focus on how complementors respond to platform owners and other core firms' strategic choices (Iansiti and Levien 2004, Gawer and Henderson 2007, Zhu and Liu, 2016, Wen and Zhu 2017). In contrast, this paper illustrates that when complementors strategically respond to changes in external environments, core firms in the same ecosystem may be worsen off, unless they also dynamically adjust their strategies (Helfat and Raubitschek 2018).

1.2. Theoretical Framework

Users and other types of community-based innovations are playing increasingly larger roles in innovation systems (Altman and Tushman 2017). Firms increasingly embrace communities as a key innovation partner to provide technical supports to end customers (Franke and Shah 2003, Lakhani and Hippel 2003), identify new product and organizational innovation (Bayus 2013, Dahlander and Piezunka 2014), and increase the value of their own products by adding complementary products (Boudreau and Jeppesen 2015, Jeppesen 2004).

A critical necessary condition for successful innovation communities is the voluntary free revealing of innovation by participants. Existing literature provides rich empirical evidence on the benefits from free revealing by relying on various intrinsic and extrinsic motivations that arise inside the communities. including intrinsic motivations such as social recognitions (Gallus 2016, Jeppesen and Frederiksen 2006, M. Zhang and Zhu 2011), enjoyment (Lakhani and Wolf 2005), and extrinsic motivations such as learning (Lakhani and Hippel 2003, Nagle 2018), consumption of improved goods (Harhoff et al. 2003), and career benefits (Hann et al. 2013, Lerner and Tirole 2002, Xu et al. n.d.).

In contrast, a burgeoning literature focuses on the incidence and process in which community-based innovators become entrepreneurs to commercialize their ideas. Understanding their transition is important because these innovators are often the ones who lead the emergence of new industry category (Shah and Tripsas 2007, Shah and Tripsas 2012). Despite the importance, we have less theory and evidence on under what circumstances innovators embedded in communities participate in commercialization.

In this section, I develop a simple theoretical framework to guide the empirical analysis. First, I theorize how lower development costs affect commercialization by community-based innovators. I then theorize what types of user complementors are more likely to respond to

external commercialization opportunities created by easier access to critical production tools. Finally, I hypothesize how these commercialization opportunities affect their contribution patterns.

1.2.1. How Tools of Production Affect User Complementors' Commercialization

A series of recent environmental changes reduce the cost of commercialization dramatically. Technological changes play an important role. For instance, the introduction of many cloud-based IT services, such as Amazon's Web Services (AWS), lowers the initial setup costs required to provide web-based services (Ewens et al. 2018). Another change in the business environment is the proliferation of platform-based ecosystems (Helfat and Raubitschek 2018, Iansiti and Levien 2004, Jacobides et al. 2018). Leading firms orchestrating the ecosystem provide various infrastructures and design toolkits, such as application program interfaces (APIs), at cheaper costs because their success depends on the quantity and quality of complementors (Boudreau 2012). Practically, we observe that recent industry changes lower the commercialization costs dramatically, leading to massive market entry by crowds (Boudreau 2018, Qiu et al. 2017, Waldfogel 2016).

As commercializing ideas become cheaper, we observe new patterns of idea-based entrepreneurship. For instance, reduced entry costs lead to massive market entry by crowds and individuals (Boudreau 2018, Qiu et al. 2017) and much higher level of product variety from younger, smaller entrepreneurs (Benner and Waldfogel 2016, Waldfogel 2016). These entrepreneurs rely less on external resource providers for growth (Hallen et al. 2017). However, our understandings are much limited on 1) how community-based innovators who used to freely disclose their ideas respond to lower commercialization costs, and 2) what are the consequences of commercialization on their contribution.

In this section, I develop a simple theoretical framework to guide the empirical analysis. First, I theorize how lower development costs affect commercialization by community-based innovators. In doing so, I apply the technology commercialization strategy literature, or “profiting from innovation” framework, (Gans and Stern 2003, Gans et al. 2002, Teece 1986) to the innovation communities’ context and theorize how community-based innovators respond to lower commercialization costs. Because the access to complementary assets has been a significant entry barrier for community members, I argue that they are more likely to pursue commercialization when cheaper development option becomes available. Next, I hypothesize how lower development costs affect contribution. I build my argument based on the existing literature on what motivate innovators’ incentive to freely contribute to communities.

Early literature on innovation communities predominantly depicts the community-based innovators as more intrinsically motivated, less interested in pecuniary benefits, and ones with anticommercial attitudes (Krogh et al. 2012, O'Mahony 2003). In contrast, more recent literature focuses on the incidence and process in which community-based innovators become entrepreneurs to commercialize their ideas. Understanding their transition is important because these innovators are often the ones who lead the emergence of new industry category (Shah and Tripsas 2007, Shah and Tripsas 2012). Despite the importance, we have less theory and evidence on under what circumstances innovators embedded in communities participate in commercialization.

To conceptualize the individual-level decision to commercialize ideas, I draw on the technology commercialization strategy (TCS) literature (Gans and Stern 2003, Gans et al. 2002, Teece 1986). This framework considers how an innovator captures value from a given innovation and focuses on the roles that appropriability regimes and access to complementary

assets play in determining the innovator's optimal strategic choice. The TCS framework is a useful perspective to study community-based innovators' commercialization choice because these innovators possess potentially promising ideas to commercialize. First, members of innovation communities often develop ideas that fulfill the needs that existing products cannot satisfy. Second, communities have advantages in refining and improving innovation at a much lower cost because members provide free assistance (Franke and Shah 2003, Hienerth et al. 2014). Third, members benefit from early feedback and information cues on market demands which in turn lowers uncertainty related to commercialization (McMullen and Shepherd 2006). Examples demonstrate that community-based innovators pursue commercialization only when their free innovation is adopted by many members (Autio et al. 2013).

However, ideas from innovation communities are hard to commercialize because members of the communities find it difficult to access to various complementary assets. To be fair, community-based innovators are not the only would-be entrepreneurs facing such difficulties. It is rather a defining characteristic of technology-based entrepreneurship, because incumbent firms controlling access to complementary assets are often incentivized to deter market entry (Gans and Stern 2003). However, community-based innovators face additional challenges because their strategic options to help access to complementary assets are much limited for several reasons. First, because innovation communities are established for knowledge creation and not for production or manufacturing, it is unlikely that community-based innovators are able to find related capabilities internally (Shane and Stuart 2002). Second, partly because of the vague organizational boundary, innovation communities are unlikely to provide institutional reputation that helps building collaborative relationship with partners with complementary assets (Sine et al. 2003). Third, while IP rights are widely used as a tool to signal the underlying

quality to external resource providers (Conti et al. 2013, Hsu and Ziedonis 2013), most communities give up IP rights as a way to encourage external participation (Harhoff et al. 2003).

In sum, access to complementary assets is a critical barrier for community-based innovators' commercialization. When some key complementary assets become affordable, community-based innovators would be most responsive because the barriers to entry is the highest for them. Several case-based examples in the literature support the view. For instance, Hienerth (2015) describes the access to "low-cost manufacturing techniques" is critical to start a new industry based on user innovation. Many successful examples of commercialization from community-based innovation come from environments in which the access to complementary assets is easy, such as app store environments (Mollick 2016, Eckhardt et al. 2018). Together, I develop the following hypothesis:

Hypothesis 1 (H1): *When the access to critical production tools gets easier, user complementors increase commercialization-related activities.*

However, I posit that not all user complementors would respond to the global shock equally. Pursuing entrepreneurship and commercialization in cultural industry is inherently risky. Particularly for innovators within communities, pursuing commercial opportunities may leave negative reputational costs (Mollick 2016). In such settings, certain types of behavioral characteristics for risk-loving tendency and overconfidence tend to increase one's entry into entrepreneurship (Astebro et al. 2014).

Yet user complementors' commercialization decision may be different because they can evaluate the potential from community responses. In other words, prior experiences within ecosystems provide vicarious learning and experimentation opportunities that are necessary for evaluating entrepreneurial ideaa. Examples demonstrate that community-based innovators pursue

commercialization only when their free innovation is adopted by many members (Autio et al. 2013) Similarly, members benefit from early feedback and information cues on market demands which in turn lowers uncertainty related to commercialization (McMullen and Shepherd 2006).

Therefore, I predict that:

Hypothesis 2 (H2): *When the access to critical production tools gets easier, user complementors increase commercialization-related activities particularly when their innovation has received positive signals for market success.*

1.2.2. How Tools of Production Affect User Complementors' Contribution

Finally, I address how easier access to critical production tools affect user complementors' contribution activities. Users' contribution activities are the key for focal firms Understanding this is important User complementors choice affect focal firms in two ways. First, potentially compete together, thereby lowering price. Also, it could lower the value capture by focal firm by lowering Willingness-to-pay. Empirical research documents between negative relationship between number of complementors and incentives to contribute (Boudreau and Jeppesen SMJ)

Some literature would argue that external commercialization opportunities may not affect user complementors' contribution patterns. For instance, there is rich theory and evidence documenting that innovators participate in communities for enjoyment-based intrinsic motivation, or "joy of performing" (Deci and Ryan 1985). Many software developers participating in open source software development mention the joyful feeling of helping other developers as an important motivating factor (Lakhani and Hippel 2003, Lakhani and Wolf 2005).

However, I would argue that there are several reasons to believe that user complementors' contribution will be reduced when easier access to critical production tools

generates commercial opportunities. First, a classical economic theory of time allocation predicts that when external commercialization opportunities are growing, community-based innovators would reduce contribution to the community (Becker 1965). Because time is constrained, one would want to allocate more time to activities with higher marginal utility. When commercialization opportunity is growing because of more accessible complementary assets, an innovator would contribute less even though the marginal benefit of contribution remains the same.

Second, innovators may contribute less because of reduced career incentives. Signaling incentives in the external labor market is another established motivator for contribution (Hann et al. 2013, Huang and Zhang 2016, Lerner and Tirole 2002, Xu et al. Forthcoming). By active contribution, high-quality innovators can increase the likelihood of being hired by employers. Several empirical evidences support the view. Huang and Zhang (2016) document that in the context of SAP Community network, developers' more contribution to knowledge communities leads to a higher likelihood of job-hopping. In the same vain, Xu et al. (Forthcoming) show that once a job seeker lands in a new position he or she contribute less in online knowledge communities, providing another evidence on career incentives. Viewing commercialization and transition into entrepreneurship as alternative career path, I expect that innovators pursuing commercialization opportunities are less incentivized to contribute to communities.

Third, contribution to communities may be reduced because of less social interactions. Extant literature on innovation communities has demonstrated that a bigger group size increases innovators' incentive to contribute (Boudreau and Jeppesen, 2015; Fershtman and Gandal, 2011; Jeppesen and Frederiksen, 2006; Zhang and Zhu, 2011). For instance, the value of social recognition would be higher for bigger communities (Gallus 2016). Smaller group size may

reduce potential benefits from peer learning (Lakhani and Wolf 2005). If some of previously active contributors leave the community to pursue commercialization, then remaining members would face lower incentives to contribute to community.

Together, at the aggregate level all mechanisms described so far unanimously suggest that when development costs to pursue commercialization decrease, innovators would contribute less to innovation communities. Therefore, I predict that:

Hypothesis 3 (H3): *User complementors reduce contribution activities when access to complementary assets becomes cheaper.*

1.3. Setting

The empirical context for this study is the video game industry, and more specifically, video games on PC platforms. The video game industry is one of the largest and consistently growing entertainment industries. In 2016, consumers in the United States alone spent about \$25 billion to purchase new video game contents. About 65% of US households have at least one person who spends more than 3 hours a week to play video games, implying that the welfare implications from product innovation may be substantial (Brynjolfsson et al. 2003). While mobile game is the fastest growing segment, games on computer platforms still accounts for about one fourth of the entire industry sales.

1.3.1. User Complementors, or “Modders”

I focus on computer games industry because there are vibrant communities of user innovators. These “modders” are highly motivated users and consumers of PC games who modify existing games to introduce new features and contents and freely disclose the innovation output to the communities. This “modding” is possible because of the modular architecture of video games (Baldwin and Clark 2000). In fact, it is a common industry practice that game developers provide

development toolkits to customers, so that customers can easily participate in mod development (Hippel and Katz 2002).

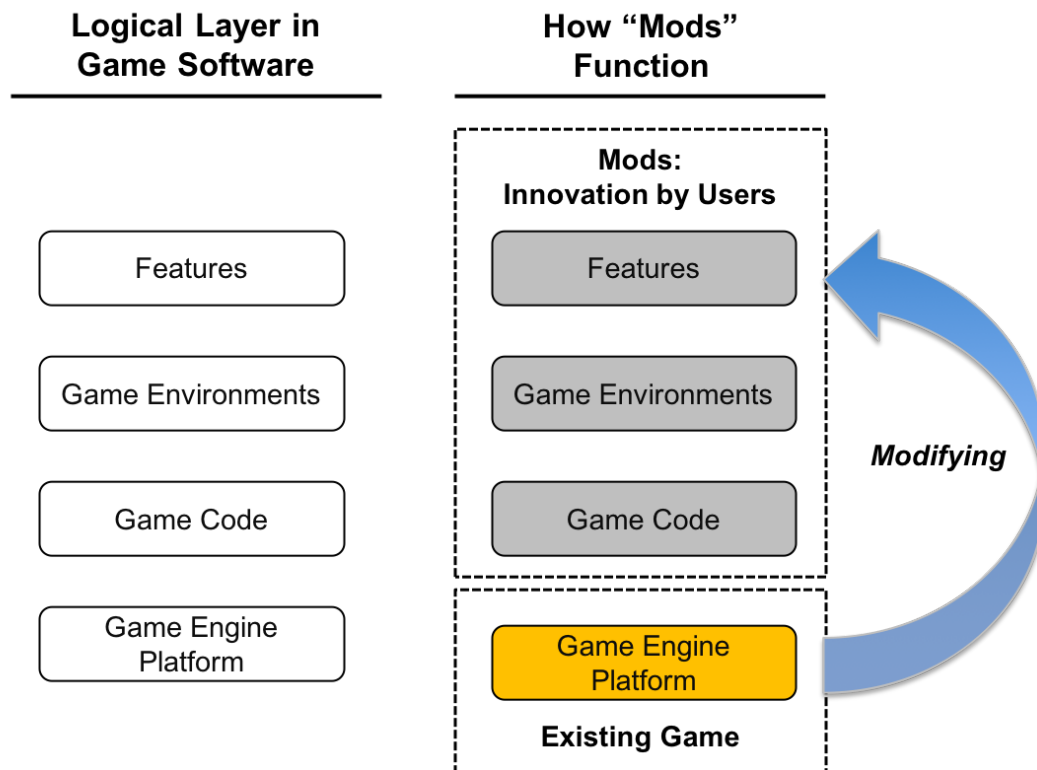


Figure 1.1. Architecture of Video Games and Mods

To understand this unique culture, I focus on two questions. First, why do game developers allow and even encourage users' modification? Game developers benefit from the presence of such user innovators as unpaid complementors. There are two ways in which game developers may benefit from these. First, developers observe features from mods that consumers find attractive and may incorporate them in the next revision. Perhaps more importantly, high-quality mods can drive the sales of games by developers. While the user-generated mods provide entirely new contents, it is still the game engine layer from the existing game that controls complex interactions among these contents. Consumers need to purchase and run that parent

game in order to enjoy user-generated mods. Because of these benefits, it is a popular industry practice among game developers to provide development toolkits to customers. It allows them to outsource the innovation process to the enthusiastic users at a significantly lower cost.

Second, who do users participate in the unpaid innovation process? Many mods are minor changes of existing games, for instance by simply adding new levels, characters, or items. However, modders sometimes replace all of the original content with entirely new contents that the resulting modes bear little resemblance to the original game. These mods are called “total conversions,” and they are essentially an entirely new game from consumers’ perspectives. Developing such mods is no different from developing a new standalone game, at least in terms of people-hours invested. A study shows that it requires “three years of development work, 140,000 lines of code and an investment of up to \$20,000 US in hardware, software, website hosting etc.” to launch a total conversion mod (Boudreau 2012, Jeppesen 2004).

Consistent with the open and user innovation literature, community-based innovators in this setting are doing this because of intrinsic and extrinsic motivations. First, there are several intrinsic rewards associated with free sharing. User innovators in the game industry describe modding as “a community-driven hobby in which passionate gamers to build additional content as a labor of love.” Second, innovators are also rewarded from heightened reputation and signals in the labor markets. The career concern incentives are also in place in the game industry. A famous example is the story of a 19-year-old modder Alexander J. Velicky. He did not receive formal education related to game development, but after successfully releasing four highly acclaimed mods, he was hired by Bungie, Inc., an American video game developer, as an Associate Designer.

As an alternative value capture strategy, community-based innovators in the computer game industry may consider commercializing the ideas and release standalone product in the market place. In fact, some of the most popular mods have become massively successful standalone games. Examples include Counter-Strike from Valve's Half-Life and Team Fortress from Id Software's Quake game. For commercialization, however, community-based innovators need to address several commercialization bottlenecks. I will discuss the challenges facing these innovators in the following section.

Given the commercial potential and development costs for a successful mod, a natural question to follow is why user innovators do not appropriate value via commercialization and instead sharing them to the community for free. On the other hand, modders face significant economic and cultural barriers when trying to commercialize their ideas. First, user innovators may commercialize their mods by participating in the "market for ideas." Literature suggests that selling or licensing in the market for ideas is an appropriate commercialization strategy for start-ups without internal complementary assets (Gans and Stern 2003). However, the market for mods is nonexistent, partly because of repugnance (Gans and Stern 2010). Modding community maintains strong norm that mods should be freely available to anyone. An illustrative example is when Valve tries to incentivize user innovation by allowing modders sell their mods directly through Steam in April 2015. In the proposed plan, users would be charged to download Skyrim mods, and the modders would be given 25% of the payments. However, this plan faced huge backlash. Game customers describe this plan as "anti-consumerist" and "unbelievably sad," arguing that "locking mods behind a paywall" goes against the modding culture. Just after three days, Valve needed to retract the plan.

As an alternative commercialization strategy, one can consider re-packaging mods as standalone product and enter into product market as entrepreneurs. Because the final product is software and there are many digital distribution platforms available, some traditional complementary assets related to manufacturing and distribution are not a significant barrier to entry. To release independently functioning games, one needs to integrate game engine software layer to contents. We already described that a game as software consists of game engine layer and creative content layer (Figure 1). Game engine contains modules for physics, animations, rendering, sound, and other core functionality. Developing it from scratch is impossible for most users as it requires sophisticated low-level programming (Gregory 2014). Because of the technical sophistication, many game developers license game engines from off-the-shelf market. Two most regarded engines are Valve's Source Engine and Epic Game's Unreal Engine. Both provides the best graphic capabilities, richest engine feature sets, and toolkits allowing developers and consumers to build on the existing assets to create their own innovations. A few major game developers have developed and used their own in-house game engine software. These in-house game engines are not typically licensed to other game developers.

For aspiring entrepreneurs in the computer game industry, the key commercialization bottleneck is game engine software. It is because the licensing costs are very expensive. While the exact cost depends on specific contracts, the rough estimates by developers are that licensing Valve's Source Engine requires about \$250k as upfront licensing fee, and \$350k upfront licensing fee plus 3% of wholesale revenue for Unreal Engine. Because such initial investments are too financially burdensome for most individual innovators, they mostly do not consider translating their mods into standalone games. As crowdfunding platforms gain popularity, some of these innovators attempt to raise funding to commercialize the mods as standalone games.

Often their primary purpose of fundraising is to license game engine. For instance, a modder who just launched a crowdfunding campaign described: “In order to turn this game into a fully fleshed game with full STEAM access, we will need to enter into a licensee agreement with VALVE. However to afford the licensee fee, applying for Kickstarter project funding might be the only option for us.”

1.3.2. Costs of Game Engine Architecture

Starting late 2009, however, several game engine software companies start to provide subscription option to individuals developers. The first change is by Epic Games on November 2009. It changed its business model for its most recent game engine, Unreal 3, and started to provide the subscription-based option that is much more favorable to in-dependent developers. Prior to the change, to package a mod into standalone game, the individual needs to license the underlying game engine software, which used to cost more than \$20k. Under the new business model, however, an aspiring game developer only needs to pay the initial subscription fee of \$99, and later share her revenue once if it exceeds \$25,000. This change has been described as “an unprecedented milestone in game development,” providing opportunity for independent game developers as it allows “free access to the same world-class tools and technology used by many of the world's best video game developers and publishers.” Essentially, it provides low-cost development option for individual innovators who have created Unreal 3 Engine based mods, but not for other innovators who have created mods based on other engines.

Many industry analysts justify the action based on two-sided platform competition logic (Eisenmann et al. 2006). Specifically, it is competition based on installed base of programmers. It was expected that the demands for game engine software would be growing because the software provides a framework for of the rise of virtual reality contents, games for mobile

platforms, and continuous growth of video game consumers. There is no clear leader on this market. In order to increase the likelihood that these new contents developers choose UR3, it needs to increase the supply of programmers proficient on the software. Subsidizing price-sensitive users in the two-sided market has been argued to be an effective strategy. Currently Unreal Engines is widely used in Oculus VR's internally-developed virtual reality.

Over time, Epic's business model change has been imitated by other players as well. Another game engine Unity also announced the plan. But because it is focused on mobile at that time, not many modders. In 2015, Valve Software, announced that its latest game engine Source 2 will be offered for free. The only condition is that the resulting game should be released on its Steam platform. Value royalty is about 30%. Similarly, another popular game engine for 3D contents, Unity, announced in the same year about its free game engine. In the meantime, Epic further reduced the price. In 2015, when they are releasing new version UR4, Epic went a step further by releasing Unreal Engine 4 for free, with developers only having to pay a 5% royalty on any project that makes over \$3,000 in revenue for a quarter.

The decreasing cost has a significant impact on entry. Figure 2 provides suggestive evidence that lowered engine costs affect entrepreneurial entry for sure. Here, I present the number of indie games using Unreal and Source engine. Source Engine is comparable to Unreal 3 Engine in many aspects. First, they are high end game engines, providing the most extensive tools and functionalities. Second, they are two most popular engine choices by modders. Many influential standalone games that originally started as mods, such as Counter-Strike, and Portal, were in fact based on Source Engine. Third, both engines ultimately embrace the subscription-based business model but at different times.

By 2009 there is literally no indie developers developing games based on these expensive engines. However, starting from 2010, there is stark difference. The number of indie games on Unreal Engine increases substantially, whereas only a few indie game developers use Source Engine.

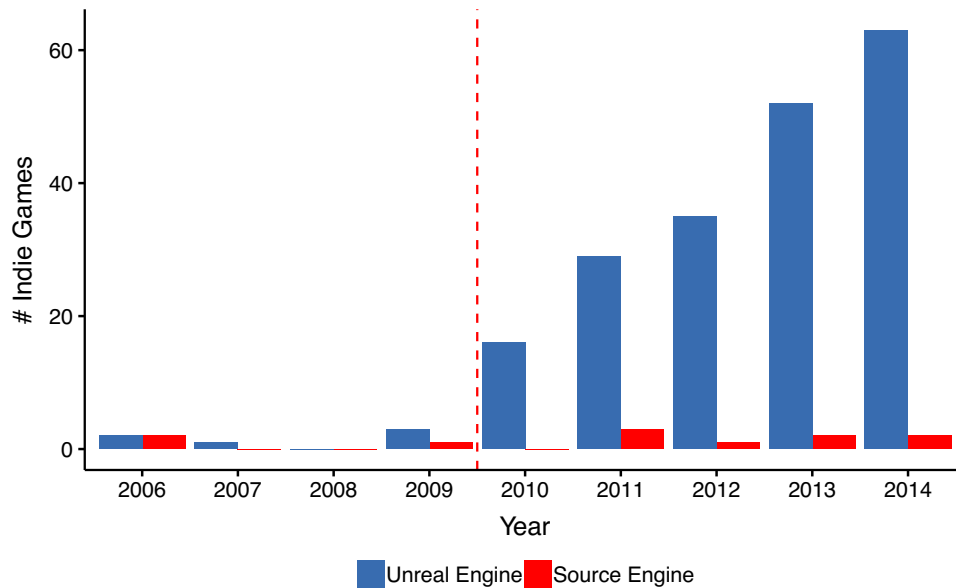


Figure 1.2. Engine Adoption by Indie Games

NOTES: This figure plots the number of indie games that are built from Unreal 3 Engine (by Epic Games) and Source Engine (by Valve).

The unanticipated business model change by Epic Games on its Unreal 3 Engine triggered heated debates on the future of video game modding culture. Some predicted the demise of modding culture, because: “modding was so popular because it was a shortcut to professional-grade 3D engines,” but as more high-quality platforms for game development are available for free, “current modding community would or could step away from their parent games and develop for these platforms.” However, there are others who still remain positive on the innovation community, because: “many mods were born out of love of the original game”

and “[modding] gives you access to a ready-made community.” This mirrors the theoretical ambiguity that I set up in the literature review. The change also provides an ideal natural experiment to examine the robustness of innovation communities, which I will discuss in the following section.

