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Who Should You Learn From? Theory and Evidence from the Videogame Industry

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by
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Ndatenda chose.

Tatenda Pasipanodya

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Abstract

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Knowledge spillovers can be a major driver of performance for those who successfully absorb them. This dissertation studies potential spillover recipients and characterizes how they may best benefit from the knowledge generated and possessed by their peers. Across three interconnected chapters, I examine whether the choice of peer whose spillovers a would-be recipient draws from affects the recipient's outcomes. My pursuit is guided by the overarching question: who should knowledge seekers target as ideal sources of new knowledge? I focus my investigation on the extent of a source's knowledge relative to the focal recipient – what I term knowledge distance – and study its relationship with the recipient's subsequent performance to understand how recipients accumulate knowledge, and how they should make decisions on who they attempt to learn from.

Chapter 1 uses as its foundations the body of R&D research in strategy and economics, and the body of research on interorganizational learning to construct a theory of who to learn from,

exploring the tradeoff between learning opportunity (the extent of potentially exploitable knowledge possessed by a source that an aspiring recipient stands to benefit from) and the recipient's capacity to effectively assimilate the knowledge possessed by a given source. I show that the answer to this dissertation's question of interest depends in large part on the functional form assumptions for assimilation capacity, and present two alternative models of spillover absorption that differ only in how I conceptualize assimilation capacity. In one model, spillover absorption is increasing in knowledge distance. In the second, there is an inverted U-shaped relationship between knowledge distance and spillover absorption.

Chapter 2 empirically evaluates the predictions from the two alternative models employing microdata on individuals embedded within eSports teams interacting in the competitive eSports game *Call of Duty: Warzone*. I find support for the second model, which suggests that there exists an optimal knowledge distance between any source and recipient pair that maximizes learning for the recipient. Chapter 3 extends these findings to a firm-level setting, examining the interfirm mobility patterns of individual developers in the computer and videogame development industry. Results are consistent with those in Chapter 2, and with the second model characterized in Chapter 1. The three chapters are all parts of a whole, and together connect ostensibly disparate theories and assumptions in the R&D spillovers and interorganizational learning literatures, and shed light on optimal learning behavior for would-be knowledge recipients.

Chapter 1

A THEORY OF WHO TO LEARN FROM

1.1 Introduction

Knowledge spillovers have emerged as a major driver of behavior and performance for knowledge seekers across settings and levels of aggregation. Research has widely documented their impact on productivity at the individual level (Boekhorst et al., 2022; Carrell et al., 2009; Chan et al., 2014; Levin & Cross, 2004) and the analogous benefits for teams (Bresman, 2013; Myers, 2021), startups (A. Chatterji et al., 2019; Dimitriadis & Koning, 2022; Mostafa & Klepper, 2018), and established firms (Alcácer & Oxley, 2014; Argote et al., 1990; Bloom et al., 2013; Kim & Miner, 2007; Knott & Turner, 2019; Miao et al., 2021). However, learning from the knowledge produced and held by external sources is not a costless process and necessitates concerted and directed effort. This is because knowledge is often complex, difficult to communicate, and inextricably linked with the source's routines and processes (Bhagat et al., 2002; Garud & Nayyar, 1994; Inkpen & Tsang, 2005). Further, there is