1.4. Data and Methods

1.4.1. Data Source

Studying how community-based innovators allocate efforts in different resources is challenging because of many data limitations. For instance, scholars have made significant progress in understanding when employees or academic scientists become entrepreneurs by using publication and patent records to characterize their career histories. In contrast, existing studies on commercialization of community-based innovators are mostly qualitative because there is no systematic data with comparable coverage.

In this paper, I overcome the challenge by constructing a novel dataset by scraping two websites: moddb.com and indiedb.com. First, I use the dataset from moddb.com to measure voluntary, free contribution by individual innovators. Moddb.com is known as the largest, most comprehensive online platform for user innovators modifying existing computer games. As of 2017 October, more than 15,000 mods are freely downloadable from this innovation community. It contains detailed information on each mod and individuals involved. For instance, I am able to collect some individual-level demographic information such as nationality and joining date. Importantly for the analysis, it displays information on technical compatibility, or what game engine platform each mod is based on. For instance, Figure 2 shows an example from a mod named “Depth.” It was developed by modifying an existing game “Unreal Tournament 3” and thus is compatible with Unreal 3 engine that Unreal Tournament 3 adopted. In addition, I

observe different types of activities on each modding project, including: articles (announcements from development team), files (freely downloadable contents such as maps, items, executable patches etc.), comments (discussions among innovators and adopters). Each activity contains information on who initiate each activity, what projects it is related to, and when the activity occurs. Using data from moddb.com. I construct timestamped individual-activity level data on contribution. For each year, I count the number of contribution activities.

Second, I scrap another website indiedb.com to collect information on commercialization. Indiedb.com is a platform designed to support independent game developers (“indie developers”) and their games. Independent game developers promote their in-progress or complete games by creating webpage for each project and providing descriptions. Developers promote their project by sharing their development milestones, medias featuring their products, and screenshots, short video clips, and even demo versions and patches. Developers also provide links to digital distribution platforms such as Amazon and Steam so that interested visitors purchase the product. As such, various activities on indiedb.com are related to commercializing games. Using a similar methodology as before, I construct another timestamped individual-activity level data on commercialization.

A particularly attractive feature of these datasets is that both platforms are run by a single organization and thus share the same individual IDs, which allows me to combine timestamped contribution data from moddb.com and also timestamped commercialization data from indiedb.com at the individual level. Using the data, I observe how innovators allocate their efforts between voluntary, free contribution to the innovation community and commercialization and what factors affect the allocation.

1.4.2. Identification Strategy

In an ideal experiment, I would estimate the impact of lower development costs on individual-level commercialization and contribution activities by randomly providing compatible game engine software to only a certain group of innovators. I would then compare the level of commercialization and contribution with access to game engine, to other innovators without the access.

I use a difference-in-differences strategy and approximate this ideal experiment by using an unexpected price decrease of Unreal 3 Engine in November 2009. First, I classify as treated group 157 innovators who have modified Unreal 3 Engine-based games by October 2009. It is before Unreal 3 Engine's new subscription-based business model was first announced; therefore, the treated innovators' choice of underlying technology (game engine) is not systematically correlated with their commercialization intent. The first modding activity based on Unreal 3 Engine started in July 2007. Second, I classify as control group 1,390 innovators who have modified games based on other game engines in the same period. I carefully select the list of game engines used in constructing the control group to ensure that the technical sophistication is comparable to that of treated group. I only include fifteen engines that most successful mods have based on. I also drop open source- based engines because development costs in using them engines are close to zero.

Comparison between the two groups over time provides several advantages. By including individual fixed effects, I am able to remove time-invariant individual-level differences. I also include year fixed effects to control for industry-level changes that affect all innovators. The second issue is critical because there are other industry level changes in the game and other creative industries that reduce the entry cost dramatically. In the computer games industry, for

instance, digital distribution platforms such as Steam lower the costs of distribution to customer bases, perhaps making commercialization more attractive options. Because it affects all innovators simultaneously, it does not affect our analysis as long as I include year fixed effects.

Formally, I estimate the following standard DID specification using OLS:

$$Y_{it} = \alpha_i + \theta_t + \beta TREAT_i \times POST_t + \gamma'X_{it} + \varepsilon_{it} \quad (1)$$

where the dependent variables Y_{it} measure either commercialization or contribution by individual i in year t . $TREAT_i$ indicates whether an individual i has developed any Unreal 3 Engine-based mod before the treatment. $POST_t$ indicates whether the observation is equal to or after 2010, that is, after the price of Unreal 3 Engine decreases drastically. The interaction term essentially captures whether an individual has access to compatible game engine software at a cheaper price. The coefficient of interest is β . It compares the average level of commercialization and contribution activities by innovators who face reduced development costs to those who do not face reduced development costs. During the sample period between 2006 and 2014, Unreal 3 is the only game engine that experienced substantial price reduction. I control for time effects and time-invariant individual effects. Standard errors are clustered at the individual level. The unit of observation is at the individual and year level. It is unbalanced panel because the first observation for each individual begins in his first mod development year.

My identification strategy relies on several identification assumptions. First, users' choice of engine (technology) should not be made under the prediction that Unreal 3 Engine will be free in the future. This assumption is likely to be met because Epic Game's announcement was unexpected. Under the plausible assumption that the business model change of Unreal 3 Engine is unexpected, their engine choice is not driven by any commercialization opportunity. Their

choice is not affected by the business model change by Unreal because the choice is made before the shock.

Second, reduced price of Unreal 3 Engine should not benefit the individuals based on other engines equally. In econometrics term, it corresponds to the stable unit treatment value assumption (SUTVA). It is likely to be satisfied because of high costs of learning new skills and convert existing contents to make them compatible with new engine. For instance, Robert Briscoe, a lead developer of a successful mod-turned-game Dear Esther, described the difficulty of switching game engines as follows:

“Initially Source seemed like the ideal choice, ... I deeply wish [Epic’s announcement of the subscription version of Unreal 3 Engine] had happened months ago as either of these would much more suitable for me to develop [Dear Esther] on, however at this point in the project I think I have crossed the point of no return, mainly due to having limited finances to fund the project full time, and partly the motivation to start again in a new engine.”

Second, reduced price of Unreal 3 Engine should not benefit the individuals based on other engines equally. In econometrics term, it corresponds to the stable unit treatment value assumption (SUTVA). It is likely to be satisfied because of high costs of learning as described above.

1.4.3. Sample and Variables

I construct an unbalanced individual-year panel dataset over the period 2006-2014. I choose 2014 because Source Game announces the next version Unreal 4 Engine, and Valve announced its plan for free subscription model. It is unbalanced because the data begins when an individual starts any contribution activity. It contains all innovators in the user innovation community who have contributed at least once between 2006 and 2009 by modifying games based on high-quality, proprietary game engines. Specifically, I only include game engines that have been basis

of mods nominated for the “Mod of the Year Awards” by moddb.com. It results in 1,547 individuals and 10,923 individual-year observations.

Table 1 provides summary statistics at the individual and individual-year level. All sample innovators have contributed at least once before 2009. About 10% of all observations belong to the treated group. Panel A shows that by 2014, an average innovator has 8.7 contribution and 1.5 commercialization activities. Panel B displays similar allocation patterns between commercialization and contribution but at the year level.

Table 1.1. Summary Statistics

	N	Mean	Sd	Min	Max
A. Individual Level					
Treated	1,547	0.10	0.30	0.00	1.00
Year Joined	1,547	2,007.12	1.63	2,002.00	2,009.00
First Modding Year	1,547	2,007.77	1.30	2,002.00	2,009.00
% United States	1,547	0.38	0.48	0.00	1.00
% Europe	1,547	0.47	0.50	0.00	1.00
# Contributions	1,547	8.76	8.05	1.00	159.00
# Commercialization	1,547	1.51	6.33	0.00	48.00
B. Individual-Year Level					
# Contribution	10,923	1.21	3.01	0.00	30.00
# Commercialization	10,923	0.21	1.78	0.00	49.00
# Contribution to New Projects	10,923	0.16	0.40	0.00	4.00
# Contribution to Existing Projects	10,923	1.05	2.73	0.00	27.00
1(Contribution to New Projects > 0)	10,923	0.15	0.36	0.00	1.00
1(Contribution to Existing Projects > 0)	10,923	0.19	0.40	0.00	1.00

Dependent variables. I use two dependent variables to capture commercialization and contribution activities separately. To measure commercialization, I create a variable $COMM_{it}$

which is the number of activities on indiedb.com in year t by an individual i . Most of these activities are about sharing promotional contents, such as development logs, media features, and demo video clips. Therefore, these activities are related to commercialization. In practice, this variable contains many zeros and highly skewed because only a few innovators participate in commercialization. I use the inverse hyperbolic sine transformation, which behaves approximately similar to a log but defined at zero (Doran et al. 2014). Two data transformations are used for both dependent and independent variables: log normalization (with a small constant) and inverse hyperbolic sine (IHS) normalization. Since many variables, such as capital acquisition variables, have many 0s, the IHS transformation is preferred. While IHS approximates log, estimated coefficients are not as readily interpretable. Since in almost all cases log and IHS estimates are essentially equivalent, log-normalized interpretations appear in the text and IHS estimates appear in tables.

To measure contribution, I create another variable $CONT_{it}$. It counts the number of activities on moddb.com in year t by an individual i . Typical activities on this platform include uploading freely downloadable contents such as maps, items, and executable patches, which are related to free contribution to the members of innovation communities. I similarly use the inverse hyperbolic sine transformation to deal with skewness.

Independent variables. In most specification we include individual fixed effects to control for individual-level unobserved heterogeneity. While this is a convenient strategy for identifying causal impact of lowered development costs on innovators' behaviors, it absorbs potentially interesting variations across individuals. To explore this further, I drop individual fixed effects in some specifications and instead include other time-invariant control variables to see how different individual- and innovation-level characteristics affect the response. These

include an innovator's self-reported country of residence, game genre, and the popularity index. I construct the popularity index by calculating the percentile rank of the number of unique followers for the initial year among innovation projects within same cohort (defined at the quarter level).

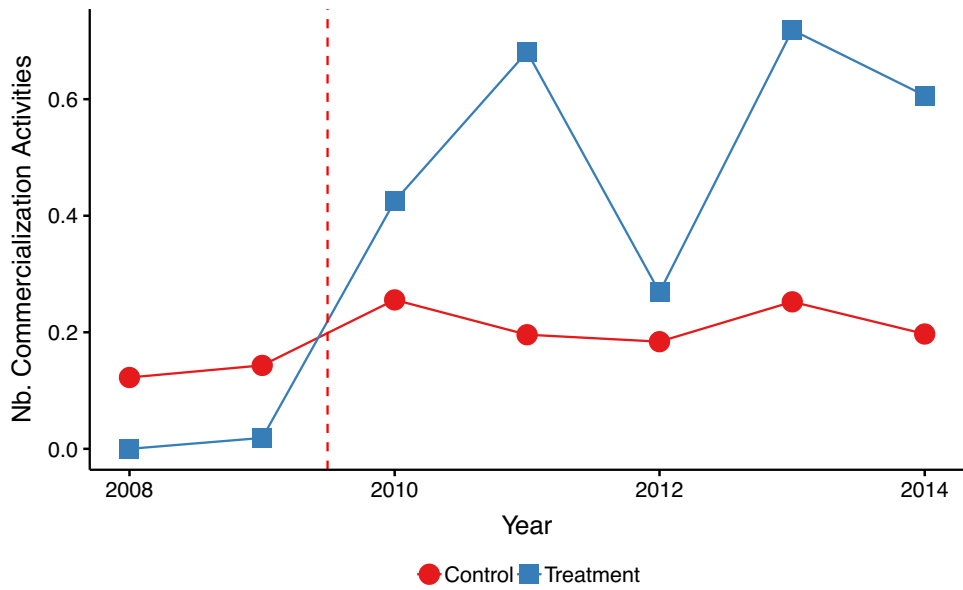
Finally, in some specifications I include two time-varying individual-level characteristics X_{it} . First, I construct a variable $EXPER_{it}$ that measures the number of years an individual has spent on this community. Second, $TOP100_{it}$ is a proxy of external signal. It indicates whether at least one mod of an individual i has been nominated for the "Mod of the Year Awards" by moddb.com. Since 2001 about 100 mods are nominated for this award annually. This variable helps to capture the underlying quality of any mod and quality signals from external evaluators, which may affect the likelihood of entrepreneurial entry.

1.5. Results

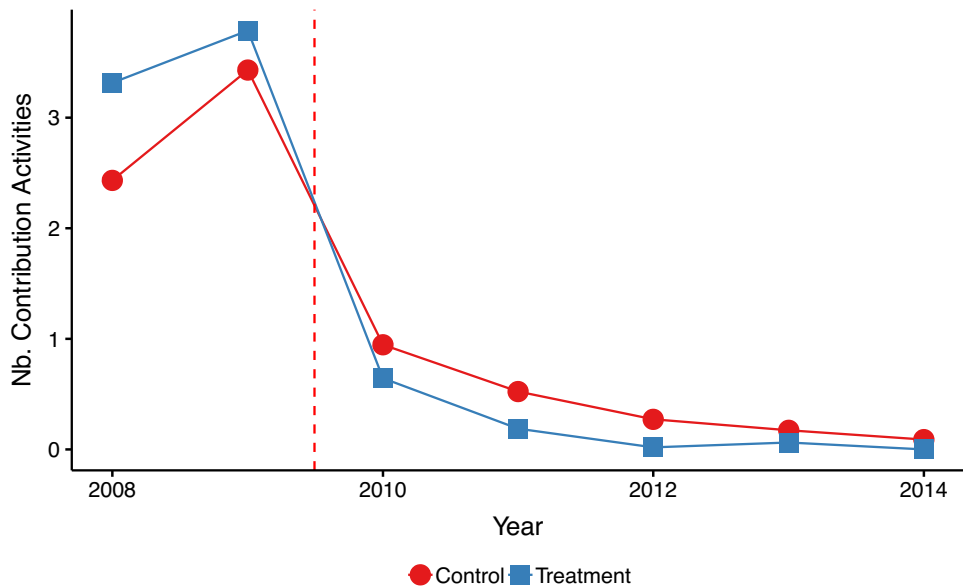
In this section, I present estimation results from several difference-in-differences specifications to understand the effects of reduced development costs on commercialization.

1.5.1. Descriptive Evidence

Before presenting the results from the empirical models, I first provide some descriptive evidence related to H1 and H3. Figure 3 presents the simple mean of commercialization and contribution activities for the treated and control group between 2008 and 2014. In terms of commercialization (Panel A), innovators in the treated group on average participate less in commercialization than innovators in the control group in 2008 and 2009. 2010 and onwards, however, treated innovators participate more in commercialization than innovators in the control group, which is consistent with H1.



A. Commercialization



B. Contribution

Figure 1.3. Commercialization and Contribution Activities over Time

Regarding contribution (Panel B), we observe the opposite pattern. In 2008 and 2009, innovators in the treatment group tend to contribute more to the community than innovators in

the control group. We then see sharp decrease in the number of contribution activities between 2009 and 2010. It is due to the way that I construct the sample. My sample consists of innovators who have made at least one contribution by 2009. The majority of innovators do not continue contributing to the community, which is consistent with the findings in the open source literature (Shah 2006). While this pattern applies to both innovators in the treated and control group, the degree to which it applies seems to be different between innovators in the treated and control group. 2010 and onwards, innovators in the control group contribute more to the community than treated innovators, supporting H3.

Table 2 displays descriptive statistics comparing treated and control group at the individual level. This summary table provides some evidence to our research question on how reduced development costs affect innovators. Panel (A) and (B) of Table 3 show the baseline differences between 157 treated and 1390 control samples before the treatment. Panel (A) discusses basic demographics. Innovators in the treated group tend to be slightly less experienced (about 4 months) in terms of contributing to the community, and more likely to live in the United States. However, they joined on the platform around the same time period. In Panel (B), I compare the samples based on contribution and commercialization related measures in the pre-treatment period. Between 2006 and 2009 an average innovator participates in only one project mostly and made about 7 contributions.

Importantly, there are no significant differences in the rate of contribution and commercialization participation between the two groups. In contrast, their participations in commercialization activities are negligible, except a few outliers in the control group. Also, mods from the control group tend to be more popular (by about 10%). I discuss several empirical strategies to deal with the remaining differences in the results section.

Table 1.2. Balance Table

	Treated (N = 154)	Control (N = 1092)	Diff.	p-value
A. Baseline				
Year of First Activity	2,008.019	2,008.263	-0.243	0.008**
Idea Quality (1-4)	2.162	2.392	-0.230	0.015*
B. Before Treatment				
# Contribution	7.175	7.024	0.152	0.733
# Commercialization	0.097	0.263	-0.165	0.428
C. After Treatment				
# Contribution	0.831	2.187	-1.356	0.038*
# Commercialization	2.701	0.862	1.840	0.000**

NOTES: This table displays means of key variables for treated and control individuals. The final column presents the p-value from the test that the means of the corresponding variable are equal between treated and control individuals. +, *, and ** denote statistical significance at 10%, 5%, and 1% level, respectively.

Because the two groups seem to be balanced in the pre-period, if there are any changes in the post-period, they are likely to be driven by differences in development costs. Table 2, Panel (C) suggests that lowered development costs affect the allocation patterns by innovators. After the cost of using Unreal 3 Engine decreases substantially, modders based on Unreal 3 Engine are less likely to participate in contributions, but more likely to participate in commercialization activities. This pattern shows some suggestive evidence that the availability of low-cost development option may increase the rate of commercialization and decrease contribution.

1.5.2. Regression Results on Commercialization

Table 4 shows how reduced design costs affect commercialization by community-based innovators. As a first step, I estimate the specification in Equation (1) but without individual and year fixed effects using OLS and present the results in column (1). The results describe how the

innovators' commercialization changes over time. By 2009, innovators in the treated group are less likely to participate in commercialization. After 2010, all innovators are about 3% more likely to participate in commercialization than before. It could be because of the success of digital game distribution platforms such as Steam and Desura, which allow independent entrepreneurs to distribute their products to wider customers at a much lower cost. Also, innovators with more popular contents are more likely to participate in commercialization. This is consistent with the literature that positive feedback from crowds may trigger entrepreneurial entry (Autio et al. 2013, Eckhardt et al. 2018). Most importantly for our purpose, the estimated coefficient on the interaction term suggest that innovators facing reduced development costs participate about 9.4 percent more in commercialization activities than other innovators ($p < 0.01$).

To measure the causal impact of reduced design costs on commercialization, I estimate the difference-in-difference specifications in Equation (1). Column (2) shows the results from the basic difference-in-differences specification. In this way, unobservable individual-specific time-invariant characteristics are absorbed, as well as time trends that affect all observations equally. The estimated coefficient on the interaction term similarly indicates that reduced development costs increase commercialization activities by 9.4 percent ($p < 0.05$). Column (3) further includes as control variables 1) innovators' community experience and its squared term, as well as 2) nomination to Top 100 award as a measure of quality signal. By including these controls, I address remaining concerns arising from differences between treated and control group in terms of innovator experience and idea popularity that we have discussed in Table 3. Including those variables does not change the result. The estimates show that reduced development costs increase commercialization activities by about 9.3 percentage point.

Table 1.3. Difference-in-differences Estimates on Commercialization

	1(Commercialize)			IHS(#Commercial Activities)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.005 (0.008)			-0.018 (0.014)		
Post	0.005 (0.004)			0.014+ (0.009)		
Treated x Post	0.036* (0.015)	0.038* (0.015)	0.038** (0.015)	0.104** (0.038)	0.102** (0.038)	0.102** (0.037)
Top 100			0.070* (0.034)			0.141* (0.065)
Constant			0.000 (0.000)			0.000 (0.001)
Year FE	No	Yes	Yes	No	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Quality x Age FE	No	No	Yes	No	No	Yes
Observations	7818	7818	7818	7818	7818	7818
Nb. Individuals	1246	1246	1246	1246	1246	1246
Adj. R-squared	0.003	0.279	0.281	0.005	0.300	0.301

NOTES: Observations are at the individual by year level. Column (1) includes game genre and country fixed effects. Robust standard errors clustered at the individual level are presented in parentheses. +, *, and ** denote statistical significance at 10%, 5%, and 1% level, respectively.

To interpret the difference-in-differences estimates causally, the critical assumption of the parallel trends should be satisfied. Panel A of Figure 4 already provides some assuring evidence that this is likely to be the case. In 2008 and 2009, innovators in the control group commercialize more than innovators in the treated group. More importantly, the sample means from the two groups seem to follow parallel trends in the pre-treatment period.

To validate this assumption more formally, I estimate the dynamic version of difference-in-differences specifications similar to Autor (2001). I expand Equation (1) by estimating the difference between treated and control groups in all sample years, in a following way:

$$Y_{it} = \alpha_i + \delta_t + \sum_{\tau=2008}^{\tau=2014} \beta_{\tau} \text{TREATED}_i \times \text{YEAR}_{\tau} + \varepsilon_{it} \quad (2)$$

where $YEAR_{\tau}$ represents an indicator variable for each year between 2008 and 2014. Year 2007 is the excluded year. Y_i

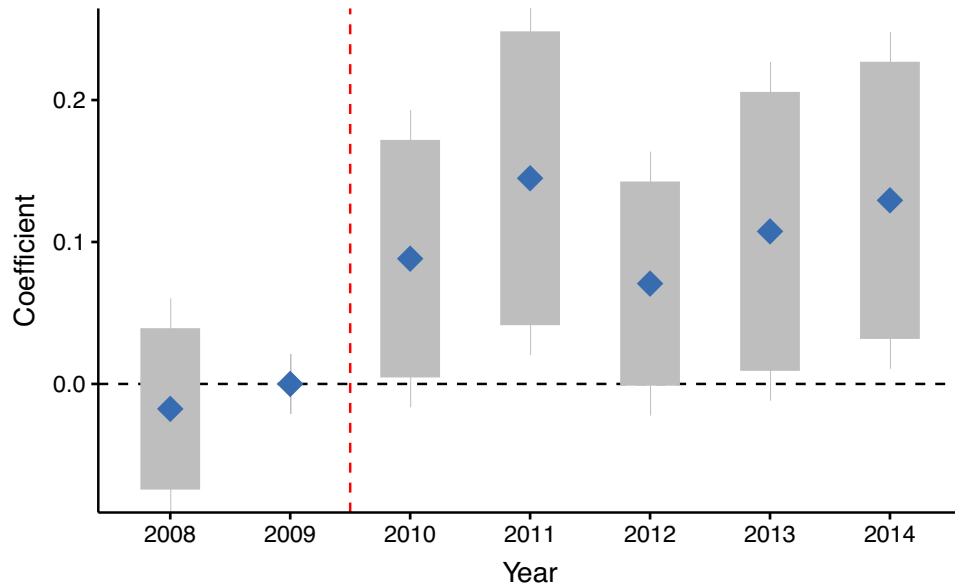
Panel A of Figure 4 presents estimates of β_{τ} from Equation (2). The dashed red line indicates the treatment year in which Unreal 3 Engine started to be offered as subscription basis. The error bars represent 90 percent confidence intervals. It displays that the differences between the treated and control groups are parallel in the pre-treatment period. Additionally, it tells that the increase in commercialization is most pronounced two years after the treatment.

1.5.3. Regression Results on Contribution

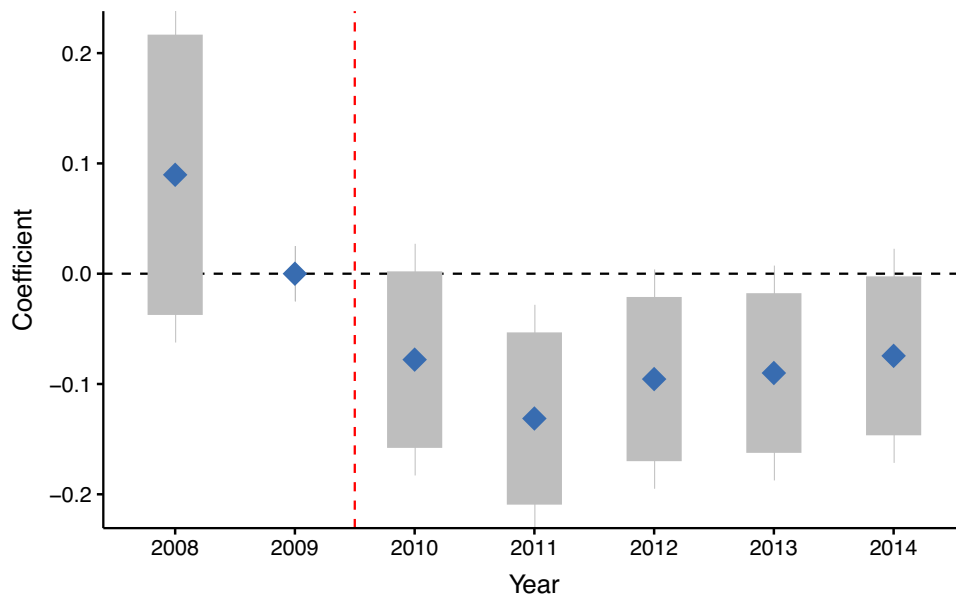
To test H3, I estimate the same specification as Equation (1) but use the (log) number of contribution activities as dependent variables. The results are presented in Table 4. In all specifications, I find a strong, negative, and statistically significant effect of reduced development costs on the level of contributions.

In column (1), I present the results from estimating Equation (1) but without individual and year fixed effects. Consistent with our previous visual inspection, the results show that innovators in the treated group have contributed more in the pre-treatment period, and that all innovators sharply reduce the level of contribution after 2010. Interestingly, innovators working on popular projects tend to maintain higher level of contribution. Most importantly, the estimated coefficient on the interaction term indicates that innovators facing reduced development costs decrease contribution by about 7 percent ($p < 0.05$), supporting H2.

To measure the causal impact of reduced design costs on contribution, I estimate the difference-in-difference specifications in Equation (1). Column (2) shows the results from the



A. Commercialization



B. Contribution

Figure 1.4. Relative Time Model Estimates

Notes: The dotted vertical line indicates the time period in which the treated game engine Unreal 3 starts to be provided as subscription-based business model.

basic difference-in-differences specification. Similar to the results in column (1), the estimated coefficient on the interaction term similarly indicates that reduced development costs increase commercialization activities by 7.9 percent ($p < 0.05$). Column (3) include additional time-varying control variables on community experience and idea quality to control for remaining imbalances between the treated and control group. The estimates show that reduced development costs decrease contribution activities by about 7.4 percentage point ($p < 0.01$).

To interpret the estimated coefficients in a causal manner, I validate the critical assumption of the parallel trends in the pre-treatment period. I estimate Equation (2), a dynamic version of difference-in-differences specifications, and present the results in Panel B of Figure 4. I find that the differences between the treated and control groups are parallel in the pre-treatment period. Between 2009 and 2010, the difference between the two groups increase in magnitude and persist since then, indicating that reduced development costs decrease contribution.

1.6. Robustness Checks and Alternative Explanations

Several robustness checks are conducted. First, I conduct subsample analysis using innovators with only one project experience to rule out the possibility that the difference in experience level between the treated and control group drives the results. Second, I conduct another subsample analysis using innovators who initiate each modding project only. Results presented in column (4) and (5) show that my findings on the relationship between development costs and contribution is robust.

Table 1.4. Difference-in-differences Estimates on Contribution

	1(Contribute)			IHS(#Contribution Activities)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.019 (0.022)			-0.002 (0.062)		
Post	-0.396** (0.009)			-0.918** (0.024)		
Treated x Post	-0.063** (0.024)	-0.077** (0.022)	-0.077** (0.022)	-0.096 (0.067)	-0.123+ (0.064)	-0.120+ (0.063)
Top 100			0.198** (0.050)			0.456** (0.123)
Exper-sq.			0.011** (0.001)			0.026** (0.002)
Constant	0.490** (0.008)			1.108** (0.021)		
Year FE	No	Yes	Yes	No	Yes	Yes
Individual FE	No	Yes	Yes	No	Yes	Yes
Quality x Age FE	No	No	Yes	No	No	Yes
Observations	7818	7818	7818	7818	7818	7818
Nb. Individuals	1246	1246	1246	1246	1246	1246
Adj. R-squared	0.210	0.268	0.362	0.196	0.230	0.318

NOTES: Observations are at the individual by year level. Robust standard errors clustered at the individual level are presented in parentheses. +, *, and ** denote statistical significance at 10%, 5%, and 1% level, respectively.

Table 1.5. Robustness Checks

	1(Comm)	IHS(Comm)	1(Cont)	IHS(Cont)	1(Cont, Existing)	IHS(Cont, Existing)
	(1)	(2)	(3)	(4)	(5)	(6)
<u>A. Subsample: Founders Only</u>						
Treated x Post	0.038* (0.018)	0.103* (0.044)	-0.062* (0.025)	-0.115 (0.075)	-0.043* (0.018)	-0.091* (0.040)
Observations	6,681	6,681	6,681	6,681	6,681	6,681
Nb. Individuals	1,068	1,068	1,068	1,068	1,068	1,068
Adj. R-squared	0.265	0.260	0.270	0.234	0.114	0.087
<u>B. Subsample: Individuals Participating in One Project Only</u>						
Treated x Post	0.029* (0.014)	0.072* (0.033)	- 0.067** (0.022)	-0.107+ (0.062)	-0.040* (0.016)	-0.082* (0.034)
Observations	7,146	7,146	7,146	7,146	7,146	7,146
Nb. Individuals	1,143	1,143	1,143	1,143	1,143	1,143
Adj. R-squared	0.288	0.312	0.273	0.227	0.123	0.099
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

NOTES: Observations are at the individual by year level. Robust standard errors clustered at the individual level are presented in parentheses. +, *, and ** denote statistical significance at 10%, 5%, and 1% level, respectively.

I conduct additional robustness checks to make sure that the results are not spurious. Column (4) and (5) of Table 5 use two different subsamples to rule out the possibility that the increases in commercialization are driven by underlying differences between the treated and control groups. Recall that in Table 3, we observe that innovators in the control group tend to experience more technologies (engines) and have more founder experiences. To rule out the alternative explanation that these differences may drive the differences in the post-period, I use innovators with only one project experience and re-estimate Equation (1). The results in column

(4) still indicate that reduced development costs increase commercialization ($p < 0.05$). In column (5), I use subsample of innovators who start each mod project (“founders” subsample) to present the results. Again, I find reduced development costs positively affect commercialization.

In Appendix Table 6, I show that the results are robust to different operationalization of commercialization. Here, I estimate how reduced development costs affect the likelihood that community-based innovators become user entrepreneurs (Shah and Tripsas 2016). To estimate the relationship, I consider entrepreneurship as absorbing state and drop observations who already become entrepreneurs. The results suggest that an innovator is about 2 percentage point more likely to be an entrepreneur in each year when facing reduced development costs. Given that the baseline probability is about 10 percent, it indicates that reduced development costs increase the entrepreneurial transition by about 20 percent. Note also that our working definition of entrepreneurship here is extremely loose. In my operationalization, an innovator is classified as an entrepreneur if he or she uploads at least one commercialization-related contents.

Taken together, the results so far suggest that reduced development costs have a positive and significant impact on the level of commercialization by community-based innovators. Now I examine how the increased commercialization participation in turn affect their contribution.

1.7. Discussion and Conclusions

In this paper, I study how user complementors in the PC video game industry change their value creation and capture strategies as external environment changes in a way that makes a platform’s bottleneck obsolete. innovators embedded in communities respond to reduced development costs necessary to commercialize their ideas. I use timestamped individual-level data on contribution and commercialization from a user innovation (modding) community in the computer game industry. I also leverage an unexpected, substantial price decrease of Epic Game’s Unreal 3

Engine in November 2009 and apply difference-in-differences specifications to identify causal estimates.

Overall, I find that there is a tradeoff between commercialization opportunities outside innovation communities and voluntary contribution within communities. When development costs decrease, innovators within communities perceive heightened commercialization opportunities outside the community and adjust their efforts from contribution to commercialization. I found that innovators with reduced development costs increase the commercialization activities by about 10 percent annually and decrease contribution activities by about 12 percent. The underlying mechanism behind the tradeoff is subtle, with implications to firms collaborating with outside innovators. Particularly, I find that external commercialization opportunities not only change the rate of contribution, but also the direction of contribution. It lowers the contribution to new projects (exploration) more significantly than contribution to existing projects (exploitation). It implies that the effectiveness of innovation communities as a source for explorative search may be reduced when community-based innovators are able to capture value from commercializing ideas outside the community.

Some of these findings have direct implications to firms in ecosystems partnering with communities for innovation. First, as digital transformations and other industry changes lower the costs of commercializing ideas dramatically, firms may need to evaluate whether they can attract and retain innovators within communities. For instance, game developers are losing unpaid modders as some of them choose to develop their own indie games using subscription-based game engines. To retain some of these modders, companies like Blizzard provide options to sell mods on their platform. Rather than regarding community members as given, firms need

Table 1.6. Estimates from Discrete Time Event History Analysis

Dependent Variable:	1(Participate in Commercialization)				
	(1)	(2)	(3)	(4)	(5)
Treated	-0.006 (0.005)				
Post	0.000 (0.002)				
Treated x Post	0.022** (0.008)	0.027* (0.011)	0.027* (0.011)	0.026* (0.011)	0.024* (0.011)
Popularity Score	0.018** (0.004)				
Experience			-0.003 (0.003)	-0.004 (0.003)	-0.004 (0.004)
Experience-sq.			-0.000+ (0.000)	-0.000+ (0.000)	-0.000+ (0.000)
Nominated as Top Idea			0.033 (0.021)	0.027 (0.024)	0.033 (0.021)
Year FE	No	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	Yes
Observations	10435	10416	10416	9468	9138
# Individuals	1538	1519	1519	1384	1330
Adjusted R-squared	0.006	0.173	0.173	0.173	0.167

NOTES: Observations are at the individual by year level. Robust standard errors clustered at the individual level are presented in parentheses. +, *, and ** denote statistical significance at 10%, 5%, and 1% level, respectively.

assess their needs and alternative opportunities, and provide incentives to retain them. Our results also provide important policy implications for platform companies (Helfat and Raubitschek 2018).

From the theory perspectives, I make two contributions. First, I contribute to the community-based innovation literature by demonstrating that commercialization opportunities outside innovation communities is understudied factor influencing innovators' incentive to contribute. This finding further implies that there is certain boundary condition in which the community-based model of knowledge creation is more likely to work. Second, it adds to the

knowledge-based entrepreneurship literature by showing that community-based innovators can be a good source of entrepreneurship when access to complementary assets is provided.

Going forward, it would be interesting to evaluate how much of our conventional wisdom on entrepreneurship should be updated when various industry changes lower entry costs for potential entrepreneurs. One possible research is to examine how lowered search and reputational building costs affect the patterns of entrepreneurial entry (Goldfarb and Tucker 2017). Another fruitful avenue is to measure the economic impact of such industry level change. For instance, it has been argued that the emergence of digital platforms and the provision of API reduce the cost of recombining different functionalities to deliver unique services. Do such platforms also affect the likelihood that high-skilled individuals pursue entrepreneurship as a viable career option? If so, how does the increased rate of entrepreneurial entry affect the geographic distribution of the high-skilled individuals across regions? I hope that this study stimulates future research on these and other intriguing questions related to innovation, entrepreneurship, and regional economic performance.

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Chapter 2. Homesick or Home Run? Distance from Hometown and Employee Performance

2.1. Introduction

How geography affects individual-level mobility and performance has received significant attention from social scientists. One established fact is that individuals tend to stay close to their hometown (Schwartz 1973). A variety of explanations exist, including information asymmetry (Sjaastad 1962) and social attachment to their hometown (Dahl and Sorenson 2010). How far individuals are located from their hometown also affects their economic performance. In the entrepreneurship setting, for instance, locals tend to perform better because they can take advantage of their local knowledge and established networks for opportunity identification and resource mobilization (Dahl and Sorenson 2012).

In contrast, individuals are more likely to leave their hometown when they become employees working for firms (Michelacci and Silva 2007). One reason is that firms sometimes assign their employees to far-flung locations to fill critical roles and develop human capital within internal labor markets (Bidwell and Keller 2014). Examples include expatriate assignments (Tung 1987) and rotational assignments (Campion et al. 1994). Particularly in emerging markets where the supply and demand of human capital are imbalanced across locations, several organizations provide employees with limited control over where they work (Chattopadhyay and Choudhury 2017). The resulting workplace can be far away from hometown to which employees are socially attached. Yet, we know very little about how moving employees

closer or farther from hometown affects their performance, not to mention what practices help reduce potential downside.

To make progress, one needs to address at least two empirical challenges. The first challenge is related to self-selection. The economics of immigration literature maintains that individuals migrate into location far away from hometown only if potential financial gains in new location are large enough to compensate for monetary and psychic costs related to migration (Borjas 1987, Roy 1951). In such cases, we would observe positive correlation between distance from hometown and performance even when distance does not have any impact on performance. In other words, we cannot be certain whether the observed correlation is due to treatment effects or selection bias, unless some exogeneous variation in distance from hometown is used for analysis.

The second concern is that multiple theories are simultaneously at force, hindering a deeper understanding on the mechanism. We consider three theories. First, cultural distance theory from the strategy and international business literature has long argued that distance from hometown can entail cultural dissimilarity and the liability of foreignness (Kogut and Singh 1988, Zaheer 1995), affecting employee performance negatively. Second, information costs theory asserts that employee may suffer from lack of job-related information while working far away from hometown (Dahl and Sorenson 2012). Finally, social attachment to places theory describes that distance from hometown reduces the frequency of interactions with family and friends, and provides mixed predictions on performance. Distance could affect performance positively because it increases the productivity and utility of 'working time' vis-à-vis the productivity and utility of 'consumption time' (Becker 1965, Gronau 1976), but it could affect negatively because the 'psychic costs' of missing from family and friends lowers productivity

(Oswald et al. 2015, Sjaastad 1962). When all of these concepts are simultaneously correlated with distance from hometown, even randomly assigning employees in different locations may not be sufficient. It only helps us measure the overall impact of distance on performance, and not on underlying mechanisms.

In this paper, we make progress by presenting first empirical evidence on how distance between workplace and hometown (hereafter, distance from hometown or DFH) affects employee performance. In doing so, we focus on the role of social attachment to hometown as a key mechanism. We study entry-level engineers in an Indian IT firm because this setting helps us isolate the social attachment mechanism from other mechanisms discussed above. Though the social attachment to place theory is relevant to all employees, it is arguably most salient for those at the beginning of their careers because they are particularly strongly attached to their hometowns, as well as to their parents and families. Also, we exploit an employee-assignment protocol, unique to our setting, that helps us control for the self-selection issue discussed above. The IT firm recruits fresh college graduates from across India, and—most importantly for our empirical analysis—randomly assigns them to production centers at nine different locations in India without regard for individual characteristics, including performance during training or distance from hometown. Our data also contains detailed information including their hometown locations and type of projects assigned, which allows us to construct control variables to isolate the role of social attachment from cultural distance and information access. Together, we believe that our setting and data provide a unique opportunity to deepen our understanding of how distance from hometown affects employee performance.

Because the extant theory on how DFH affects performance is nascent, we first conduct 36 in-depth field interviews with workers at two production centers to guide our analysis

(Edmondson and Mcmanus 2007). The interviews and ensuing literature review help us identify three key constructs that explain how social attachment to hometown may affect employee performance. First, consistent with the framework of utilization of time (Becker 1965), DFH increases the amount of time allocated to work and other related skills development, which in turn improves performance. Second, building on the concept of psychic costs (Sjaastad 1962) and literature on work-family balance, DFH decreases productivity and performance because of its negative impacts on health and happiness (Oswald et al. 2015). Third, the literature on workplace flexibility leads us to predict that the negative impact of DFH on performance outweighs the positive impact when employees have less schedule flexibility (Kelly et al. 2014).

For quantitative analysis, we use hand-collected personnel dataset on 443 college graduates who are newly hired in 2007 by the Indian IT firm (hereafter called TECHCO). The dataset contains rich employee-level description, including demographic information such as gender, proxies for ability measured during recruiting, performance during training, and performance ratings measured one and three years after initial location assignment. It also specifies an employee's hometown and the location of the production center to which he or she is assigned; thus we can determine distance from hometown, measured as the shortest travel time from workplace to hometown via train, the most frequently used transportation option by newly hired employees in the firm. For each employee, we code travel time to home using hand-collected data from the Indian Railways timetable.

We then relate employees' first- and third-year performance ratings to DFH, while controlling for gender, innate ability, cultural distance between hometown and workplace location, and location-specific management quality. Because employees are randomly assigned to different locations, our estimates are arguably free from selection bias. We compare short- and

longer-term performance because employees' flexibility to schedule vacation decreases over time. Our interviewees tell us that it was more difficult to take leave in their preferred timing, especially during Diwali, over the longer-term than in the short-term as they take more responsibilities at work. We thus hypothesize that DFH is positively associated with employee performance in short-term, and negatively associated with performance in longer-term.

Our findings provide strong support to our predictions. We find that DFH has differing effects on short- and longer-term employee performance. DFH is positively associated with performance ratings in the first year; that is, the farther an employee is assigned from his or her hometown, the more likely he or she receives higher performance rating in the first year. After three years, however, this relationship reverses. Employees far away from hometown tend to receive lower performance ratings.

We also find several evidences that are consistent with our proposed mechanisms. We utilize micro-data on enrollment in optional skill-development courses; number of days of leave taken during Diwali, an important Indian festival; and each employee's fraction of working days spent on coding projects (compared to being benched). We find that our mechanism of interest, i.e. how employees allocate time (to work related activities), results in heterogenous effects based on the location of the production center. We find a positive correlation between DFH and short-term performance for employees assigned to relatively smaller towns; we do not find this effect for employees working in larger cities. Additionally, distant employees working at such production centers located in smaller towns tend to devote more time to optional skill-development courses than counterparts who work in cities. We also find that distant employees' performance declines over the longer term. Furthermore, though DFH is positively correlated in the short-term with taking leave during Diwali, there is no statistically significant relation

between DFH and leaves taken during Diwali in the longer term. Our field interviews and quantitative analysis also suggest that DFH has a disproportionately negative effect on women's longer-term performance. We attempt to control for several alternative explanations, including cultural distance, attrition and burnout.

Our findings contribute to several literatures, including those on the determinants of worker performance, geography of work, hiring, migration, and early career experiences. We make a theoretical contribution by urging researchers studying determinants of worker performance to take the perspective of the focal employee; in doing so, the study of determinants of worker performance expands beyond the consideration of work practices and workplace characteristics to include employee-level characteristics and factors jointly determined by workplace characteristics and employee characteristics. Our results also have managerial implications for hiring managers and for individuals' management of their own careers.

2.2. Setting: An Indian IT Firm

2.2.1. Hiring and Training Entry-Level Employees

Such employees, hired from college campuses, are a suitable sample for several reasons. First, newly hired entry-level employees maintain strong social ties to family and friends in their hometowns, and must develop new social attachments at the new workplace. Thus, they constitute a suitable group to study the role of social attachment to hometown. Second, measuring performance is more objective and reliable for entry-level employees. The tasks assigned to them tend to be homogeneous, and objective performance measures are available (in our setting), allowing for comparisons across employees. Moreover, we are able to control for employees' innate abilities and prior performance using various test scores collected during recruitment and training.

Every year TECHCO hires about 10,000 graduates from more than 250 colleges across India. Typically, these new hires attend engineering colleges and have had no prior full-time employment experience. TECHCO tends to hire from a wider geographical distribution of colleges in India than several of its peer Indian IT firms and assigns each employee to one of several technological areas, such as .NET, Java, or Mainframe. New hires then undergo an intensive four-month induction training at a centralized training center in the southern city of Mysore. The corporate training center has a 337-acre campus, 400 instructors, and 200 classrooms. Employees are trained in batches of about 50-100; starting dates range from May to November. According to our field interviews, TECHCO spends around \$3,500 to train each new college graduate.

Upon completion of the training, each employee is randomly assigned to one of nine production centers scattered across India.¹ TECHCO has over 120,000 employees spread across those production centers; it serves clients from around the world. Importantly for our empirical analysis, individual-level characteristics do not affect assignment decisions. As will be described in greater detail, assignment is automated: pre-determined algorithms embedded in the centralized enterprise resource-planning system prevent employees from exerting influence on the process. It is highly uncommon for an employee to transfer to a different location after initial assignment.

2.2.2. Exploratory Interviews

Because the extant theory on how DFH affects performance is nascent, we first conduct 36 in-depth field interviews with workers at two production centers to guide our analysis (Edmondson

¹ As we explain later, we dropped one production center from our sample as only one employee in our sample was assigned to it.

and Mcmanus 2007). Here, our goal is not testing established theories but identifying key theoretical constructs on which our quantitative analysis is based. We begin with semi-structured qualitative field interviews. We conducted 36 such interviews, with 16 workers at the Bhubaneshwar production center and 20 workers at the Hyderabad production center. Bhubaneshwar is a smaller urban location (a town); Hyderabad is a large city. Each interview lasted around thirty minutes.

The field interviews generated several insights into how the location of the production center—whether it is located in a city or a town affects allocation of time by the worker. A distant employee from Tamil Nadu employed at Bhubaneshwar told us: “There are relatively few things to do over the weekend here. There is only one large mall near our campus, and there too they do not serve our local food or do not play movies in our local language [Tamil]. I spend most of my Saturdays in office, and on Sundays I watch TV, cook food for the week, do my laundry and call my parents.” In contrast, distant workers in Hyderabad described a richer array of malls, movies and restaurants. Several workers in Hyderabad reported that they spent much of their Saturdays exploring these options with local friends, often from their training cohort. The prior literature too has observed that cities and towns provide different levels of leisure options (Roback, 1982). Workers assigned to towns versus cities might have different incentives to allocate time to local social attachment building versus work-related activities.

Finally, our interviews indicate that scheduling flexibility, or employees’ ability to leave the workplace at their preferred timing. Interestingly, we find that such scheduling flexibility decreases over time. Our interviews indicate a consistent and interesting finding: it was more difficult for distant workers to take leave, especially during Diwali, over the longer term than in the short-term. Our interviews indicated that, during their third year of employment, workers

were assigned greater responsibilities; it was thus difficult to take leave during the important festival of Diwali. Project managers typically preferred to grant leave to “freshers,” or first-year workers. Our interviews indicated that, for distant employees, being prevented from returning home on Diwali led to dissatisfaction and psychic costs. “This is my third year here. While I miss home all the time, I really missed home last year when my manager did not give me leave during Diwali,” an employee from Ranchi assigned to Hyderabad told us. “I am more senior now and the offshore team had an important milestone that needed me to be in office. On the other hand, the freshers all went home, and I had to take over their tasks for that week.”

2.3. Hypothesis Development

Motivated by the interviews, we develop theoretical framework of how DFH affects employee productivity because of employees’ social attachment to their hometown. Our model synthesizes the personnel economics literature, the economics of immigration literature and the management literature on work-life balance and productivity. Unlike cultural distance and information costs theories (which predicts a negative relation between DFH and worker performance), the theory on social attachment to place does not provide an unambiguous prediction related to how DFH will affect worker performance. In this section, we discuss what countervailing forces are at work and under what circumstances DFH positively or negatively affects employee performance. We conclude by presenting testable hypotheses.

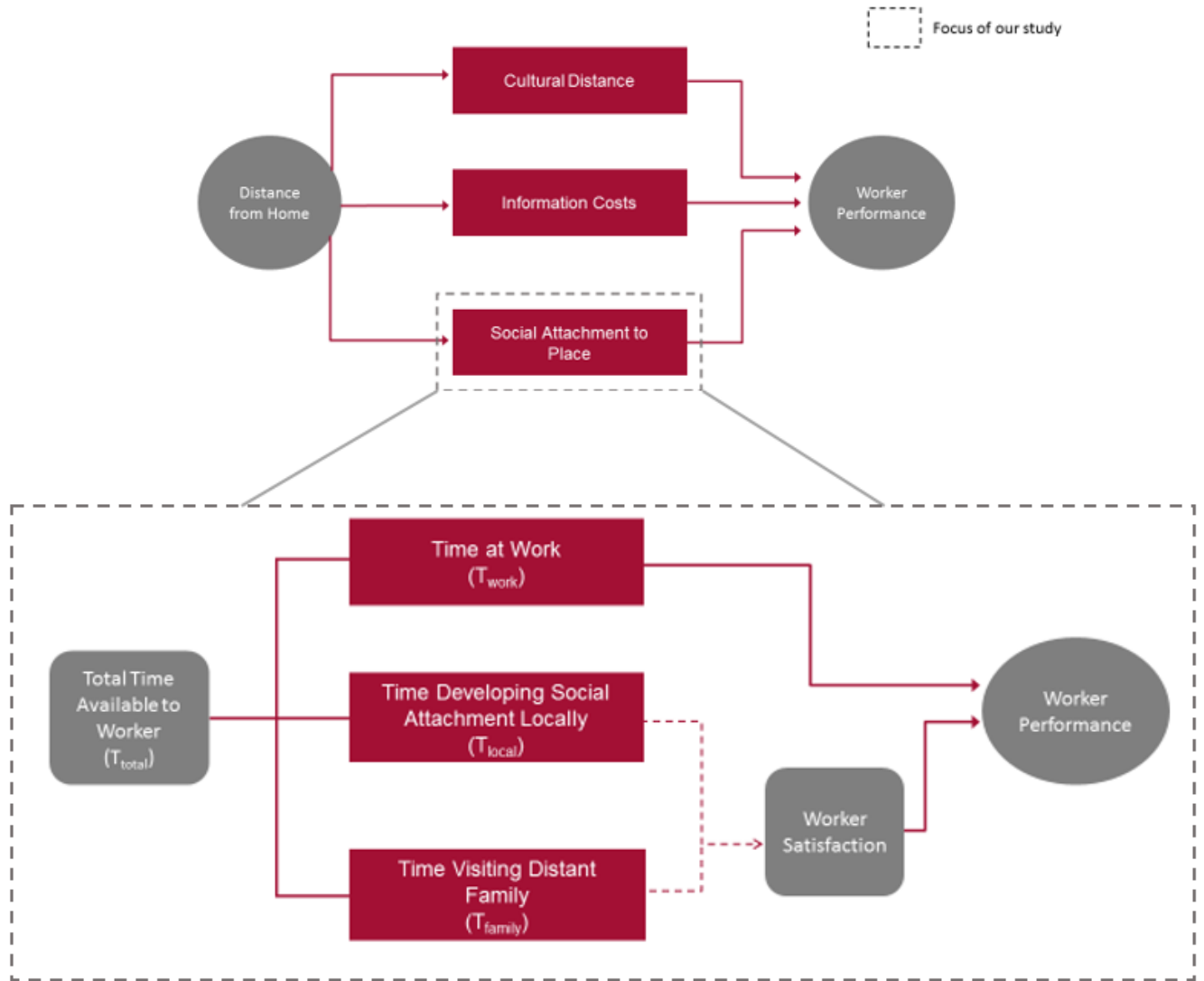


Figure 2.1. Theoretical Framework

Note: The upper panel of Figure 1 outlines three theories about how and why distance from home might play an important role in determining worker performance. The lower panel of Figure 1 draws on the framework for allocation of time (Becker, 1965; Gronau, 1976) to theorize about how distance from home and social attachment to the hometown/workplace could affect worker performance. Broken lines designate the focus of our study.

2.3.1. Distance from Hometown and Allocation of Time

It is possible that distant knowledge workers with low social attachment to workplace might allocate disproportionate time to work related activities, thus experiencing enhanced performance. To see this logic more formally, we draw on the framework for allocation of time

(Becker, 1965; Gronau, 1976) to theorize about how distance from hometown could affect performance. Becker's (1965) framework for measuring allocation of time specifies two elements of an individual's time: time spent at work (T_w) and time spent at consumption (T_c), where total time available to the individual equals $T_w + T_c$. Becker (1965) also outlines the underpinnings of a substitution effect between working time and consumption time (leisure): individuals may "forfeit money income in order to obtain additional utility, i.e., they exchange money income for a greater amount of psychic income. For example, they might increase their leisure time" (Becker 1965, page 498). The substitution effect between working and leisure time has received empirical support as well. For instance, Aguiar et al. (2017) shows dramatic and concurrent declines in work hours and increases in video gaming among young men.

Extending Becker's framework to our context, we assume that an employee who is moved far from home can allocate time to three sets of activities: (1) work related activities, (2) developing social attachment locally and (3) visiting distant family. First, distant employees who allocate disproportionate time to work related activities might experience enhanced performance. We build on Lazear (1997), Prendergast (1999) and Van Eerde and Thierry (1996) to assume that time spent on work-related activities will be positively related to worker performance. It is particularly likely that distant employees with lesser number of options to engage in leisure at their workplace location (i.e. workers with lesser social attachment to their workplace) will allocate disproportionate time to work related activities. In addition to work-related tasks and on-the-job learning, such workers could also devote time to develop skills that lead to enhanced performance.

2.3.2. Distance from Hometown and Psychic Costs

In contrast, social attachment to hometown could result in psychic costs for distant workers, which might negatively affect their performance. Economists too have long recognized the psychic costs that individuals incur when separated from their hometowns. The construct of the psychic costs of migration dates back to two seminal studies in the economics of migration, Sjaastad (1962) and Schwartz (1973). Schwartz (1973) describes psychic cost as “a result of the departure from family and friends. The longer the distance migrated, the lower will be the frequency of reunion; hence the higher will be the psychic cost” (Schwartz, 1973; page 1160). Sjaastad (1962) argues that, because people tend to be reluctant to leave familiar surroundings, migration entails a psychic cost that contributes to the private cost of migration to an individual. The subsequent empirical literature offers some evidence of social attachment costs/psychic costs. Other studies, such as those of Fabricant (1970), Nelson (1959), and Greenwood (1969), found evidence suggestive of psychic costs.

In the sociology literature, the construct of social attachment to place and dissatisfaction with remoteness from family and friends are discussed most prominently by Dahl and Sorenson (2010b, 2012). They write: “One commonly cited reason for why people do not move more often is that they value being near family and friends, or at least the more frequent and more extended interactions that propinquity allows” (Dahl and Sorenson 2010b, page 637). Using panel data on the Danish population, Dahl and Sorenson (2010a) report a strong revealed preference on the part of scientists and engineers to live near family and friends.

Together, how DFH affects performance depends on relative effects of time allocation and psychic costs. We argue that one important factor determining this is organizational flexibility. Given social attachment to hometown, ability of distant workers to visit their

hometowns and spend time with their families, is likely to be related with enhanced performance. Here, we build on the literature of work-family enrichment (Greenhaus and Powell, 2006; Rothbard, 2001) to argue that time spent with family and friends increase both worker satisfaction and worker performance. As Greenhaus and Powell (2006) assert, time spent with family and friends could buffer a worker against work-related stress, leading to more positive attitudes and greater satisfaction. A longstanding literature with roots in human relations theory has also argued that worker satisfaction is strongly related to worker performance (Vroom, 1964; Schwab and Cummings, 1970; Petty, McGee and Cavender, 1984). In other words, time spent with family and friends leads to greater individual satisfaction, which in turn leads to improved worker performance. When scheduling flexibility moderates the relative influence of DFH on performance, we can predict the following hypothesis.

Hypothesis 1 (H2). *In the short-term in which scheduling flexibility is high, DFH is positively related to employee performance.*

Hypothesis 2 (H2): *In the longer-term in which scheduling flexibility is low, DFH is negatively related to employee performance.*

2.4. Data and Methods

2.4.1. Identification Strategy

It might be tempting to simply regress individual performance on distance from home to characterize the relationship, but such an approach has two empirical shortcomings. First, as Yonker (2017) points out, firms are likely to hire employees from neighboring regions to lower search costs. This is particularly likely in the case of entry-level employees, whose skills are largely homogeneous. If this is the case, the naïve regression is unlikely to produce significant results because there is little variation in the travel-time variable among employees. More

importantly, the naïve-regression framework is likely to generate biased estimates because some unobservable is correlated with both the assignment decision and individual performance. For instance, it is possible that employees hired from Bangalore are of high quality because of knowledge spillovers from the many technology firms in that region. If TECHCO also tended to assign these employees to the production center in Bangalore simply because it was close to their hometowns, we would see a spurious correlation between travel time and individual performance in the naïve-regression framework. Luckily for our purposes, TECHCO adopted a computerized central talent-assignment system in which neither distance from home nor other individual-level characteristics are considered when assigning employees to production centers. The following subsections present qualitative and quantitative evidence on this assignment protocol and describe how we exploit it in the empirical analyses.

2.4.2. The Employee Assignment Protocol

Understanding how each employee is assigned to a production center is central to our empirical analysis. Allocation is performed by a computer application called Talent Planning, part of the firm's enterprise resource-planning software. Talent Planning matches two factors: (1) individual production-center requirements (HR at each center provides data on the number of employees needed in various technological areas); and (2) data from HR at the training location. Two weeks prior to the end of a four-month training session, HR at the training location releases data on which employees are expected to complete the training. The two variables that the Talent Planning team considers while performing the matching on the automated system are 1) the technology on which an employee was trained and 2) the estimated date of training completion.

Most importantly for our econometric analysis, the assignment of trainees to production centers is *not* correlated with their distance from home, demographics, backgrounds, or various

test scores before or during the induction training. Field interviews with the head of talent development at TECHCO reveal that the primary rationale for this random, computer-driven talent-allocation policy is to ensure that TECHCO's end customers are indifferent to the location of the production center that executes their projects. The secondary motivation is to discourage regional and ethnic cliques at production centers. "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," TECHCO's head of talent development told us. "If that happens, both our clients and employees from other parts of the country are adversely affected."

To provide quantitative support for our claim that distance from home is determined exogenously, we first conduct Monte Carlo simulations to determine whether or not the realized mean value of distance from home differs from the hypothetical distance-from-home values one would expect to see if employee assignment is truly random. We randomly draw (with replacement) from the entire employee sample the same number of employees actually assigned to one of the eight locations. We conduct 1,000 random draws and present the sampling distribution of mean travel-time values as a histogram. By comparing the sampling distribution with the realized mean value of distance from home, we are able to evaluate how similar or different the realized assignment results are from a truly randomized employee-assignment protocol. Figure 2 presents the sampling distribution of mean travel time when employee assignment is completely random. We also plot the realized mean travel time as a dashed line for comparison purposes. The realized mean value of travel time (i.e., the mean value of travel time observed in our data) is not statistically different from the hypothetical mean value of travel time (i.e., where employee assignment is entirely random). This pattern strengthens our confidence in the validity of the random-assignment protocol.

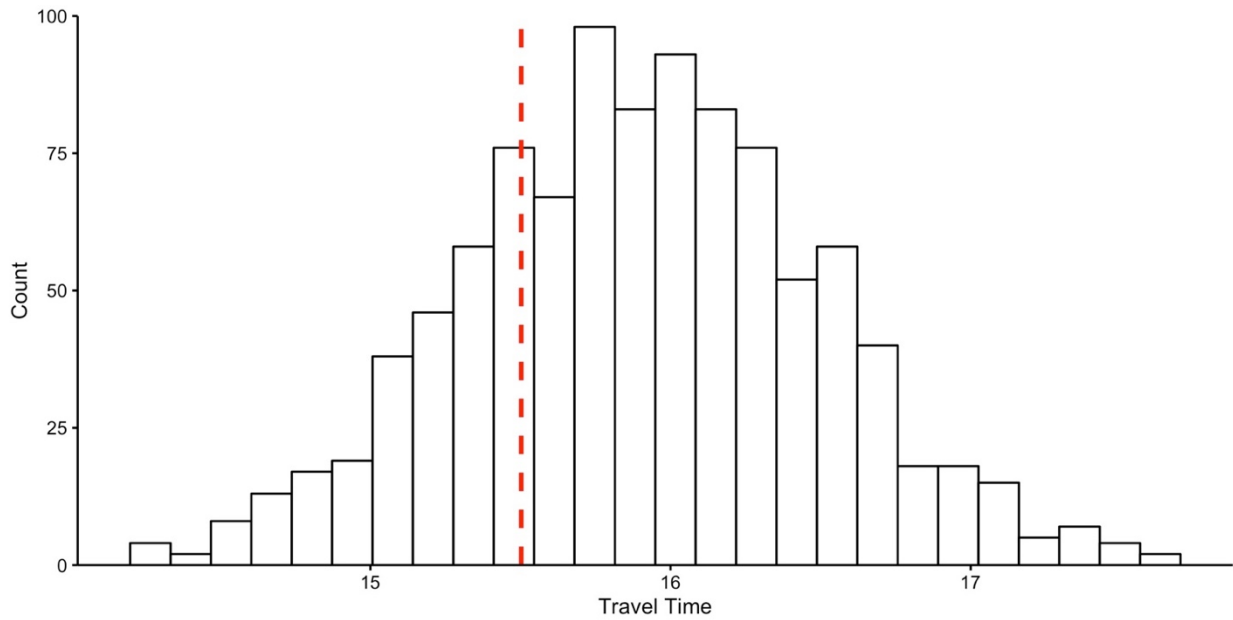


Figure 2.2. Simulated vs. Realized Value of Travel Time

Note: This figure compares the distribution of travel time from Monte Carlo simulation to the realized mean value of travel time. For the simulation, we randomly draw (with replacement) from the entire employee sample the same number of employees actually assigned to one of the eight locations. We conduct 1,000 random draws and present the sampling distribution of mean travel time values in the histogram. The realized mean value of travel time is presented as a thick dotted line. The realized mean value of travel time is not statistically different from a hypothetical mean value of travel time when employee assignment is entirely random, thus providing additional quantitative evidence that the employee assignment process is random.

Second, we estimate a logit choice model with covariates, including CGPA training, male (gender), prior migration experience, logical score, and verbal score, to test whether any of the covariates are correlated with the likelihood of being assigned to Bangalore. We also include travel time from each employee's hometown to Bangalore as an independent variable. The production center in Bangalore is the largest and is regarded as the most important. If TECHCO strategically assigned newly hired employees based on individual-level characteristics, it would probably want to assign to Bangalore either those with higher underlying ability and/or revealed performance, to maximize the center's performance. If workers had control over location assignment, we would observe a statistically significant correlation between distance (of hometown) from Bangalore and the assignment to Bangalore.

Table 1 contains the estimation results from the logit choice model. It shows that none of the individual-level observables is systematically correlated to assignment to Bangalore. No observed performance or ability measures, such as CGPA at the end of training or standardized test scores at recruitment, are significantly related to assignment to Bangalore. Nor is the decision whether to allocate an employee to Bangalore correlated with other observable individual characteristics, such as gender or distance (travel time) to Bangalore. This pattern validates our maintained assumption that no individual-level characteristics are considered in the employee-assignment process.

Table 2.1. Validity of Random Assignment

	Assigned to Bangalore				
	(1)	(2)	(3)	(4)	(5)
Travel Time to Bangalore	-0.014 (0.016)	-0.014 (0.016)	-0.014 (0.016)	-0.014 (0.016)	-0.011 (0.016)
CGPA Training		0.034 (0.373)	0.030 (0.375)	0.029 (0.376)	-0.089 (0.372)
Male			0.139 (0.240)	0.111 (0.241)	0.107 (0.247)
Migration Experience				-0.323 (0.228)	-0.308 (0.236)
Logical Score					-0.048 (0.037)
Verbal Score					0.016 (0.036)
Location FEs	Yes	Yes	Yes	Yes	Yes
Observations	443	443	443	443	413
Log-Likelihood	-242.016	-242.011	-241.841	-240.854	-228.750

Note: Logit regression is used for estimation, and robust standard errors are presented in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$. In column 5, the sample size is smaller because of missing logical and verbal score values for 30 employees.

2.4.3. Model Specification

To examine how employees' travel time from their workplace to their hometown affects individual performance, we estimate the following equation separately for short- and longer-term performance:

$$Perf_{ij} = \alpha + \beta \cdot TRAVEL TIME_i + \gamma' X_i + \delta_j + \epsilon_{ij}$$

Here, $Perf_{ij}$ indicates the performance rating for an employee i working at production center j . We use two performance ratings, measured at the end of 2008 and 2010 respectively, to shed light on the short- and longer-term effects on performance of distance from home. The main independent variable $TRAVEL TIME_i$ is the minimum time (in hours) that an employee would expect to spend traveling from the production center to his or her hometown by train. Our main coefficient of interest is β , which measures how an employee's performance is systematically related to distance from home. We include employee-level observables X_i to control for other factors that may affect performance, such as gender, migration experience, similarity of languages between hometown and workplace, and some proxies for ability/revealed performance such as cumulative grade-point average at the end of training and scores on standardized recruitment tests. In the base case, we estimate ordered logit models using Maximum Likelihood Estimation (MLE), given that performance rating is measured in normalized bands.

We also include location fixed effects, for two reasons. First, they capture production-center-level differences across locations. Though various management practices at TECHCO are designed to reduce quality differences across production centers, it is still highly plausible that some quality differences remain. For instance, a production center located near India's major technology cluster, such as in Bangalore, is likely to have a higher concentration of knowledge because of agglomeration economies. By comparing employees within the same production

center, we make sure that such external forces do not affect our results. Second, and specifically for our research design, we include center fixed effects so that distance from home does not differ systematically across centers. Though employees are randomly assigned to production centers, employees at certain production centers in central India are likely to have shorter travel times than those at production centers in remote areas. Including center fixed effects controls for that possibility.

2.4.4. Sample Construction

We begin our sample construction process using data on 1,696 graduates hired by TECHCO in 2007 and assigned to the .NET technological area. We focus on a single technological area to minimize bias arising from demand-and-supply fluctuations that could affect the performance ratings of employees working in different technology areas. About 17% of all graduates hired in 2007 were assigned to the .NET area; they were trained in 16 batches (details in the appendix, Table A2). Similarly, we focus on a single cohort to minimize unobserved heterogeneity from macroeconomic trends.

Because some employees in this sample received no performance rating in the first year, we further narrow our sample to those who did receive a performance rating in the first year. If receiving a first-year rating were correlated with an employee's performance or with any factors affecting it, we would worry about potential sampling bias. This is not the case in our setting, where receiving a first-year rating is largely determined by "the nine-month work rule," which specifies that an employee receives a performance rating only if he or she has worked on a coding/testing project for at least nine months. Our field interviews with HR managers at TECHCO suggest that whether an employee worked on a project for at least nine months in 2008 (the first full year after being hired in 2007) was determined by (1) when he or she completed

induction training and (2) the availability of new coding/testing projects at the production center where an employee was assigned. Thus, factors that might affect an employee's performance, such as performance during training and test scores at recruitment did not affect the determination of which employees worked at least nine months in 2008. Given that whether an employee received a first-year performance rating is orthogonal to individual-level characteristics, we are confident that our estimates are not biased by dropping observations with missing 2008 performance ratings. In the appendix (Table A3), we report individual-level observables of employees with and without 2008 ratings; as expected, there is no systematic difference between the two groups.

Our final sample consists of 443 employees hired and trained in 2007 and assigned to one of TECHCO's eight production centers in 2008. These workers belonged to eight training batches that completed training by December 2007 and hence received a performance rating in 2008 (given the nine-month work rule; see the appendix Table A2 for additional details on these batches). We further dropped observations of a few employees whose hometowns were in foreign countries or in locations inaccessible by train, or missing from the personnel database. We also dropped the one employee in the cohort assigned to Chandigarh, for whom within-center comparisons would have been impossible.

2.4.5. Variables

Table 2 presents summary statistics and correlations for the variables used in the analysis. All variables are constructed at the employee level. Our main data source is TECHCO's administrative employee database, which includes an employee's gender, performance during training and at recruitment, hometown location (by district) and production-center location. We

use the same personnel database to observe employee performance. We supplement this data by hand-collecting the shortest travel time from workplace to hometown by train.

Dependent variable. To measure individual performance, we use an employee's yearly performance ratings in 2008 (the first full year after assignment to a production center) and 2010 (three years after assignment). An appealing feature of this dependent variable is that it is based on objective measures and thus less prone to measurement errors. At the end of each year, managers enter a performance rating for each employee. Field interviews with the head of talent development, a senior HR manager and several employees in the sample confirm that performance ratings for entry-level employees are based on objective measures, including quality of coding and/or testing, measured using coding "mistakes," and timeliness, completeness in coding/testing/documentation, all tracked by automated software. HR managers check the rating entered by the manager against the underlying scores to correct errors in computing the overall rating.

In his or her first year, a newly hired employee receives one of three performance scores: one (high), two (average) or four (low). The final performance rating represents the employee's performance relative to that of his or her peers. The distribution of performance scores is included in the Appendix (Figure A1). In 2008, an employee received the highest rating (one) if he or she fell into approximately the top 35% of the relative performance distribution, and the second-highest rating (two) if he or she belonged to the middle of the distribution (61% employees received this rating). The lowest rating (four) was given only if an employee fell into the bottom 4% of the distribution.

In their third year, the employees in our sample again received relative performance rating scores. However, the third-year rating uses a five-point scale, from one (highest) to five

Table 2.2. Summary Statistics and Correlations Table

	N	Mean	Sd	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Travel Time, in Hours	443	15.50	10.38	0.33	48.97	1.00										
(2) CGPA Training	443	4.55	0.33	2.89	5.00	0.04	1.00									
(3) Male	443	0.66	0.47	0.00	1.00	0.04	0.04	1.00								
(4) Similar Language	443	0.40	0.49	0.00	1.00	-0.46	0.14	0.03	1.00							
(5) Migration Experience	443	0.63	0.48	0.00	1.00	0.06	0.01	-0.13	0.09	1.00						
(6) Logical Score	413	5.07	3.29	-4.00	9.00	-0.08	0.09	-0.05	0.11	-0.11	1.00					
(7) Verbal Score	413	4.32	3.78	-8.00	15.00	-0.01	0.08	-0.00	-0.07	-0.12	0.36	1.00				
(8) Assigned to Large City	443	0.70	0.46	0.00	1.00	0.04	-0.08	0.06	0.13	0.07	-0.04	-0.08	1.00			
(9) Left the Company	443	0.28	0.45	0.00	1.00	0.04	0.07	-0.03	-0.03	-0.03	-0.04	0.07	0.10	1.00		
(10) Performance Rating in 2008	443	-1.72	0.66	-4.00	-1.00	0.06	0.34	0.06	0.09	-0.22	0.17	0.12	-0.01	0.03	1.00	
(11) Performance Rating in 2010	385	-2.75	0.90	-5.00	-1.00	-0.07	0.21	0.16	0.06	-0.13	0.07	0.11	-0.04	-0.20	0.22	1.00

Notes: The variable travel time represents the shortest travel time (in hours, one-way) from an employee's workplace to hometown by train. In his or her first year, a newly hired employee receives one of three performance scores: one (high), two (average) or four (low). The final performance rating represents the employee's performance relative to that of his or her peers. In 2008, an employee received the highest rating (one) if he or she fell into approximately the top 35% of the relative performance distribution, and the second-highest rating (two) if he or she fell into the top 96%. The lowest rating (four) was given only if an employee fell into the bottom 4% of the distribution. In their third year, the employees in our sample again received relative performance rating scores. However, the third-year rating uses a five-point scale, from one (highest) to five (lowest). Approximately the top 13 percent of employees received ratings of one; only 8 employees, whose performance fell into the bottom 2 percent, received the lowest rating. In the regression analysis, we multiply the original performance ratings by -1 and use this transformed variable as our dependent variable. Originally, the lower an employee's performance rating, the higher his or her relative performance; after the transformation, a numerically higher rating score indicates higher performance. This transformation makes interpretation of the regression results more intuitive. For example, we can interpret a positive coefficient as a positive association between an independent variable and performance. It should be noted that the magnitude of estimated coefficients remains the same before and after the transformation. Also, logical and verbal scores can be negative because of penalties for incorrect answers to questions in the recruitment test. Drawing on the recent Indian linguistics literature (Sengupta and Saha, 2015), we create a dummy variable Similar Language that is equal to one if the official language of an employee's hometown and the region surrounding the workplace belong to the same language family. Using various machine-learning techniques, we classify Indian languages into a few families based on similarity. The dummy variable Migration Experience indicates whether a newly hired employee has prior migration experience. To construct this variable, we compare an employee's hometown location to his or her university location, at the district level, and code the variable as one if the locations differ.

(lowest). The distribution is reported in the appendix (Figure A1). Approximately the top 13 percent and next 12 percent of employees received ratings of one and two respectively (i.e. the highest and second highest rating); only 8 employees, whose performance fell into the bottom 2 percent, received the lowest rating.

In the regression analysis, we multiply the original performance ratings by -1 and use this transformed variable as our dependent variable. Originally, the lower an employee's performance rating, the higher his or her relative performance; after the transformation, a numerically higher rating score indicates higher performance. This transformation makes interpretation of the regression results more intuitive. For example, we can interpret a positive coefficient as a positive association between an independent variable and performance. It should be noted that the magnitude of estimated coefficients remains the same before and after the transformation.²

Independent variables. As a measure of distance from home to workplace, we manually construct a variable (*travel time*) that represents the shortest travel time (in hours, one-way) from an employee's workplace to hometown by train. Our field interviews indicate that almost all newly hired college graduates travel to their hometowns by train. Our interviews shed light on *why* distant employees use trains. First, distant employees travel to their hometowns predominantly during major Indian festivals, such as Diwali, or to attend to a family emergency. Emergencies necessitate last-minute ticket purchases, and even for Diwali uncertainty about approvals of leave applications leads to last-minute ticket purchases. Even on a low-budget airline, a ticket could cost close to 70% of these workers' monthly salaries, making it

² We also collect data on whether an employee left the company by 2011 and code the variable left the firm. About 28% of employees in the sample had left by 2011, when we completed data collection.

unaffordable.³ Furthermore, flights are usually scheduled in the morning; train schedules allow workers to travel in the evening or at night, thus avoiding a lost workday. As a robustness check, we examine whether the presence of flights connecting the workplace and hometown moderates how DFH is associated with performance; all results remain robust. After identifying an employee's hometown and production center, we code the shortest travel time manually from the official Indian Railways timetable. When there is no direct train connecting the two locations, we include extra time for a transfer. On average, it takes about 15.5 hours for an employee in the sample to travel home from the production center. The distribution of travel time is included in the appendix (Figure A2).

Controls. Several employee-level controls are included to control for other factors affecting worker performance. First, the dummy variable *Male* indicates an employee's gender. About 66% of the sample is male. An employee's cumulative grade-point average at the end of the four-month induction training (*CGPA Training*) represents performance during training; it is expected to be positively correlated with on-the-job performance.

As a proxy for cultural distance between the hometown and production-center locations, we build on Berry and Guillen (2010) and Ghemawat (2001) and create a language-similarity measure. Drawing on the recent Indian linguistics literature (Sengupta and Saha, 2015), we create a dummy variable *Similar Language* that is equal to one if the official language of an employee's hometown and the region surrounding the workplace belong to the same language

³ Our field interviews reveal that, at the time of our study, workers' monthly salary was around \$569 (INR 200,000 per year at an exchange rate of INR 29.28 to the U.S. dollar). Workers in this pay bracket were subject at the time to a 20% tax rate. The typical last-minute round-trip fare on a low-budget airline (on the Hyderabad-Kolkata route) was around \$300.

family. Using various machine-learning techniques, we classify Indian languages into a few families based on similarity.⁴

The dummy variable *Migration Experience* indicates whether a newly hired employee has prior migration experience. To construct this variable, we compare an employee's hometown location to his or her university location, at the district level, and code the variable as one if the locations differ. We include this control to rule out the alternative explanation that distant employees tend to have prior migration experience that promotes better long-term performance because of superior ability to adjust to new environments. Finally, to capture innate ability, some specifications include employees' logical and verbal scores on standardized multiple-choice tests administered during recruitment. This information is missing for about 30 employees; given this we exclude these employees from baseline specifications. All results remain robust to the inclusion of these variables.

2.5. Results

2.5.1. Relation of DFH to Short- and Longer-Term Worker Performance

We first examine baseline results on the relationship between distance from home and worker performance in the short and longer term. The appendix presents descriptive evidence, using a binned scatterplot, that indicates a positive association between travel time and performance ratings in 2008.⁵ Table 3, Panel A, examines this association in regression models. In all specifications we find a positive and significant relationship between travel time and performance rating in the first year. That is, the more distant an employee is from his or her

⁴ Our field interviews indicate that while English is the “official language” for work related activities at TECHCO, lack of familiarity with the local language hinders communication with local peers, neighbors and the population at large in areas where workers live.

⁵ The sample employees are grouped into 20 equal-sized bins based on travel time. We compute the average performance rating for each bin and plot the conditional mean in the scatterplot.

hometown, the more likely his or her short-term performance is high. Column 1, which reports the baseline result with travel time and location fixed effects as explanatory variables, shows that within a production center, employees far from home tend to perform better in the short-term. This pattern holds after controlling for CGPA training, which according to our field interviews is the strongest predictor of first-year performance (column 2), and after further controlling for gender (column 3). In an effort to address the cultural distance theory, we include language similarity between employees' hometown and workplace regions as an additional control variable in column 4. We also consider the possibility that travel time is correlated with employees' prior migration experience. For instance, if employees from remote areas tended to have migrated to attend college, that experience might contribute to better first-year performance via quicker adjustment to a new environment. Column 5 includes another control variable, Migration Experience, which is a dummy variable equal to one if an employee migrated from his or her hometown to attend college. We still find a positive relationship between travel time and short-term individual performance. This relationship remains robust after controlling for innate ability, captured in logical and verbal test scores during recruitment (column 6).

Given that we rely on an ordered logit model to establish the statistical significance of the effects of travel time on short-term individual performance, interpretation of the estimated coefficients from this specification is not straightforward. To understand its economic significance more intuitively, we calculate the predicted probability of receiving the highest performance rating in the first year, holding other independent variables at their mean and varying only travel time. We use the specification in column 5, our most stringent specification, to calculate the predictive probability. The "average" employee here is male; has a CGPA training score of 4.55, has prior migration experience; speaks a native language that is not similar

Table 2.3. Main Findings

Panel A: Effects of DFH on Short-Term Performance

	Performance Rating in 2008					
	(1)	(2)	(3)	(4)	(5)	(6)
Travel Time	0.018*	0.017*	0.017*	0.024**	0.034***	0.032**
	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.013)
CGPA Training		2.363***	2.365***	2.302***	2.351***	2.084***
		(0.374)	(0.376)	(0.384)	(0.403)	(0.407)
Male			0.228	0.214	0.134	0.097
			(0.215)	(0.216)	(0.220)	(0.227)
Similar Language				0.280	0.503*	0.406
				(0.257)	(0.263)	(0.272)
Migration Experience					-0.973***	-0.912***
					(0.234)	(0.237)
Logical Score						0.100***
						(0.035)
Verbal Score						-0.005
						(0.028)
Location FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	443	443	443	443	443	413
Log-Likelihood	-348.126	-320.674	-320.114	-319.509	-309.942	-290.729

Panel B: Effects of DFH on Longer-Term Performance

	Performance Rating in 2010					
	(1)	(2)	(3)	(4)	(5)	(6)
Travel Time	-0.018*	-0.020**	-0.021**	-0.026**	-0.021*	-0.022*
	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)	(0.013)
CGPA Training		1.503***	1.501***	1.547***	1.547***	1.361***
		(0.312)	(0.320)	(0.325)	(0.322)	(0.325)
Male			0.750***	0.758***	0.689***	0.621***
			(0.218)	(0.219)	(0.224)	(0.230)
Similar Language				-0.182	-0.085	0.008
				(0.257)	(0.263)	(0.274)
Migration Experience					-0.512**	-0.493**
					(0.229)	(0.241)
Logical Score						0.003
						(0.037)
Verbal Score						0.049*
						(0.029)
Location FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	385	385	385	385	385	358
Log-Likelihood	-461.640	-449.559	-443.560	-443.297	-440.570	-405.842

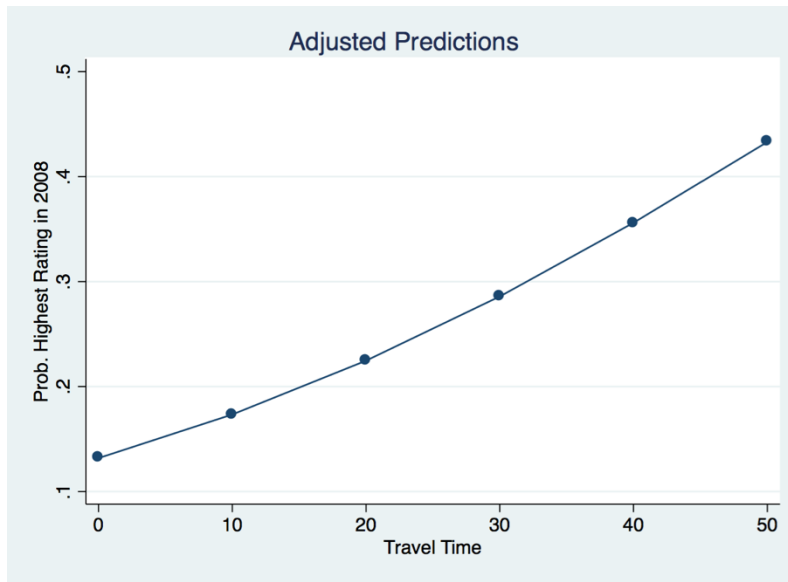
Note: Ordered logit regression is used for estimation, and robust standard errors are presented in parentheses. *p < .1; **p < .05; ***p < .01.

to the native language at the workplace; and works in Bangalore. Figure 3, Panel A, presents the results graphically. For this average employee, a 10-hour increase in travel time leads to approximately a 6-percent increase in the likelihood of receiving the highest performance rating in the first year. If the average employee's travel time were zero, the probability of receiving the highest rating in the first year would be about 13 percent; that probability increases to 43 percent if travel time is 50 hours.

Next, we examine how longer-term worker performance relates to distance from home. The appendix presents descriptive evidence that travel time and longer-term employee performance are negatively correlated. In Table 3, Panel B, we take an econometric approach, demonstrating that this negative relationship holds even after considering potential confounders. Across various specifications, we find a negative relationship between travel time and longer-term individual performance. Column 1 estimates the relationship with location fixed effects; it shows that, within each production center, employees far from home tend to perform worse over the longer term. Columns 2 and 3 show that the negative association between travel time and longer-term performance persists even after controlling for CGPA training and gender. The negative relationship appears not to reflect simple cultural unfamiliarity: the relationship is still significant after including language similarity as an additional control (column 4). Travel time continues to be negatively associated with longer-term performance after controlling for prior migration experience (column 5) and for innate differences in ability (column 6).

We then use the specification in column 5 to interpret the substantive meaning of the estimates. Specifically, we estimate the probability that an average employee will receive the high performance rating in the long-term. For comparison purposes, we calculate the likelihood of receiving the highest (1) and second-highest (2) ratings in 2010. Together, these two ratings

Panel A: Effects of DFH on Short-Term Performance



Panel B: Effects of DFH on Longer-Term Performance

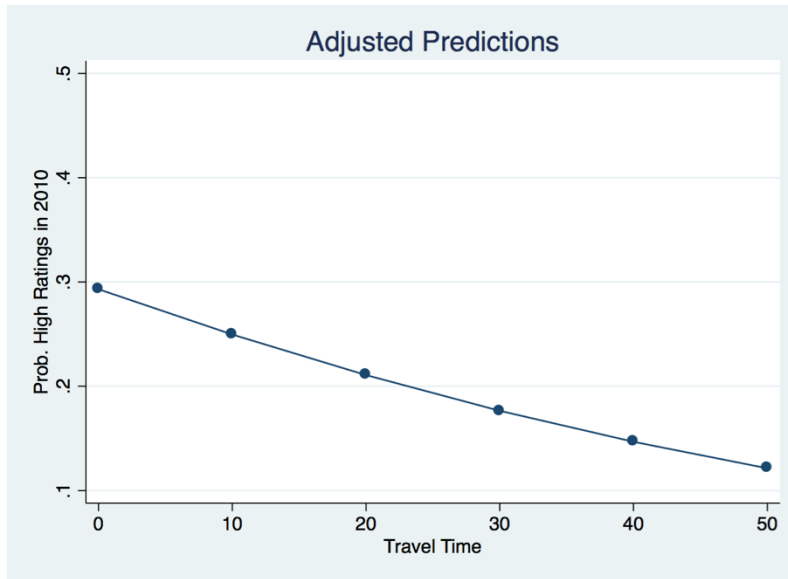


Figure 2.3. Effect of Travel Time on the Likelihood of Receiving High Ratings

Note: These graphs present the relationship between travel time and the likelihood of receiving high short- and longer-term performance ratings. We calculate the adjusted predicted values by plugging in different travel-time values for an average employee. Panel A shows the likelihood of receiving the highest performance rating in 2008; it indicates a positive relation between travel time and the probability of receiving the highest performance rating. Panel B plots the likelihood of receiving the highest or second-highest performance rating in 2010; it indicates a negative relation between travel time and the probability of receiving the highest performance rating. Our results remain robust to using only the highest performance rating to produce a similar graph for performance in 2010.

capture the likelihood that a given employee's performance falls in the top 25 percent of the relative performance distribution. This distribution resembles the likelihood of receiving the highest rating in 2008 when a three-value scale is used. The graphical result appears in Figure 4, Panel B. Again, we find a negative relationship between travel time and the likelihood of receiving the high performance rating in the longer-term. On average, a 10-hour increase in travel time between workplace and hometown is associated with a 3.4-percent decrease in the likelihood of receiving the high/highest rating. If the average employee's travel time were zero, his or her likelihood of receiving the high/highest rating is predicted to be 29 percent; that likelihood decreases to 12 percent if travel time is 50 hours (also see Panel B of Figure 3).

To summarize Table 3, we find contrasting effects of distance from home on short and longer-term individual performance: distance from home affects individual performance positively in the short-term but negatively over the longer term. The remainder of the paper builds on the mechanism illustrated in the lower panel of Figure 1, using both quantitative data and qualitative data from field interviews to explain these findings.

2.5.2. Exploring Mechanisms: Sub-Sample Analyses, Micro-Data and Qualitative Insights

To explain the contrasting effects of DFH on short and longer-term worker performance, we exploit sub-sample analyses, micro-data on courses and vacation days, and qualitative insights from thirty in-depth field interviews.

The upper panel in Figure 1 offers three theoretical lenses with which to explain the effect of DFH on worker performance. Though our study focuses on exploring the social attachment to place theory, we also attempt (at least partially) to assess the theories that focus on information costs and cultural distance. To address the cultural distance theory, we control for language-based cultural distance ("similar language") across all specifications. The information

costs theory encompasses a wide variety of information pertinent to opportunity identification; most crucial for the workers in our sample is information on the nature of projects: local employees might have disproportionate access to information on “sustainable” projects, and selection into such projects might be correlated to subsequent performance. We use additional data on how many days in a month that an employee allocates her time between coding (production), waiting for next project assignment (bench), training, and taking holidays. We calculate the share of production days in 2008 and 2010, and examine whether how much one is assigned to projects is correlated with DFH. Results in the appendix indicate no significant correlation between DFH and the probability of being assigned to a project. Though this finding suggests that local employees did not enjoy disproportionate informational advantages pertinent to project assignment, we cannot completely rule out that the information costs theory might be in play in our setting.

Among the plethora of possible mechanisms in play, we hone in a single mechanism pertinent to how employees allocate time to work-related activities and to visits to distant family. In other words, we focus on the mechanism of time allocation by the worker to identify how social attachment to place might affect worker performance in our setting. To reiterate, we do not rule out the relevance of other mechanisms to our setting or to other settings.

To shed light on the mechanism illustrated in the lower panel of Figure 1, we begin with semi-structured qualitative field interviews. We conducted 30 such interviews, with 15 workers each at the Bhubaneswar and Hyderabad production centers. Bhubaneswar is a smaller urban location (a town); Hyderabad is a large city. Each interview lasted around 45 minutes. The field interviews generated several insights into how the location of the production center—whether it is located in a city or a town affects allocation of time. A distant employee from Tamil Nadu

employed at Bhubaneswar told us: “There are relatively few things to do over the weekend here. There is only one large mall near our campus, and there too they do not serve our local food or do not play movies in our local language [Tamil]. I spend most of my Saturdays in office, and on Sundays I watch TV, cook food for the week, do my laundry and call my parents.” In contrast, distant workers in Hyderabad described a richer array of malls, movies and restaurants. Several workers in Hyderabad reported that they spent much of their Saturdays exploring these options with local friends, often from their training cohort. The prior literature too has observed that cities and towns provide different levels of leisure options (Roback 1982). Workers assigned to towns versus cities might have different incentives to allocate time to local social attachment building versus work-related activities. The lower panel of Figure 1 suggests that this pattern might lead to differences in worker performance.

To gain empirical traction from these insights, we split the sample into two groups: those assigned to cities and towns respectively. We classify Bangalore, Chennai, Hyderabad, and Pune as cities and Bhubaneswar, Mangalore, Mysore, and Trivandrum as towns.⁶ We then perform two sets of analyses. First, we analyze the impact of DFH on short-term performance separately for employees assigned to cities and to towns. Table 4 presents the results, using the most stringent specification used in the previous analysis. Table 4, column 1, reproduces the result presented in Table 3, column 5, which suggests an overall positive relationship between travel time and short-term individual performance. But this overall result masks heterogeneous effects across production-center locations: we do not find a positive relationship between travel time and worker performance for employees assigned to cities (column 2); the positive relationship is exclusive to employees assigned to towns (column 3). The difference is statistically significant.

⁶ To distinguish cities from towns, we use the classification system outlined by the Sixth Pay Commission report of the Government of India (released in October 2006).

We attempt to explain this result by presenting more direct evidence on time allocated to work-related activities by workers assigned to cities and towns respectively. Here we utilize micro-data on the number of optional skill-development courses taken by each worker; we use this number as a proxy for time allocated to developing work-related skills. Though these courses are optional, our field interviews indicate that they enhance work-related skills pertinent to both computer programming and industry domain knowledge. Typical course titles include “.NET Foundation Certification,” “Foundation Course in Banking–I” and “CSP Basic Telecom Datacom Certification.” Our interviews also indicate that each course entailed around thirty hours of independent study and one or more rounds of online assignments and testing. Though managers encouraged workers to enroll in these courses, doing so was not taken into account in determining performance scores. Furthermore, employees could not study during normal business hours (9 a.m.–6:30 p.m. or 6 p.m.–3:30 a.m., based on their work shift) and typically did all the coursework on Saturdays and holidays.

Table 5 examines the association between travel time and the number of courses taken, controlling for individual-level characteristics and location fixed effects. For employees in cities, travel time is not significantly correlated with the number of courses taken; for employees in towns, it is positively and significantly correlated (columns 3 and 5). Consistent with the mechanism illustrated in the bottom panel of Figure 1, these results suggest that, in the short-term, workers assigned to towns allocate more time to work-related activities (such as enrolling in optional skill-development courses) and that this pattern might be in turn related to their enhanced short-term performance.

Next, we examine how DFH affects longer-term performance. Table 4 indicates a negative relationship between DFH and longer-term performance (column 4). It appears that

Table 2.4. Heterogeneity by Production-Center Location

	Performance Rating in 2008			Performance Rating in 2010			Performance Change		
	All (1)	City (2)	Town (3)	All (4)	City (5)	Town (6)	All (7)	City (8)	Town (9)
Travel Time	0.034*** (0.012)	0.015 (0.014)	0.071*** (0.024)	-0.021* (0.012)	-0.035** (0.014)	0.009 (0.021)	-0.014*** (0.004)	-0.015*** (0.005)	-0.013** (0.007)
CGPA Training	2.351*** (0.403)	2.549*** (0.491)	1.969*** (0.735)	1.547*** (0.322)	1.627*** (0.370)	1.021 (0.748)	-0.174* (0.101)	-0.163 (0.113)	-0.229 (0.220)
Male	0.134 (0.220)	-0.027 (0.273)	0.503 (0.387)	0.689*** (0.224)	0.484* (0.271)	1.217*** (0.407)	0.088 (0.072)	0.132 (0.095)	-0.009 (0.108)
Similar Language	0.503* (0.263)	0.565* (0.295)	0.246 (0.599)	-0.085 (0.263)	-0.092 (0.315)	-0.080 (0.506)	-0.160* (0.084)	-0.164 (0.100)	-0.137 (0.163)
Migration Experience	-0.973*** (0.234)	-0.747*** (0.276)	-1.740*** (0.471)	-0.512** (0.229)	-0.353 (0.281)	-1.020** (0.430)	0.097 (0.074)	0.055 (0.097)	0.207* (0.116)
Location FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	443	312	131	385	270	115	385	270	115
Log-Likelihood	-309.942	-210.878	-91.576	-440.570	-308.411	-124.605			
R ²							0.081	0.058	0.161

Note: Ordered logit regression is used for estimation in Columns 1–6; OLS is used in Column 7–9. Robust standard errors appear in parentheses. *p < .1; **p < .05; ***p < .01. To distinguish cities from towns, we use the classification system outlined by the Sixth Pay Commission report of the Government of India. 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.

regardless of production center location types, DFH affects employee performance negatively. While DFH did not affect short-term productivity for employees assigned to large cities (Table 3, column 2), it has a significant negative effect in the longer term (Table 4, column 5). Similarly, distant workers assigned to small towns used to perform better in their first year (Table 3, column 3), but they do not perform better in the longer term (Table 4, column 6). To formally test this idea, we examine how DFH and performance change from the short to the longer term are correlated.⁷ We find a significant negative effect for the entire sample of workers (column 7) and for the sub-samples of workers in cities (column 8) and in towns (column 9).

To validate these insights empirically, we collected micro-data on leave days taken during Diwali. Our interviews indicated that TECHCO officially granted only one day of leave for each major festival; the official policy was that employees who wanted to travel to their hometowns must apply to use their quota of “earned leaves.” For a sub-sample of employees, we collected micro-data on earned leaves taken throughout an entire year and identified those taken during the week of Diwali in 2008 and 2010, the years corresponding to when workers received their short-term and longer term performance ratings. Diwali was celebrated in different weeks in 2008 and 2010: the exact dates were October 28, 2008, and November 5, 2010.

Using these micro-data on earned leaves, Table 6 estimates the relationship between travel time and length of leave (in days) during the month of Diwali. Columns 1–3 examine how

⁷ To operationalize this analysis, we construct a new dependent variable: $\Delta Performance_i = Performance_{i,2010} - Performance_{i,2008}$. This variable is positive if the performance of an employee improves over time; it is negative if performance declines. Because TECHCO employed different performance rating scales in 2008 and 2010, it is challenging to observe how an employee’s performance changed over time. Luckily for our purposes, we can construct rescaled performance rating scores for 2010 by exploiting the fact that a performance rating score is based on individual performance relative to that of peers, and that some cutoffs in the relative performance rating distributions are arguably consistent between 2008 and 2010. The right-hand plot in Figure A# (in appendix) presents the distribution of the rescaled performance rating scores that we use throughout this paper. The figure shows that the cutoffs for three performance ratings are stable over time. We then estimate the following specification using OLS, with the usual control variables and location fixed effects: $\Delta Performance_i = \alpha + \beta \cdot Travel Time_i + \gamma' X_i + LOCATION_j + \epsilon_i$

the number of days of leave in October 2008 is correlated with travel time. We find that, in the short-term (the first year of employment), DFH is positively correlated with leave days during Diwali; this finding is consistent, regardless of employment in a city or a town. In the longer term (the third year of employment), we find no statistically significant associations between DFH and days of leave during Diwali (columns 4–6). These results validate insights from our interviews and provide suggestive evidence related to why distant employees exhibit a performance decline in the longer term: in keeping with the framework illustrated in the lower panel of Figure 1, our results suggest that workers’ inability to spend time with their distant families during Diwali might be related to dissatisfaction and performance decline in the longer-term.

Table 2.5. Days of Leave during Diwali

	2008 October			2010 November		
	(1)	(2)	(3)	(4)	(5)	(6)
Travel Time	0.056*** (0.014)	0.056*** (0.017)	0.073** (0.035)	0.031 (0.021)	0.014 (0.022)	0.012 (0.030)
City			-0.886 (0.984)			-0.327 (0.883)
Travel Time x City			-0.024 (0.041)			0.005 (0.043)
Location FEs	No	Yes	Yes	No	Yes	Yes
Observations	200	200	200	144	144	144
Log-Likelihood	-405.275	-396.272	-	-	-	-
			395.058	332.757	301.995	301.954

Note: Dependent variable is number of leave days during the month of Diwali. Poisson model is used for estimation; and robust standard errors appear in parentheses. * $p < .1$; ** $p < .05$; *** $p < .01$. TECHCO made available administrative data on leaves for four out of the eight training batches related to employees in the sample; as a result, we have almost complete data for workers within these batches, but we do not have data for workers in every training batch. TECHCO did this to simplify the workload at their end; the training batches for which data was made available were admittedly selected randomly. In columns 1–3, the sample consists of employees who worked at least one day in October 2008; In column 4–6, the sample consists of employees who worked at least one day in November 2010.

Additionally, our field interviews indicate gender-based differences in long-term allocation of time to local social attachment and pressures to reunite with family. A female

worker in Bhubaneswar told us: “As a girl, it is very difficult for me. I do not have other [female] friends from my training cohort, and if I hang out with boys in the mall, everyone will be talking about this next Monday. In fact, a few weeks back, I wore a western dress to the mall and a lot of people were looking weirdly at me the next Monday.” After this incident, she reported spending most of her weekends alone. Distant female workers also reported greater pressure (compared to men) from their families to return home and marry locally; they characterized these conversations as often stressful.

The appendix reports how correlation between travel time and individual performance varies by gender in the longer-term. When we investigate how DFH affects longer-term performance, separately for male and female workers, we find that DFH is negatively associated with longer-term performance almost exclusively for female workers, but not so much for male workers. Unfortunately, our relatively small sample size does not permit us to examine how the association between DFH and longer-term performance is jointly moderated by gender and location. However, given the orthogonality between gender and employee assignment decision, we believe that gender certainly plays some moderating role in the relationship between DFH and longer-term performance.

2.6. Mechanisms and Alternative Explanations

So far, our analyses explore the three theories presented in the upper panel of Figure 1. In particular, we examine the theory of social attachment to place using the framework outlined in the figure’s lower panel. This section considers other mechanisms that might explain our empirical results, specifically burnout and endogenous attrition.

The first alternative explanation is burnout. Distant employees perform better than local employees in the short-term; if this is the case because they exert greater effort, it may not be

sustainable over the longer term. As a result, distant employees may burn out more easily over the long-term; their performance decreasing faster than that of local employees. Our analysis suggests, however, that this is not the case in our setting. If the burnout mechanism were a dominant explanation, the effects of the negative relationship between travel time and performance changes over time would be larger for the high-performer sub-sample. To conduct the sub-sample analysis, we divide the 2008 sample into low performers and high performers. Because of statistical-power concerns, we group two ratings, Below and Average, into one. As a result, the low-performer sub-sample consists of 234 employees; the high-performer sub-sample consists of 151 employees. We then separately estimate the relationship between travel time and performance change between 2008 and 2010, using the same specification introduced earlier. For the low-performer sub-sample, we find a negative and significant relationship between travel time and performance changes between 2008 and 2010 in all specifications; we do not find similar results for the high-performer sub-sample. Thus the burnout mechanism fails to explain our findings. These results are presented in the appendix.

Another possible explanation for our results is endogenous attrition.⁸ To rule out this possibility, we conduct two additional tests. First, we repeat the short-term regressions but with only the samples with performance ratings in 2010. We compare the results from the full sample (N=443) and the subset of samples with longer-term performance ratings (N=385) in Table A# in the appendix. Our findings are substantially similar; we still find that DFH and short-term performance are positively associated, and that employees assigned to small towns are driving

⁸ To be clear, employees with missing performance ratings in 2010 have not necessarily left the firm. Of the 58 employees with missing performance rating in 2010, only 51 employees had left the firm. Ratings for the other 7 employees are missing because of the nine-month rule. Table A# compares observables for employees with 2010 performance ratings to those of the 7 employees with missing performance rating in 2010. The sample size is too small to reach a concrete conclusion, but we find the two groups to be comparable except for their logical scores.

the result. Therefore, it is unlikely that attrition is drive the changes in how DFH affects employee performance over time.

Second, we also examine whether distant employees are more likely to leave the company than comparable local employees. If endogenous attrition were able to explain the results, then it should be the case that DFH is systematically correlated with attrition, and distant employees with high short-term performance ratings are more likely to leave the firm.

We test whether this condition is observed in the dataset. We use whether or not an employee leaves the firm as a binary dependent variable, and examine whether it is correlated with the interaction term between travel time and short-term performance. Because the dependent variable is binary, we estimate the following logit model specification using MLE:
Left the firm_i

$$= \alpha + \beta_1 \cdot Travel\ Time_i \\ + \beta_2 \cdot Travel\ Time_i \times High\ Performer\ in\ 2008_i + \gamma'X_i + LOCATION_j + \epsilon_i$$

The dummy variable High Performer in 2008 is equal to one if an employee received the highest rating in the first year. Other control variables include gender, CGPA training, language similarity, logical and verbal scores, and prior migration experience.

The estimated coefficients appear in Table A# in the appendix. The coefficient on travel time is near zero and not statistically significant, suggesting that distance from home plays no role in employee attrition in our sample. The results with the interaction term appear in column 2: we find no evidence that high-performing distant employees are more likely to leave the company. Thus we conclude that the attrition-based mechanism does not explain the contrasting effects of travel time on employee performance over time.

Next, we explore whether the estimates change with different functional form assumptions. We also examine whether a few outliers drive the entire results. To test whether our results are sensitive to specific functional form assumptions, we re-run all specifications using OLS rather than the ordered logit model estimated by the MLE. In the previous analyses, we use the ordered logit model because it does not impose the assumption that the differences between the cut-off points are substantially homogeneous. Estimating the main specification using OLS gives us substantially similar results (see Table A# in appendix).

To explore the possibility that a few outliers drive the main results, we perform two sensitivity tests. First, we use the winsorization technique and replace the extreme distance-from-home values beyond the bottom and top 5 percentiles with less-extreme values at each percentile; we get very similar results when we re-run the analyses. Second, we drop observations from the three smallest production centers—Mangalore, Trivandrum and Chandigarh—and re-run the analyses. (As Table A# shows, fewer than 20 employees in the sample were assigned to Mangalore and Trivandrum, and only one employee was assigned to Chandigarh, making within-center comparisons unfeasible.) Our results are robust to dropping employees assigned to these three centers.

We also tested whether our final sample resembles or differs from other 2007 employees without first-year performance ratings in 2008. If there were statistically significant differences across these sub-samples, our findings might not be informative even about TECHCO because of generalizability issues. Reassuringly, we do not find such evidence. The appendix reports the observable characteristics of employees in our sample and those of other 2007 intakes without first-year performance ratings in 2008. To avoid confounding issues, we use three individual-level characteristics that are predetermined before assignment to training batches: gender and

logical and verbal scores on the recruitment test. The p-values indicate that we cannot reject the null hypothesis that our sample employees and the other 2007 intakes are from the same population.

2.7. Conclusion

This paper attempts to establish a causal relationship between distance from hometown (DFH) and short- and longer-term individual worker performance. We exploit a unique HR protocol at a large Indian technology firm that randomly assigns entry-level employees hired from colleges across India to eight production centers, also distributed across the country. Our findings suggest that travel time between workplace and hometown has opposing effects on individual performance in the short-term and over the longer term. In the short-term, travel time to hometown positively affects individual performance: the further an employee works from his or her hometown, the more likely it is that his or her first-year performance rating is high. However, that relationship reverses over the longer term: employees with longer travel times tend to receive lower performance ratings three years after assignment. Additional analyses (available from the authors) show that the negative relationship between travel time and longer-term performance is particularly salient for employees whose travel time exceeds 23 hours. Among the plethora of possible explanatory mechanisms, we hone in on exploring whether allocation of time across activities (work, socializing with local friends and visiting distant family) can explain our results. We utilize field interviews, sub-sample analyses and micro-data to shed light on this mechanism.

Our results contribute to the literature on the determinants of worker performance (Brass, 1981, Huselid 1995; Ichniowski, Shaw and Prenzushi, 1997, Lazear 1996; Prendergast 1999, Bandiera, Barankay and Rasul, 2005, Bernstein 2012, etc.). This literature has focused on how

work practices, HR practices and workplace characteristics, including pecuniary and nonpecuniary factors affect worker performance and engagement. In some sense, this literature arguably has taken the perspective of the focal manager, who thinks about levers related to work practices and workplace characteristics as it relates to worker performance. We make a theoretical contribution by urging researchers to take the perspective of the focal employee; in doing so, the study of determinants of worker performance expands beyond the consideration of work practices and workplace characteristic to include employee-level characteristics and factors jointly determined by workplace characteristics and employee characteristics. In that regard, our contribution is related to the nascent literature on how workers' preferences affect their performance; for example, Stern (2004) studies "taste for science" among scientists.

Though workers in our sample do not have a say in where they work, our study arguably makes a valuable contribution to the nascent literature on how personal preferences drive the geography of work for individuals (Dahl and Sorenson, 2010a, 2010b, 2012, Kulchina 2016, Yonker 2017). Not only do we establish a causal relationship between distance from home and individual performance; we also provide a framework (in the top panel of Figure 1) that synthesizes three theories about possible drivers of the relationship between distance from home and worker performance. Though our study focuses on the social attachment to place theory, it is plausible that, in other settings, the information costs theory and/or the cultural distance theory could be more salient. For example, Dahl and Sorenson (2010) suggest the particular importance of opportunity identification and access to locally relevant information in entrepreneurs' choices of location. Future research on how distance from home affects the location choices of CEOs, workers, entrepreneurs and scientists could utilize our framework to specify the relative

importance of competing theories on the geographic preferences of different types of knowledge workers.

Our findings also contribute to streams of the literature on strategic human capital that focus on hiring, employee mobility and early career experiences. That literature has long explored the topic of external hiring (Bidwell 2011; Dokko et al., 2009; Bidwell and Keller, 2014). The theory literature on hiring is largely based on models matching workers to jobs (Schein 1978, Heckman and Sedlacek 1985, Hall 1986). The rewards offered by a job, including wages and personal happiness, might be a good match for a worker's preferences, leading to "horizontal fit" between worker preferences and job traits (Bidwell and Mollick, 2015). As Bidwell and Briscoe (2010) suggest, a job that offers greater flexibility, more autonomy, and better work-life balance might be a superior match with worker preferences and might lead to superior individual performance. Our study suggests that individual worker-level characteristics (such as the location of the individual's hometown and the distance between hometown and workplace) might be salient to a job-worker match. Firm locations are subject to agglomeration economies with respect to location (Shaver and Flyer, 2000; Alcacer and Chung, 2014), and being hired by a given firm often entails relocation (Song et al. 2003). Our results suggest that distance from home might lead to better or worse matches between the worker and the job, and to variation in worker performance.

Our insights are also relevant to the literature on employee mobility. From a learning-by-hiring and knowledge-flows perspective, firms can benefit from hiring distant employees (Rosenkopf and Almeida 2003, Song et al. 2003, Dokko and Rosenkopf, 2010). As Rosenkopf and Almeida (2003) have asserted, external hires can serve as bridges to distant contexts. Song et al. (2003) argue that external hiring can extend the geographical boundaries of interfirm

knowledge transfer; they offer evidence that hiring distant employees, both domestic and international, is conducive to learning-by-hiring. Our research adds to this literature by highlighting the effects of distance from home on individual productivity. Future research should study how firms can reconcile this important tradeoff by measuring the learning benefits of hiring distant employees against the costs of lower performance over the longer term. An interesting question is whether firms should encourage temporary relocation. In fact, a recent study (Choudhury, 2017) highlights the effect of “temporary mobility,” or intra-firm assignments to a distant location that last for a few weeks, on subsequent individual-level innovation outcomes. Our results suggest that, for distant employees, temporary and permanent mobility can have very different effects on employee performance. Our results also contribute to a third stream of the human-capital literature, focused on early career experiences (Campbell 2013, Dokko et al. 2009; Tilcsik 2014; Chattopadhyay and Choudhury, 2017), by highlighting the importance of distance from home for the performance of early-career workers.

Our findings are also relevant to the migration literature. Though the concept of psychic costs was prominent in this literature in the 1960s–1970s, to our knowledge there has been no empirical study of how psychic costs affect migrants’ long-term individual productivity. Borjas’s seminal 1994 study of migration, for instance, discusses the “costs of migration” but does not discuss psychic costs: “Migration costs C will differ among workers. For instance, newly arrived immigrants may be unemployed while they look for employment, suggesting that high-wage migrants might have higher migration costs. High-wage migrants, however, are more likely to have prior job connections and better information about job opportunities, suggesting a negative correlation between migration costs C and wages. The immigrant also incurs transportation costs” (Borjas, 1994, page 1688). Our results indicate that the underlying model of self-selection

in the context of migration (i.e., Roy, 1951) should acknowledge variable migration costs and the psychic costs of migration. Borjas (1994) does, in fact, urge the field to consider an extension of the Roy (1951) model by incorporating variable migration costs.

Our study has several limitations. Given that we focus on a single firm (in keeping with the insider-econometrics approach), the external validity and generalizability of our results are open to question. First, our findings might not be applicable to smaller countries, or to countries whose transportation system is more developed than India's. The mean travel time for individuals in our sample is about 16 hours, and the maximum is 49 hours. It would be interesting to determine whether a relationship between distance from home and employee productivity exists in smaller countries where air travel is more economical and feasible, or in international settings where employees are assigned to foreign workplaces. Second, given that the psychic costs of remoteness from family and friends might be higher early in employees' careers than later, a follow-up question for research is whether the pattern we found changes when employees acquire families of their own.⁹ A third limitation of our study is its three-year time frame. It is plausible that the longer-term negative effect of distance on individual performance is reversed when an employee marries and begins a family. This possibility recalls the theory of U-curve adjustment in the field of cross-cultural adjustment (Lysgaard 1955; Adler 1986), which posits four phases in migrants' cultural adjustment: (1) honeymoon, (2) culture shock, (3) adjustment and (4) mastery. It is plausible that our short-term and longer-term results correspond to the honeymoon and culture-shock phases respectively. Future work should explore whether psychic costs undergo inversion over longer periods of time. Most importantly, though we focus on a single theory—social attachment to place—and concentrate on allocation of time

⁹ It is noteworthy that *none* of the employees in our sample were married or had children during the period of our study. We confirmed this observation in our field interviews.

to work-related activities and to visiting distant family, we do not rule the possibility that other theories and mechanisms are in play.

Our insights open up several avenues for future research. It would be interesting to study workplace substitutes for and complements to family and friends. It would also be enlightening to study interventions that firms could implement to mitigate the psychic costs incurred by employees hired from far away. Finally, it would be worthwhile to determine whether the effects of distance from home on employee performance vary across countries (on dimensions such as size of the country and homogeneity in languages spoken) and career stages of the worker.

Our study has several managerial implications for the many firms in emerging markets that hire at scale and do not offer a post-employment choice of location. Such organizations include the Indian Administrative Services in India, SK Telecom in Korea and XXX. Our findings are also pertinent to two trends that shape individuals' location choices. Several recent articles in in general-interest U.S. periodicals indicate that individuals increasingly prefer to live near their hometowns. In one such study, 61% percent of U.S. respondents said their likelihood of relocating for work was low—41% said that doing so wasn't at all likely.¹⁰ Also, given the current policy environment for skilled immigration, it is plausible that knowledge workers will be even less likely to migrate far from home in the future. If future research corroborates this pattern, managers would be well served to hire locally and/or to mitigate the psychic costs incurred by distant employees by creating a "home away from home" in the workplace. Another practical managerial implication, stemming from our findings about the use of earned leaves to travel home for Diwali, is that it is important to grant leaves to distant employees for important holidays when the psychic costs of separation from distant family is likely to be high.

¹⁰ Source: <https://www.theatlantic.com/business/archive/2015/03/staying-close-to-home-no-matter-what/387736/>. Website accessed February 8, 2017.

In summary, our study provides important causal evidence on how distance from home affects individual performance in the short-term and over the longer term. While providing a synthesis of theories on how DFH could affect performance, we exploit field interviews and micro-data to explore one theory (social attachment to place) and a single mechanism (workers' allocation of their time) to advance our understanding of this subject. Our results speak to the literatures on determinants of worker performance, workers' geographic preferences, hiring, employee mobility, early career experiences and migration, and have several valuable managerial implications. In conclusion, our study responds to the call of Barley and Kunda (2001) for more detailed work studies and for "bringing work back in."

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Chapter 3. Managing Through Organization Change: Employee Alignment in the Presence of Unexpected Career Concerns

3.1. Introduction

This study examines performance consequences in the presence of unexpected career concerns. A large body of analytical research examines career concerns where career-related incentives arise due to the existence of a labor market that allows for the valuation of the agents' ability. In these models, agents derive incentives to exert better performance in order to mitigate adverse consequences over time as the market learns about their true ability. In line with this stream of research, a number of empirical studies have examined career concern-related incentive effects and its relationship with incentive contracting, especially in the context of executives (e.g. Fama 1980; Holmstrom 1999; Gibbons and Murphy 1992) or professionals (e.g. Hong, Kubik, and Solomon 2000; Hong and Kubik 2003).

Yet, career-related incentives that hinge on the market's valuation of the agent's ability are less prevalent for lower-level employees as their ability is relatively easily replaceable. Instead, such employees are subject to rather *unexpected* career concerns that arise due to institutional reasons. For example, unexpected career concerns arise when employees experience feelings of job insecurity due to sudden organizational changes that can accompany a discontinuation of existing business units or product lines. A focus on the effects from unexpected career concerns is particularly important as recent rapid developments in the fields of technology, transportation, and communication force organizations to undergo frequent organizational changes that can include restructuring efforts by consolidating existing product

lines or businesses. However, we do not fully understand whether and how such unexpected career concerns affect employee behaviors.

This paper aims to fill this gap by providing first empirical evidence on how employees change their behaviors when subject to unexpected career concerns. We study a rental car company at which its management made an explicit announcement to all its employees of its intent for a merger. Consistent with the literature on horizontal merger (Fee and Thomas 2004), industry experts predict that consolidation of duplicate resource would follow, which created unexpectedly heightened career concerns of current employees.¹ Exploiting this event, and also relying on rich micro-level data on employee performances around this time frame, we are able to examine how unexpected career concerns affect employee behaviors and performance. Thereby, our study provides a more comprehensive view of career-concern-related incentive effects within organizations.

In particular, our study examines the incentive effects and effort allocation effects associated with unexpected career concerns. First, we examine how overall employee performance is affected when subject to unexpected career concerns. Unexpected career concerns may be associated with two countervailing incentive effects. On the one hand, employees may have incentives to exert better performance in order to minimize potential layoff risks. On the other hand, the associated termination threat may discourage employees to perform at the current organization and result in adverse performance consequences. Second, if performance is measured based on multiple measures, unexpected career concerns may also

¹ Mergers and acquisitions comprise a significant business strategy for an increasing number of organizations. For example, according to the IMAA, since 1985, more than 300,000 mergers and acquisitions transactions have been announced with a known value of almost 33,200 billion US dollars (<https://imaa-institute.org/m-and-a-us-united-states/>). Moreover, a larger number of anecdotal evidence suggests that mergers and acquisitions are associated with subsequent restructuring efforts, and accompany layoff risks for employees. (For example, <http://www.businessinsider.com/signs-your-company-is-conducting-mass-layoffs-2015-10>)

create incentives to allocate effort across these measures differently. For example, unexpected career concerns may create pressures to mitigate layoff risk that can incentivize myopic behaviors to fixate on short-term at the expense of long-term performance. Thereby, we shed light on whether employees consider the sensitivity-congruity trade-off of performance measures, and allocate their effort considering the different measure attributes when subject to unexpected career concerns.

Several studies in economics, management, and accounting highlight the advantages of employee alignment – the extent by which employees are aligned with the overall organizational objectives and strategy – as an important organizational control channel (as opposed to the alignment of incentives via explicit contracting mechanisms).² Similarly, several anecdotal evidence suggests that greater employee alignment is correlated with heightened retention rates and better execution.³ Building on this argument, we further hypothesize and investigate empirically that employee alignment may be a significant moderating force in explaining the effects arising from unexpected career concerns. To do so, we first operationalize employee alignment based on the notion of the ‘clan mechanism’ articulated by Ouchi (1979) which describes an informal control system sustained by shared values of the organization’s constituents that is consistent with the overall organizational objectives and strategy. We then show whether and how employee alignment is associated with different performance consequences in the presence of unexpected career concerns.

² See literatures in economics (e.g. Prendergast 2008), accounting (Campbell 2012; Abernethy et al. 2015), and management (Kaplan and Norton, 1996; Joshi, Kathuria, and Porth, 2003) that point to the importance of goal alignment in organizational management systems for increasing organizational performance.

³ A survey of nearly 100 respondents from large companies revealed that firms with higher-performing employees report “a formal linkage between corporate and individual goals”, and that such firms were “2.2 times more likely to be top performers than their peers” (Available at <https://hbr.org/sponsored/2016/06/how-employee-alignment-boosts-the-bottom-line>).

As previously mentioned, our study on how unexpected career concerns and employee alignment jointly affects employee behaviors is only possible because of the administrative dataset from a company. The dataset contains various employee-level performance measures from a rental car company with store locations across US airports. Our research site provides us with an ideal setting to address our research question for several reasons. First, the management of the company made an internal announcement to all company-affiliated employees regarding its plans to merge with another major rental car company. Especially customer-facing employees were subject to termination threats due to the possibility that the merger would involve restructuring efforts to combine existing store locations at each airport. Accordingly, we exploit the internal merger announcement date as a trigger date to proxy for heightened unexpected employee career concerns. Second, thanks to the rich micro-level data, we are able to examine different types of performance effects of the customer-facing employees at each store location at the individual level. More specifically, we examine two performance measures that exhibit different properties: a relatively sensitive short-term sales-based measure and a relatively congruent long-term customer satisfaction measure. This allows us to examine not only overall performance incentive effects, but also effort allocation effects. Third, our research site implements periodic employee engagement surveys at each store location. Using the survey results, we can distinguish between store locations with higher and lower levels of employee alignment. Finally, alternative formal management control channels including the management team and the design of employee incentive contracts remain constant over the course of the merger event. Therefore, the empirically documented performance effects subsequent to the merger announcement are not prone to changes in explicit management control channels. In

other words, our empirical results are not confounded by noise in the performance measure that captures group- or firm-level outcomes.⁶

Our study reveals several changes in employee performance subsequent to the merger announcement. First, we find that unexpected career concerns are associated with positive incentive effects. In particular, we show that performance on both performance measures increases significantly subsequent to the merger announcement. This result is consistent with predictions from prior literatures that career concerns may substitute explicit incentives and provide additional performance incentive effects due to the threat of replacement. Moreover, we find corroborating empirical evidence that the source for such incentive effects are unexpected career concerns. Specifically, we distinguish between airport store locations where employees are more or less likely to be subject to the merger-related career concerns. Employees at airport store locations where the target rental car company also maintains store operations face relatively higher merger-related career concerns as the perceived likelihood of potential restructuring efforts is relatively higher. The results show that the positive incentive effects are driven by employees at such airport store locations where the merger-related career concerns are more predominant.

Second, we find evidence that unexpected career concerns are associated with effort allocation effects. In particular, we examine the extent of improvement on the sales-based measure relative to the customer satisfaction measure, and whether it varies between store locations with higher and lower levels of employee alignment. We find that the improvement of the customer satisfaction measure is significantly greater than the improvement of the sales-based measure for employees at locations that exhibit higher levels of employee alignment.

⁶ Empirical studies that examine career concern-related incentive effects for executives, or CEOs are subject to the limitation of having to rely on aggregate firm performance measures.

Conversely, employees at locations that exhibit lower levels of employee alignment improve significantly greater on the sales-based measure than the customer satisfaction measure. Collectively, these findings suggest that, when subject to unexpected career concerns, employees may have incentives to fixate effort levels on relatively short-term oriented performance measures at the expense of decreasing effort towards more long-term performance measures. More importantly, our results suggest that greater employee alignment can mitigate such myopic employee behaviors due to unexpected career concerns. Further additional tests corroborate this finding. In particular, we exploit the different subcomponents for overall customer satisfaction to identify more direct proxies for employee effort. Whereas subcomponents such as “speed of service”, and “staff courtesy” is directly reflective of the employee’s effort, other subcomponents such as “billing as expected”, and “vehicle condition” are managed centrally by the organization. We show that the results are driven by the former which provides further evidence that the performance effects are a result of corresponding employee behaviors.

This study makes contributions to largely four streams of literatures. First, this study contributes to the large body of literatures that examine the optimal design of employee incentive systems. A large stream of literature in economics and accounting is devoted to studying the design of optimal contracts to mitigate incentive problems in economic relationships. In the standard principle-agent framework, the classic theoretical insight suggests that employee performance should be evaluated using performance measures that are informative about managerial effort or talent (Ross 1973; Holmstroem 1979). Many studies have examined the provision of incentives within the bounds of the explicit contract. For example, research investigates the creation of better performance metrics or the optimal balance of the combination of different performance measures to mitigate contracting limitations due to the incompleteness

of performance measures. Moreover, a large number of studies investigate how to reduce the risk that must be imposed on the agent due to the influence of uncontrollable events, and suggest that the use of relative performance evaluation and/or subjectivity can mitigate such drawbacks.⁷ This study sheds light on incentive effects that are outside of the bounds of explicit contracting mechanisms by empirically documenting performance consequences that arise due to unexpected career concerns. Thereby, we add to the literature by providing a more comprehensive perspective of employee performance incentives.

Second, this study contributes to the growing stream of literature that examines alternative means as a viable control mechanism to maximize desirable organizational outcomes other than formal contracting channels. For example, research shows that the delegation of authority via organizational design choices (Jensen and Meckling 1992; Baiman, Larcker, and Rajan 1995; Nagar 2002; Campbell, Datar and Sandino 2009; Indjejikian and Matejka 2012 etc.), and strengthening of relationships (Baker, Gibbons, and Murphy 2002 etc.) and/or social norms (Cardinaels and Yin 2015; Abernethy, Bouwens, Hofmann, and van Lent 2015) may address such limitations in the design of explicit contracts. Our findings contribute to these studies by shedding light on how firms can benefit from greater employee alignment with overall organizational objectives and strategy in the presence of unexpected career concerns.

Third, this study contributes to the literature on management control systems. The existing literature primarily emphasizes the role of management control systems as a significant determinant for successful firm strategy execution. Successful management control systems

⁷ For literatures on the use of subjectivity, see Baker, Gibbons, and Murphy 1994; Baiman and Rajan 1995; Bol 2008; Ederhof 2010; Bol 2011; Hoeppe and Moers 2011 etc. For literatures on the use of relative performance evaluation, see Antle and Smith, 1986; Janakiraman, Lambert, and Larcker 1992; Albuquerque 2009 etc. Albuquerque (2009) provides a summary of the empirical evidence for and against relative performance evaluation in CEO compensation and turnover.

shape the culture of the firm, and guide employees to execute effort on desirable behaviors that is consistent with the organizational objectives (Simons 1987; Sandino 2007). Accordingly, prior management accounting research has primarily studied the deliberate choice of management control system of firms, and factors that are associated with different types of management control systems adopted by firms. By examining employee behaviors subject to a sudden organizational change event (i.e. a merger announcement), this study highlights the possibility that existing management control systems may result in distorted employee incentives with constantly changing business strategies to adapt to the dynamic business environment.

Finally, our findings contribute to the literature on mergers and acquisitions. A large number of works investigate factors that are associated with post-acquisition firm performance (e.g. Larsson and Finkelstein 1999; Bowman and Singh 1993; Anand and Singh 1997; Kim and Finkelstein 2009). Whereas prior literature has primarily focused on assessing overall aggregated firm performance of the newly created firm, there is a lack of understanding regarding whether and how the performance of individual employees is affected by a merger decision. By documenting how individual employee performance is affected by career concerns due to a merger announcement, our study enhances the understanding of post-acquisition firm performance.

The remainder of the paper is organized as follows. In Section 2, we review the prior literature and develop our hypotheses. Section 3 describes our research setting and Section 4 describes our empirical research design. We explain our empirical results in Section 5, and conclude with Section 6.

3.2. Prior Literature and Hypotheses Development

3.2.1. Unexpected Career Concerns and Incentive Effects

A number of studies investigate performance incentives due to career concerns. However, the prior analytical literature primarily focuses on one particular type of career concern where the assumption of a well-functioning labor market for managerial talent is crucial. In other words, the fundamental incentive problem embedded in such career concerns arises due to the expected valuation of the manager's true ability in the labor market over time. For example, Fama (1980) argued that explicit incentive contracts are not necessary because managers are disciplined through the managerial labor market such that superior performances will generate high wage offers; and poor performances will result in low offers. Since the market infers the ability of managers by gauging the overall level of compensation, the manager is also incentivized to exert greater effort through the signaling aspects attached to higher compensation levels. Holmstrom (1999) demonstrates the dynamic incentive problem analytically. His model assumes that output is a function of the manager's true ability and effort, and that the market only observes the output level, but does not observe the manager's true ability and effort. Over time, when more output data points become available, the market learns about the manager's true ability. The model demonstrates that the optimal level of managerial effort declines as the market's learning progresses (i.e. the market can approximate the manager's true ability more accurately as time progresses). Gibbons and Murphy (1992) examine how such career concerns interact with the design of optimal incentive contracts. Specifically, they define career concerns as the expected effects of current performance on future compensation, and show that career concerns can still create important incentives, even in the presence of incentive contracts.

Despite the wealth of theoretical justification for such career-concern-induced incentive effects, due to empirical research design limitations, there is only limited empirical evidence,

primarily on CEOs or professionals, that examines the incentive effects due to career concerns, and their association with incentive contract design choices. Using the Compustat population of firms, Matejka, Merchant, and Van der Stede (2009) show that loss-making firms put more emphasis on nonfinancial performance measures in their annual bonus plans. Arguing that managers at loss-making firms are likely to leave the firm in the near future (i.e. have a short employment horizon), they suggest that employment horizon concerns affect the relative emphasis on financial versus nonfinancial performance in annual bonus plans. Hallman, Hartzell, and Parsons (2011) exploit industry-specific organizational features that CEOs at certain companies are much harder to terminate than at other firms. They show that firms take into account the incentive effects of such inherent termination threats in the design of their financial incentives by showing that the financial incentives at Real Estate Limited Partnerships (RELPs) where termination threats are less credible, exhibit higher pay-for-performance sensitivity. Using data on security analysts, Hong, Kubik, and Solomon (2000) show that inexperienced analysts are more prone to herding behaviors in terms of issuing forecasts that are more timely and closer to the consensus. These findings suggest that security analysts are subject to implicit career concern incentives by trying to manage their reputation in the labor market.

Contrary to the focus of the bulk of career concern-related literatures, anecdotal evidence suggests that the majority of employees are subject to rather *unexpected* career concerns that do not critically hinge on the existence of a well-functioning labor market. For example, unexpected career concerns arise when employees experience feelings of job insecurity due to sudden organizational changes that can accompany a discontinuation of existing business units or product lines. Under such circumstances, the career concerns (primarily for lower-level employees) arise due to rather “exogenous” reasons, and is independent of the employees’

concern of how his/her ability will be valued in the labor market. In fact, many modern firms operate in a fast-paced dynamic business environment with rapid developments in the fields of technology, transportation, and communication. In order to maintain competitive advantage, adapting to such environmental changes becomes critical, and such efforts frequently involve mergers and acquisitions to increase market share and/or acquire key capabilities in-house. For example, according to the IMAA, since 1985, more than 300,000 mergers and acquisitions transactions have been announced with a known value of almost 33,200 billion US dollars.⁸ This study aims to examine the performance effects arising from such unexpected career concerns.⁹

Theoretically, unexpected career concerns are associated with two countervailing incentive effects. On the one hand, the theorized positive incentive effects from prior literatures may also apply to unexpected career concerns. Anecdotal evidence suggests that many of the changes associated with mergers and acquisitions are evolutionary, and that final outcomes are often not known during the negotiation process. This allows for merger-related rumors to spread amongst employees. In order to avoid a potential layoff, employees may have stronger incentives to signal their ability by exerting better performance (even above and beyond what is expected based on their explicit incentive contracts). Accordingly, we state our first hypothesis as follows:

Hypothesis 1. *Employees exhibit better performance when subject to unexpected career concerns.*

On the other hand, the associated termination threat may discourage employees to perform at the current organization. In fact, the merging process involves the integration of two

⁸ See <https://imaa-institute.org/m-and-a-us-united-states/>

⁹ Unlike the bulk of literatures on expected career concerns that focuses on managers or executives, the subject of interest to examine the incentive effects for unexpected career concerns are likely lower-level employees. In particular, in this study, we consider one type of unexpected career concern that arises from potential layoff decisions due to mergers and acquisitions.

different entities with distinct organizational cultures. Anecdotal evidence suggests that after a merger, employees often feel that the organization has changed so much that “it is no longer their company” (Ashkanasy and Holmes 1995; Hogg and Terry 2014), and literatures in strategy and management highlight the importance of organizational culture fit as a significant driver of post-merger performance (Weber 1996; Van den Steen 2010; etc.). If employees are dissatisfied with the merger prospects, and their desire to stay with the organization are not sufficient, the merger-related unexpected career concerns may result in rather adverse performance incentives.

3.2.2. Unexpected Career Concerns and Effort Allocation Effects

If performance is measured based on multiple measures, unexpected career concerns may also create incentives to allocate effort across these measures differently (i.e. effort-allocation effects). For example, if unexpected career concerns generate increased performance incentives to avoid potential layoff risk, employees may focus on improving short-term performance. Prior literatures provide supporting evidence that managers have tendencies to engage in rather myopic behaviors when career concerns are present. For example, Chen et al. (2015) look at whether executives exhibit differences in performance when faced with contracts with varying degrees of protection against the downside of potential dismissals (in the form of employment agreements and severance pay agreements). They find that CEOs with less contractual protection (i.e. greater career concerns) are under more pressure to maintain high short-term performance and, thus, are more likely to engage in myopic behavior compared to those with contractual protection. Moreover, González-Uribe, and Groen-Xu (2017) also find that a longer executive contract duration can motivate executives to invest more in innovation because they provide protection against dismissals.

The incentive conflict in allocating effort across different performance activities arises due to the incompleteness of performance measures. As employee effort is inherently unobservable (Holmstrom 1979), incentive contracts rely on a diverse set of performance measures in practice. The optimal performance measure exhibits two desirable attributes. First, it should insure the agent against risk by mitigating the impact of uncontrollable events (i.e. sensitivity). Second, it should achieve interest alignment between the principal and the agent (i.e. congruity). However, any observable performance measure faces different degrees of the sensitivity-congruity trade-off (Banker and Datar 1989; Feltham and Xie 1994; etc.). Whereas sales-based financial measures exhibit relatively higher sensitivity, non-financial performance measures such as customer satisfaction constitute leading indicators for long-term firm performance (Ittner and Larcker 1997), and, thus, exhibit relatively higher congruence. As congruent performance measures are frequently intangible and many of the desired organizational outcomes have a long-term horizon, employees may have incentives to overweight relatively more sensitive performance measures when subject to unexpected career concerns. Such employee behaviors, however, may not be desirable from the overall organization's perspective in that greater effort is diverted from tasks that are detrimental in sustaining the organization's long-term performance.¹⁰

Prior literatures in economics and management suggest that the extent by which employees are aligned with the overall organizational objectives and strategy (i.e. "employee alignment") may be a significant moderating force in mitigating the incentive conflicts in effort allocation effects arising from unexpected career concerns. We define employee alignment

¹⁰ This incentive conflict has also been referred to as the "intertemporal choice" problem (Abernethy, Bouwens, and van Lent 2013). The source of the problem lies in that "the course of action that is best in the short-term is not the same course of action that is best over the long-run".

consistent with Ouchi's (1979) notion of "clan control" which hinges on shared values and beliefs among the constituents of an organization as a form of management controls. Embedded in this form of management control is the idea that employees exhibit alignment on preferences with organizational values as opposed to achieving alignment of incentives via explicit contracting mechanisms. For example, Akerlof and Kranton (2005) show that agents who identify with the firm gain utility in taking actions that benefit the firm. Similarly, Van den Steen (2010a, 2010b) demonstrates the benefits of attracting employees with values and beliefs aligned to the firm. Employees that are more aligned with organizational values also exert greater effort, and are associated with greater utility, and coordination as they are more motivated and satisfied in the work environment (Van den Steen 2005). In addition, research shows that firms rely on management controls to improve employee alignment, especially in uncertain and complex decision contexts subject to high levels of contracting difficulty (Snell 1992, Abernethy and Brownell 1997, Prendergast 2011, Campbell 2012, Abernethy, Dekker, and Schulz 2015). Consistent with the stipulated advantages from greater employee alignment, Campbell (2012) shows that improving employee selection mechanisms can be a successful means to do so. Using referral source as a proxy for the extent of employee alignment, he shows that referred employees are more likely to make decisions that are organizationally desirable.

Taken together, we hypothesize that employee alignment can mitigate adverse effort allocation incentives to fixate on short-term at the expense of long-term performance measures when subject to unexpected career concerns. Despite abundant research that stipulates the benefits of greater employee alignment, there is only limited research that examines conditions under which employee alignment is associated with positive organizational outcomes. This study

fills this void in the literature by examining whether employee alignment can be beneficial in the presence of unexpected career concerns. We formulate our second hypothesis as follows:

Hypothesis 2. *When employees are more aligned with the overall organizational objectives, unexpected career concerns result in relatively better performance on congruent measures than the performance on sensitive measures.*

3.3. Research Setting and Data

3.3.1. Company Description

The data obtained for this study are from a rental car company (hereafter, RENT) with store operations across US airports.¹¹ RENT is one of the largest players in the rental car industry, holding more than one fifth of the entire market share in the US. RENT customers usually make a reservation for a rental car specifying their pick up and return location in advance primarily via online booking channels. During the reservation making process, customers also select their preferred options for their upcoming trip, including vehicle type and additional services such as GPS device, radio, and pre-paid gas. Accordingly, customer-facing employees have only limited ability to improve sales through customer interactions.

Considering this nature of the industry, RENT mainly relies on two primary performance measures to monitor and incentivize its employees. First, when customers pick up their reserved car at the predetermined location, employees have the opportunity to solicit customers into an upgrade of their initial reservation. These can include an upgrade in the vehicle type or purchases of additional services. Such upgrades are referred to as “upsell” transactions, and result in additional revenue stream from customers. Employees receive commissions based on the number

¹¹ Due to data confidentiality reasons, the name of the company, and the exact dates for events remain unidentified. The research site will be referred to as RENT hereafter.

of upsell transactions. Moreover, they may be liable for termination, or demotion to less desirable positions, if they fail to meet the pre-determined quota in a given period. An employee who used to work at RENT described that “if you miss a quota or two, [managers at RENT] stick you at the exit gate or something like that for a week or two,” where the employee would be deprived of the opportunity to make additional earnings from commissions. Even experienced employees demonstrating a good service attitude may be fired if they are not able to generate sufficient upsell transactions.

Second, employees can also improve their performance by exerting more effort in improving the overall customer experience. Maintaining higher customer satisfaction levels has been a core of RENT’s business model, because it allows the company to attract more customers and charge a higher premium in an industry in which the focal good itself (i.e., renting a car) is a commodity. For example, one employee expresses the importance of customer satisfaction by saying: “If they leave here unhappy, we know they won’t come back, and we just cannot afford to let that happen.” To monitor customer satisfaction, RENT systematically collects customer responses after each rental transaction. Specifically, after returning the rental vehicle to the return location, customers are contacted and asked to fill out detailed customer satisfaction surveys. Several incentives, such as bonuses, are also provided if the overall customer satisfaction level at a location is particularly higher than at other locations. It is important to note, however, that the bonuses are often provided at the team level, rather than at the employee level (unlike the case for upsell transactions where commissions are based on employee-level performance). The reason is that it is difficult to attribute higher customer satisfaction to a specific employee – i.e. customer satisfaction is a performance measure that is congruent (with the long-term success of RENT), but less sensitive to the employee’s actions.

3.3.2. Proxy for Unexpected Career Concerns: Internal Merger Announcement

RENT acquired another rental car company as part of their firm strategy to expand increasing their US market share to almost 30 percent. The press highlighted this merger as potentially “the last combination of major U.S. car-rental companies that regulators will tolerate”. Figure 1 provides a timeline of the major merger-related events and our corresponding sample time period. The CEO made an explicit company-wide merger announcement to all its employees which we treat as the trigger date (t) for employees to perceive the merger as definite. The possibility of a potential merger was first mentioned seven months prior to the merger announcement date by management, but only constituted of outside media sources. We treat (t) as the event date to be associated with the highest credibility for the likelihood of the merger as the announcement was made directly by management. In order to not confound our analyses with the effects from the first media mention, we start our sample period in ($t-6$). Under the assumption that a media mention by external sources is also associated with heightened unexpected career concerns for employees, our results show that the internal announcement has an incremental effect as we compare the performance of employees in the period prior to the internal announcement, but after the initial media mention to the period following the internal announcement.¹²

¹² The availability of our data do not allow for a sample period to estimate the results using ($t-7$) as the event date.

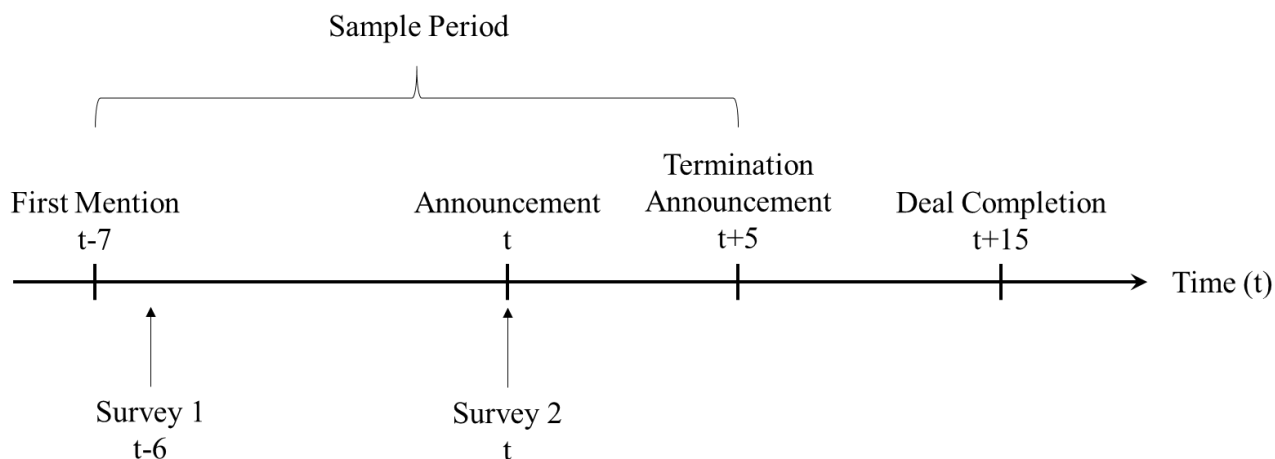


Figure 3.1. Sample Period and Timeline of Merger-related Events

Note: This figure provides a graphical illustration of the timeline for the occurrence of all merger-related announcements. The table below provides the list of all SEC filings that were filed on date (t) (i.e. the merger announcement date).

As illustrated in Figure 1, the actual merger was only completed 15 months after the RENT-initiated merger announcement date and involved a long-running bidding process including a second company-wide announcement by RENT to pull out of the merger at ($t+5$). Considering the first management-initiated merger announcement and the long-running bidding process until the finalization of the merger, the actual deal completion date of the merger in ($t+15$) only constitutes outdated news for firm insiders. We compare the annual reports that were filed in the time period covering the entire bidding process, and confirm that the annual report issued subsequent to the merger announcement date (t) exhibits the highest frequency of mentions regarding the merger relative to the annual report issued immediately before the deal completion date ($t+15$).¹³ Moreover, Figure 1 also lists relevant merger-related SEC filings that were filed with RENT's merger announcement. These firm-related disclosures provide corroborating evidence that the announcement date (t) is associated with the most heightened

¹³ Frequent references to the merger include mentions in the introductory note, under potential risk factors and legal proceedings, and the management, discussion and analysis (MD&A) section.

expectations by firm insiders for the completion of the merger. In order to avoid confounding our analyses with the effects from the announcement to pull out of the merger, we end our sample period at $(t+5)$.

The merger event considered in this study is a friendly merger where no drastic changes in RENT's management was expected. The only effective change resulting from the merger was a change in ownership of the target firm. All operations of the target firm were maintained under its own brand name such that customers did not experience a *de facto* change in their service experience for RENT rental cars. Employees of the target firm experienced some changes to assimilate operational procedures with those at RENT which included for example, the merging process of customer membership data. Most importantly for our study, employees employed at RENT did not experience any changes in their daily operations, and in their contractual employment relationship with the firm.

3.3.3. Proxy for Employee Alignment: Employment Engagement Survey

RENT implements employee surveys to gauge employee-level engagement with the strategic directions at the management-level. Specifically, it includes survey items that directly ask for employees about their satisfaction with regards to the implemented organizational changes.¹⁴ All employees are asked to provide a score between one and five (where five constitutes the highest level of agreement). Using the results from the survey items that specifically ask employees about their agreement related to the implemented organizational change (hereafter, "Alignment Score"), we distinguish between store locations with employees that exhibit relatively higher or

¹⁴ For the purpose of this study, we are interested in gauging employee alignment with the implemented changes at the organization. Therefore, we focus only on the survey items asking employees specifically about the change. An example of such a survey item would be "I understand the reasons for change." Due to confidentiality reasons associated with the identity of our research site, we are not able to disclose the full survey.

lower levels of alignment with the strategic directions of management. In particular, we partition the store locations based on the median Alignment Score.¹⁵ The employee engagement surveys were conducted every 6 months, and Figure 1 maps the timeline of the surveys into our sample time period. We use the employee engagement survey results in the same month, but prior to the merger announcement date, and define *Alignment* as stores with above-median Alignment Scores.

Our research site provides us with an ideal setting to measure employee alignment using a survey instrument at different stores within the same organization. The reason is that the airport store locations operate in isolated markets such that intra-firm spillover effects are non-existent. Employee survey data to proxy for implicit cultural aspects at individual store locations are problematic in organizations with frequent intra-store interactions among employees. The reason is that in such highly interactive settings, it is difficult to attribute the survey results to a particular individual store. The survey results in our setting are not subject to such caveats as employee interactions across stores are only minimal due to the geographical dispersion of the individual stores.

3.3.4. Employee Performance Measures

At RENT, employee performance is evaluated on two performance measures: sales-based upsell transactions, and customer satisfaction. The former (latter) is representative of a performance measure that is relatively more (less) sensitive, but less (more) congruent.

¹⁵ The results remain unchanged regardless of whether we partition the store locations based on the mean of all relevant survey items, or each individual survey item.

1.1.1 Upsell Transactions

An upsell transaction is defined as a transaction that generates more profit by soliciting the customer into an upgrade of his/her initial reservation. It is a transaction where the customer either upgrades his/her reserved car class or where the customer includes an add-on device such as a radio, GPS, and/or fuel. Therefore, an upsell transaction directly translates into higher revenues. Compared to customer satisfaction, upsell transactions are an indicator of employee performance over which employees have relatively more control (i.e. more sensitive). Yet, from management's perspective, upsell transactions are relatively more myopic in that they purely incent improving sales-based measures at the expense of customer satisfaction by potentially sacrificing customers' service experience. For instance, one frequent customer of RENT describes the tradeoffs by saying: "the top performer (in upselling) unfortunately is usually not the friendly one but usually the jerk who tries to scare people into buying insurance or gas or stretching to truth to convince the customer to get an upgraded car." Therefore, a discontinuous increase in upselling performance may be good for the company's short-term financial performance, but potentially detrimental to its long-term performance if it damages the brand image around superior customer service. We define the variable *Upsell* as a dummy variable equal to 1 for such Upsell transactions, and 0 otherwise.

1.1.2 Customer Satisfaction

Customer satisfaction is measured using a survey instrument whereby customers are asked to fill out a customer satisfaction survey with each rental experience. To complete the survey, customers are provided a hyperlink in one of two ways after they return the car: through email or on their printed receipt. Whereas it constitutes a leading indicator for future financial performance, it is a measure that is relatively less sensitive to the employee's effort levels as they

have relatively less control over customer perceptions than the actual sales numbers generated via upsell transactions. We define a variable *Overall Experience* which is the raw survey-based score for the survey item that asks customers about their overall rental experience. This raw survey-based score is used to create net promoter scores as a measure of customer satisfaction quality. It transforms the survey results into either one of three values, -100, 0, or 100 to represent “detractors”, “neutrals” and “promoters”, respectively. This measure translates RENT’s customer satisfaction surveys into comparable results with that of other competing rental car companies, and is, thus, primarily used by RENT in evaluating customer satisfaction quality for management control purposes. Accordingly, we base our main measure for customer satisfaction on the net promoter score, and construct a dummy variable *Will Recommend* that is equal to 1 if the net promoter score is in the most satisfactory “promoter” category, and 0 otherwise.

3.4. Identification Strategy

First, to examine whether unexpected career concerns are associated with significant incentive effects (H1), we test whether performance significantly improves subsequent to the merger announcement. Exploiting the monthly panel data structure of 111,078 transaction records with survey responses from 81 locations over a 12-month time period, we estimate the following regression model:

$$Y_{iejt} = Location_i + Employee_e + \beta_1 \cdot Merger\ Announcement_t + X_j' \gamma + \epsilon_{ijt} \quad (1)$$

The dependent variable, Y_{iejt} , is either one of the three employee performance measures: *Upsell*, *Overall Experience*, or *Will Recommend*. $Merger\ Announcement_t$ is a dummy variable that equals to one for the months following the merger announcement, and zero otherwise.

$Location_i$ are location-fixed effects, and $Employee_e$ are employee-fixed effects. X_j constitute

various transaction-level and survey-level covariates. These variables include *Duration* which measures the length of the car rental in days; *Weekend* which is a dummy variable that equals one if the car rental was made on a weekend, and zero otherwise; *Membership* which is a dummy variable that equals one if the car rental was made by a customer who has a membership with RENT, and zero if not; and *Business* which is a dummy variable that equals one if the car rental was made for business purposes, and zero otherwise. We also include several categorical variables that control for car types and booking channels. We do not include time-period fixed effects as they would subsume our coefficient of interest β_1 on *Merger Announcement_t* which captures the incremental performance following the merger announcement. In other words, we conduct pre-announcement and post-announcement comparisons around the merger announcement to evaluate how unexpected career concerns affect employee behaviors.

Such pre-post comparisons may be subject to several empirical threats. While imperfect, in this study we conduct several robustness tests to provide more corroborating evidence on the effects of unexpected career concerns. First, to minimize any temporal trends, we use relatively short study periods. Second, we distinguish between store locations where employees are more or less likely to be subject to the merger-related career concerns. We define a variable *Less Risk* that indicates airport store locations at which RENT employees presumably face less layoff risks due to the merger announcement which are airports at which the target rental car company has no operating store location. *Less Risk* is defined as one for such locations, and zero otherwise. If career concerns from potential consolidation is the main driver to changes in employee behaviors, then we expect that the effect should be much smaller in locations without target rental car company stores. To examine whether the merger announcement-related performance

effects are driven by store locations where the unexpected career concerns are more predominant, we estimate the following equation:

$$Y_{iejt} = \text{Merger Announcement}_t + \text{Location}_i + \text{Employee}_e + \beta_2 \cdot \text{Merger Announcement}_t \times \text{Less Risk}_i + X_j' \gamma + \epsilon_{ijt} \quad (2)$$

After establishing that unexpected career concerns affect employee performance, we then move to H2 and examine whether effort allocation tendencies differ depending on the extent of employee alignment. We employ a difference-in-differences research design, and compare locations with different levels of employee alignment *prior to* the merger announcement. We use the degree of employee alignment *prior to* the announcement to avoid reverse causality, because the actual merger announcement may affect both the level of management-employee alignment and employee behavior simultaneously. Another advantage of employing DiD design is that we can avoid measuring a potential spurious relationship that may arise due to the organizational change and the associated management practice over the relevant time period. For instance, the expectation of having to consolidate the customer memberships at RENT and the target firm prior to the merger may affect employee behaviors during our sample period. A simple temporal comparison cannot distinguish the effect of the merger announcement on employee behaviors from the effect due to such changes in associated management practices. However, by including location- and time-fixed effects together, we can rule out such possibility.

We estimate the difference-in-differences specifications using the following model:

$$Y_{iejt} = \text{Location}_i + \text{Employee}_e + \text{Year-Month}_t + \beta_3 \cdot \text{Merger Announcement}_t \times \text{Alignment}_i + X_j' \gamma + \epsilon_{ijt} \quad (3)$$

The dependent variable, Y_{iejt} , is the same as in the above regressions. The location fixed effects, Location_i , control for time-invariant, location specific characteristics, the time-period

fixed effects, $Year-Month_t$, control for any time-specific effects affecting all locations equally during the sample period, and the employee-fixed effects, $Employee_e$, control for any employee-specific characteristics. $Merger\ Announcement_t$ is a dummy variable that equals to one for the months following the merger announcement, and zero otherwise. $Alignment_t$ is a dummy variable that equals to one for airport store locations with above-median Alignment Scores, and zero for airport store locations with below-median Alignment Scores. The transaction-level and survey-level covariates X_j are the same as above. The coefficient of interest is β_3 which is the coefficient on the interaction term $Merger\ Announcement_t \times Alignment_t$. It captures the differential response of the employees in high- and low- $Alignment$ locations to the merger announcement.

3.5. Results

3.5.1. Descriptive Statistics

Table 1 provides overall summary statistics of our data across all airport store locations. As shown in Panel A, there are a total of 81 major US airport store locations in our sample. The mean Alignment Score across all stores is 3.89. A histogram that graphically illustrates the distribution of stores on the Alignment Score is provided in Figure 2.

Our performance data are at the transaction-level for car rentals at all 81 major US airport store locations over the relevant sample time period, and constitute a total of 111,078 rental car transactions. Panel B of Table 1 summarizes the rental car transaction-related characteristics.

Table 3.1. Summary Statistics

Statistic	N	Mean	Std. Dev.	Min	Max
Panel A: Location					
Alignment Score	81	3.890	0.467	2.667	4.824
Panel B: Transaction					
Duration	111,078	4.019	4.376	0	91
Weekend	111,078	0.220	0.414	0	1
Membership	111,078	0.743	0.437	0	1
Business	111,078	0.345	0.475	0	1
Upsell	111,078	0.409	0.492	0	1
Panel C: Customer Satisfaction Survey					
Overall Experience	111,078	6.976	2.548	0	9
Net Promoter Score	111,078	43.344	79.371	-100	100
Will Recommend	111,078	0.626	0.484	0	1
Staff Courtesy	99,689	7.826	1.906	0	9
Speed of Service	99,688	7.305	2.466	0	9
Vehicle Condition	99,687	7.262	2.420	0	9
Billing as Expected	99,677	7.609	2.376	0	9
Value for Money	99,675	6.911	2.334	0	9

Note: This table provides the summary statistics of variables used in this study across all locations, or rental car transactions. Panel A reports the statistics on the location-specific variable *Alignment Score*. It refers to the average score on all change-related survey items in the employee engagement survey. Panel B and C report summary statistics on the transaction-level characteristics. *Duration* measures the length of the car rental in days; *Weekend* is a dummy variable that equals one if the car rental was made on a weekend, and zero otherwise; *Membership* is a dummy variable that equals one if the car rental was made by a customer who has a membership with RENT, and zero if not; and *Business* is a dummy variable that equals one if the car rental was made for business purposes, and zero otherwise. *Upsell* is a dummy variable that equals one if the rental car transaction qualifies as an Upsell transaction. Upsell transactions generate more profit by soliciting the customer into an upgrade of his/her initial rental car reservation. *Overall Experience* is the raw score from the customer satisfaction survey on the item “Overall Experience” and can range from zero to nine. *Net Promoter Score* is the raw score that the company uses to evaluate customer satisfaction, and is either -100, 0, or 100. *Will Recommend* is a dummy variable that equals to one if the raw *Net Promoter Score* is 100, zero otherwise. *Staff Courtesy*, *Speed of Service*, *Vehicle Condition*, *Billing as Expected*, and *Value for Money* are raw scores on each of the corresponding customer satisfaction survey items.

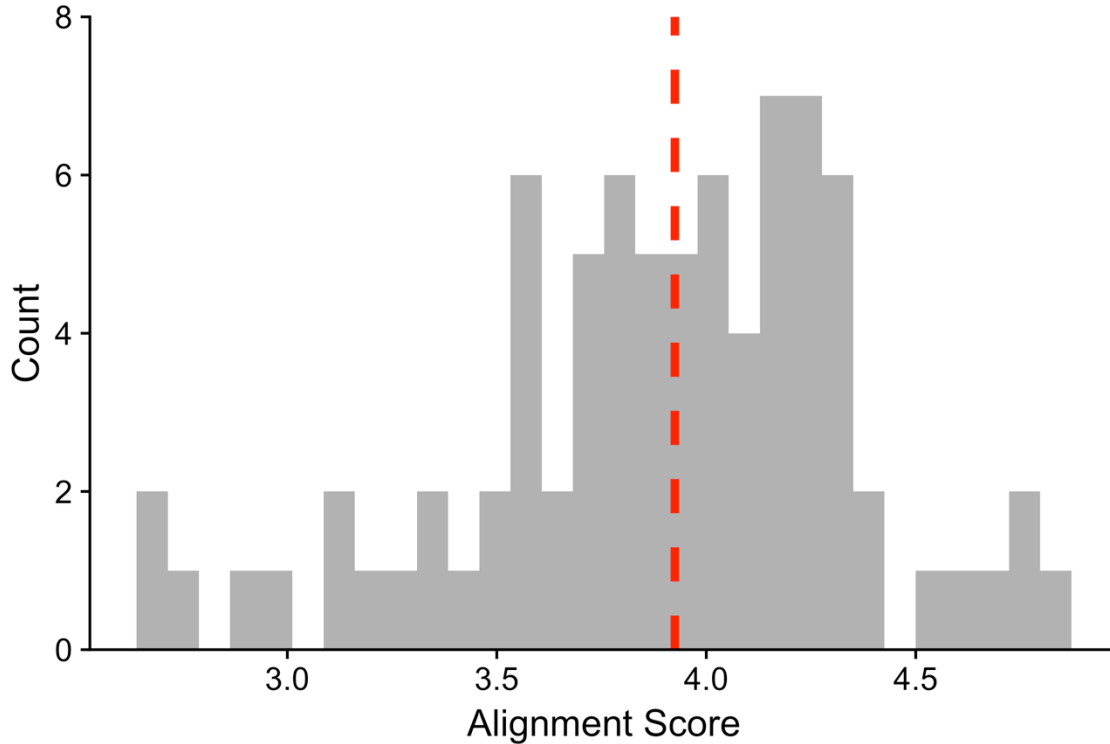


Figure 3.2. Histogram of Alignment Score

Note: This figure provides the histogram for all change-related survey items (i.e. Alignment Score) in the employee engagement survey across all stores in our sample. The X-axis represents the Alignment Score which can range from one to five. The Y-axis represents the number of stores at each score bracket on the X-axis.

From the variable *Duration*, we observe that the average duration between pick-up and return of the rented vehicle constitutes about 4 days. The variable *Weekend* indicates that about 22% of all transactions are made on a weekend, the variable *Membership* shows that about 74% of all transactions were made by RENT membership holders, and the variable *Business* shows that about 35% of all transactions were indicated to have been for business purposes. About 40% of all transactions constitute upsell transactions.

In Panel C of Table 1, we provide summary statistics on the customer satisfaction-related variables. The mean score on *Overall Experience* is about 7, and about 62% of all transactions are categorized into the most satisfactory “promoter” category. Panel C also provides the

summary statistics for the raw scores for each of the subcomponents in the customer satisfaction survey. These include “staff courtesy”, “speed of service”, “vehicle condition”, “billing as expected”, and “value for money”.

Table 2 provides the summary statistics for our main variables of interest separately for high-Alignment and low-Alignment store locations to ensure that there are no significant fundamental differences between these two location types that may impact our empirical results for our second hypothesis. The summary statistics provide confidence that both store location types are comparable in terms of their underlying operation characteristics.

Table 3.2. Comparisons between High and Low Alignment Locations

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: High-Alignment Locations					
Alignment Score	40	4.255	0.223	3.943	4.824
#Transactions	40	100.820	84.620	22.427	354.006
Upsell	40	0.356	0.083	0.056	0.521
Overall Experience	40	6.984	0.265	6.427	7.605
Will Recommend	40	0.625	0.041	0.530	0.728
Panel B: Low-Alignment Locations					
Alignment Score	41	3.534	0.353	2.667	3.925
#Transactions	41	131.736	99.590	15.384	421.575
Upsell	41	0.351	0.083	0.117	0.467
Overall Experience	41	6.938	0.284	6.153	7.565
Will Recommend	41	0.620	0.055	0.442	0.737

Note: This table compares High- and Low- Alignment locations, and provides key summary statistics separately across these two types of locations. High (Low)-Alignment locations are locations that scored above (below)-median on the change-related survey items. *Alignment Score* refers to the average score on all change-related survey items in the employee engagement survey. *# Transactions* reports the average number of total monthly rental car transactions. *Upsell* is a dummy variable that equals one if the rental car transaction qualifies as an Upsell transaction. Upsell transactions generate more profit by soliciting the customer into an upgrade of his/her initial rental car reservation. *Overall Experience* is the raw score from the customer satisfaction survey on the

item “Overall Experience” and can range from 0 to 9. *Will Recommend* is a dummy variable that equals to 1 if the raw *Net Promoter Score* is 100, 0 otherwise.

3.5.2. Incentive Effects

Table 3 presents our results on how employee performance is affected subsequent to the merger announcement from estimating equation (1). The dependent variables are *Upsell*, *Overall Experience*, and *Will Recommend* in columns 1 through 3, columns 4 through 6, and columns 7 through 9, respectively. The first two columns pertaining to each dependent variable vary in terms of the inclusion of fixed-effects. All specifications are estimated using OLS. Therefore, we interpret the estimated coefficients as marginal effects (Angrist and Pischke 2009; Ai and Norton 2003). Interpreting the second column with the inclusion of location- and employee- fixed effects, we observe that the likelihood of an upsell increases by 8.9 percent in the post-merger announcement period. Moreover, as shown in column 8, the likelihood for a rental transaction to be classified into the highest customer satisfaction category increases by 2.7 percent subsequent to the merger announcement. In columns 3, 6, and 9, we estimate the same regression model on a smaller time period window of six months which compares the three months prior to the three months after the merger announcement. Finding the effect over a smaller time period window allows us to attribute the effect more confidently to the merger announcement event as a large time period window is more likely to be convoluted by other events. The results provide corroborating evidence that the merger announcement is associated with the resulting performance improvements.

Table 4 provides the results from estimating equation (2), and provides another corroborating evidence that unexpected career concerns drive the performance improvements subsequent to the merger announcement. We estimate the model specification including all fixed effects, over a 12-months and six-months window in the first and second columns pertaining to

Table 3.3. Effect of Merger Announcement on Employee Performance

	Upsell (=1)			Overall Experience			Will Recommend (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Merger Announcement	0.088*** (0.006)	0.089*** (0.006)	0.066*** (0.008)	0.139*** (0.033)	0.157*** (0.030)	0.055* (0.028)	0.024*** (0.006)	0.027*** (0.005)	0.009* (0.005)
Duration	-0.002*** (0.0004)	-0.002*** (0.0005)	-0.002*** (0.001)	0.017*** (0.002)	0.019*** (0.002)	0.017*** (0.003)	0.002*** (0.0004)	0.002*** (0.0004)	0.002*** (0.0005)
Weekend	-0.009** (0.004)	-0.009** (0.004)	-0.005 (0.006)	-0.004 (0.022)	0.040* (0.024)	0.055* (0.029)	0.0001 (0.003)	0.007* (0.004)	0.015*** (0.005)
Business	-0.017*** (0.004)	-0.018*** (0.004)	-0.016*** (0.005)	-0.029 (0.021)	-0.058*** (0.022)	-0.040 (0.030)	-0.006 (0.004)	-0.011*** (0.004)	-0.008 (0.006)
Membership	-0.045*** (0.007)	-0.041*** (0.006)	-0.043*** (0.008)	0.448*** (0.040)	0.269*** (0.037)	0.226*** (0.050)	0.091*** (0.007)	0.057*** (0.006)	0.050*** (0.009)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sample Period (in Months)	12	12	6	12	12	6	12	12	6
Observations	111,078	108,558	56,233	101,973	99,713	51,624	101,973	99,713	51,624
Adjusted R ²	0.146	0.154	0.163	0.018	0.032	0.031	0.017	0.027	0.025

Note: Standard errors are clustered by locations, and presented in parentheses. All specifications are estimated by OLS. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

each outcome variable, respectively. Airport store locations that are relatively less subject to the merger-related layoff risks exhibit upsell performance declines as evidenced by the negative coefficient on the interaction between *Merger Announcement* and *Less Risk*. In other words, the documented performance improvements are primarily driven by store locations at which employees are more subject to unexpected career concerns. Such performance declines at *Less Risk* store locations are less evident when considering the customer satisfaction measures. The coefficient on the interaction term is only negative over the six-months window, and only significantly negative when considering the *Overall Experience* measure. The finding that upsell performance is more responsive to the merger announcement is consistent with it being a relatively more sensitive measure that the employee is more likely able to influence.

Table 3.4. Unexpected Career Concerns as Driver

	Upsell (=1)		Overall Experience		Will Recommend (=1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Merger Announcement	0.091*** (0.004)	0.067*** (0.005)	0.159*** (0.019)	0.067*** (0.023)	0.026*** (0.004)	0.009** (0.005)
Merger Announcement x Less Risk	-0.099*** (0.021)	-0.113*** (0.030)	0.022 (0.142)	-0.363** (0.156)	0.029 (0.023)	-0.009 (0.028)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period (in Month)	12	6	12	6	12	6
Observations	108,558	56,233	99,713	51,624	99,713	51,624
Adjusted R ²	0.154	0.163	0.048	0.041	0.028	0.025

Note: Standard errors are clustered by locations, and presented in parentheses. All specifications are estimated by OLS. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

3.5.3. Effort Allocation Effects and Employee Alignment

So far our results show that performance increases on both measures – the sales-based measure *Upsell* and customer satisfaction – subsequent to the merger announcement. In this section, we

examine whether there is variation in how employees allocate their effort in improving the sales-based measure relative to customer satisfaction. Specifically, we test if alignment induces employees to exert greater effort on the more congruent performance measure (i.e. customer satisfaction) relative to the more sensitive performance measure (i.e. *Upsell*). In other words, we examine whether employee alignment is a significant moderating factor that influences upsell performance relative to customer satisfaction subsequent to the merger announcement. The results are tabulated in Table 5. Panel A examines *Upsell* as the dependent variable, and Panel B examines the customer satisfaction-related performance measures as the dependent variable. Column 1 presents the baseline descriptive results without any fixed effects. Omitting the fixed effects allows for the estimation of the coefficients on *Merger Announcement* and *Alignment*. The estimated constant term, 0.367, indicates that before the merger announcement, the likelihood of an *Upsell* transaction is about 36.7 percent. The likelihood of an upsell increases about 10.7 percent after the merger announcement ($p < 0.01$). This finding is consistent with unexpected career concerns being associated positive incentive effects.

More importantly for the purpose of examining the moderating effect of employee alignment, the likelihood of an upsell starts to diverge significantly between high- and low-*Alignment* locations after the merger announcement. There are no significant differences between high- and low-*Alignment* locations before the merger announcement as shown by the insignificant coefficient on *Alignment*. However, following the merger announcement, high-*Alignment* locations are significantly less likely to engage in an upsell transaction than low-*Alignment* locations ($p < 0.01$) as evidenced by the negative coefficient on the interaction term, *Merger Announcement* \times *Alignment*. In other words, employees at high-*Alignment* locations are associated with an increase in the likelihood of an *Upsell* by 20 percent ($= (0.107 - 0.035) /$

Table 3.5. Moderating Effects of Employee Alignment

	Upsell (=1)			
	(1)	(2)	(3)	(4)
Constant	0.367*** (0.003)			
Merger Announcement	0.107*** (0.004)			
Alignment	0.005 (0.004)			
Merger Announcement x Alignment	-0.035*** (0.006)	-0.030*** (0.011)	-0.027** (0.011)	-0.029** (0.012)
Rent Duration			-0.002*** (0.0004)	-0.002*** (0.0005)
Weekend			-0.009** (0.004)	-0.008** (0.004)
Business			-0.019*** (0.004)	-0.020*** (0.004)
Membership			-0.045*** (0.007)	-0.041*** (0.006)
Other Controls	No	No	Yes	Yes
Location FE	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes
Employee FE	No	No	No	Yes
Observations	111,078	111,078	111,078	108,558
Adjusted R ²	0.009	0.034	0.149	0.157

Note: Standard errors are clustered by locations, and presented in parentheses. All specifications are estimated by OLS. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

0.367) whereas employees at low-*Alignment* locations are associated with an increase in the likelihood of an Upsell by 29 percent ($= 0.107 / 0.367$) after the merger announcement. The results from estimating the difference-in-differences specification including location-, and year-month fixed effects, are reported in column 2. The location fixed effects allows to control for unobservable factors that are correlated with some seasonality that may affect the likelihood of an upsell, and thus investigate the likelihood of an upsell within each location over time. The year-month fixed effects account for common time trends that affect all locations. Our new estimate on the interaction term confirms that high-*Alignment* locations are less likely to engage in an upsell transaction than low-*Alignment* locations in the post-period. We also report the results from the difference-in-differences specification that includes the additional transaction-level control variables (in column 3), and additional employee-fixed effects (in column 4). The direction and economic magnitude of the coefficient on *Merger Announcement* \times *Alignment* are comparable across all columns.

Panel B of Table 5 presents our results on how the merger announcement affects employee performance on the customer satisfaction-based measures. The dependent variable is *Overall Experience* in columns 1 through 4, and *Will Recommend* in columns 5 through 8, respectively. Columns 1 and 5 present the baseline descriptive results without any fixed effects. Following the merger announcement, we observe a significant 0.08 increase in the rating for *Overall Experience* (column 1), and a 1.3 percent higher likelihood for a rental transaction to be classified into the highest customer satisfaction category (column 5). Similar as in Panel A, we estimate a difference-in-differences specification to examine how customer satisfaction in high- and low-*Alignment* locations is differently affected subsequent to the merger announcement. We include location-, and year-month fixed effects (in columns 2 and 6), additional transaction-level

control variables (in columns 3 and 7), and additional employee-fixed effects (in columns 4 and 8). Again, there are no significant differences between high- and low-*Alignment* locations before the merger announcement as shown by the insignificant coefficient on *Alignment*. However, contrary to the results for *Upsell*, we observe that the coefficient on *Merger Announcement* \times *Alignment* is significantly positive across all columns which suggests that high-*Alignment* locations are significantly more likely to improve customer satisfaction than low-*Alignment* locations. The economic magnitude of the coefficients are comparable across all model specifications. For example, interpreting the results in column 4 we observe that high-*Alignment* locations experience a 2.7 percent ($= (0.083 + 0.107) / 6.965$) increase after the merger announcement, whereas low-*Alignment* locations experience only a 1.2 percent increase ($= 0.083 / 6.965$).

In additional tests tabulated in Table 6, we estimate column 4 of Table 5 Panel B using the raw scores of the different subcomponents in the customer satisfaction survey. Columns 1 through 5 use scores on the subcomponents “value for money”, “speed of service”, “billing as expected”, “staff courtesy”, and “vehicle condition” as the dependent variable, respectively. Whereas employees have control over dimensions such as “speed of service” or “staff courtesy” by taking less breaks, contemplating innovative ways to make the rental car process more time-efficient, and/or being more polite to customers; subcomponents such as “vehicle condition” and “billing as expected” are categories over which the employees at each airport store location do not have control over as they are managed centrally. The results show that the effect is primarily driven by the subcomponent “speed of service” which provides corroborating evidence that the observed improvements in customer satisfaction at high-*Alignment* locations are due to greater

effort exertion by employees to improve customer satisfaction subsequent to the merger announcement.

Table 3.6. Customer Satisfaction Subcomponents

	Value for Money (1)	Speed of Service (2)	Billing as Expected (3)	Staff Courtesy (4)	Vehicle Condition (5)
Merger Announcement x Alignment	0.074 (0.046)	0.198** (0.086)	0.061 (0.046)	0.047 (0.035)	0.021 (0.050)
Other Controls	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes	Yes	Yes
Observations	89,626	89,637	89,628	89,638	89,636
Adjusted R ²	0.013	0.026	0.028	0.017	0.019

Note: Standard errors are clustered by locations, and presented in parentheses. All specifications are estimated by OLS. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

In Table 7 we test for the lack of pre-trends (often described as the parallel trends assumption) by estimating the dynamic version of the difference-in-differences specification. To do so we interact *Alignment* with each of the individual time period dummies, and omit the month immediately prior to the merger announcement to test whether the high-*Alignment* locations and low-*Alignment* locations exhibit similar trends until the merger announcement. The dependent variable is *Upsell*, *Overall Experience*, and *Will Recommend* in column 1, 2, and 3, respectively. Figure 3 reproduces the same results as in Table 7 by plotting the estimated coefficients for each interaction over the entire sample period. Panel A plots the results for *Upsell*, and Panel B plots the results for *Will Recommend*. Consistent with the parallel trend assumption, we observe that the stores exhibit no significant performance differences in the months prior to the merger announcement, and that the effect is apparent only after the merger announcement.

To summarize, the empirical results provided in this section show that the merger announcement is associated with different effort allocation effects depending on the extent by which employees are aligned with the overall organizational objectives. Following the merger announcement, high-*Alignment* locations exhibit more improvements related to the customer satisfaction-based performance measures, but less improvement on the *Upsell* measure relative to low-*Alignment* locations. Collectively, these findings provide support for H2 that employee alignment can mitigate myopic employee incentives to fixate on short-term at the expense on long-term performance arising from incentives to minimize layoff risk when subject to unexpected career concerns.

3.6. Conclusion

This study examines incentive and effort allocation effects due to unexpected career concerns. We use data from a rental car company, and exploit an internal announcement by management regarding its intent for a horizontal merger as a source of heightened unexpected career concerns. We examine employee performance subsequent to the merger decision, and examine whether such performance effects vary depending on the degree of employee alignment. Employee performance is evaluated based on two measures: (1) a sales-based measure that is relatively

Table 3.7. Dynamic Moderating Effects of Employee Alignment

	Upsell (=1) (1)	Overall Experience (2)	Will Recommend (=1) (3)
(t-7) x Alignment	0.005 (0.018)	-0.035 (0.115)	-0.002 (0.019)
(t-6) x Alignment	0.003 (0.018)	-0.091 (0.087)	-0.038** (0.017)
(t-5) x Alignment	-0.001 (0.015)	0.052 (0.094)	-0.003 (0.015)
(t-4) x Alignment	-0.004 (0.017)	-0.015 (0.084)	-0.00001 (0.016)
(t-3) x Alignment	0.003 (0.019)	0.082 (0.126)	-0.007 (0.021)
(t-2) x Alignment	-0.009 (0.015)	-0.044 (0.112)	-0.006 (0.023)
(t) x Alignment	-0.031 (0.019)	-0.077 (0.119)	-0.014 (0.020)
(t+1) x Alignment	-0.046** (0.020)	0.078 (0.114)	0.001 (0.020)
(t+2) x Alignment	-0.047** (0.020)	0.017 (0.105)	0.009 (0.019)
(t+3) x Alignment	0.002 (0.020)	0.233** (0.113)	0.036** (0.017)
(t+4) x Alignment	-0.019 (0.019)	0.246** (0.119)	0.030* (0.018)
Other Controls	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Employee FE	Yes	Yes	Yes
Observations	108,518	99,675	99,675
Adjusted R ²	0.149	0.050	0.029

Note: Standard errors are clustered by locations, and presented in parentheses. All specifications are estimated by OLS. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

more reflective of immediate short-term financial performance, and (2) customer satisfaction which is relatively more reflective of intangible long-term performance. All existing formal management control channels remain constant over our sample period including the employee incentive contracts.

First, we document positive incentive effects associated with unexpected career concerns. Performance measures on upselling and customer satisfaction exhibit significant improvement subsequent to the merger announcement which suggests that unexpected career concerns trigger employee performance incentives to minimize potential layoff risks. Second, we document effort allocation effects associated with such unexpected career concerns. We find that greater employee alignment is associated with relatively greater levels of improvement in customer satisfaction, but not so in the sales-based performance measure. In other words, more aligned employees exhibit more willingness to trade-off improvements in customer satisfaction at the expense of immediate result in their sales-based performance measures. Taken together, these findings suggest that employee alignment can mitigate career concern-related myopic employee behaviors to fixate effort levels on relatively short term-oriented performance measures at the expense of decreasing effort levels towards more goal-congruent performance measures.

Our study contributes to a comprehensive understanding of performance incentives embedded in unexpected career concerns within organizations, and sheds new light on the benefits of employee alignment under periods of organizational change. Despite rapidly changing business environments, the management accounting literature has devoted limited attention on how to adjust existing management control systems in order to cope with organizational changes. Consistent with prior literatures stipulating the importance of employee alignment as an important complementary control mechanism to formal contracting channels,

our study proposes that creating a more aligned organizational culture can mitigate disruptions from misalignment between firm strategy changes and the associated management control system adaptations. We hope that such findings contribute to the literature on the optimal design of employee incentive systems, and particularly, the interplay between formal and informal management control systems during rapid organizational changes.

Like any empirical study, our study has several limitations. First, relying on rich administrative data from a single field site exposes our study to external validity concerns. This study examines the effects subsequent to a specific kind of organizational change, namely a management-level horizontal merger decision that may lead to corporate restructuring and layoffs. We do not claim that our findings can be generalizable to different kinds of organizational changes. Future research should examine other kinds of organizational changes to clarify important boundary conditions on whether and how the performances of incumbent employees are affected. Second, studies in this area should explore other means by which potential unintended consequences resulting from unexpected career concerns may be mitigated. This study proposes strengthening employee alignment as one such means. However, alternative means may also include *ex-post* adjustments to existing formal management control systems, and *ex-ante* inclusion of preemptive measures in the formal management control systems by which such potential unintended consequences can be mitigated.

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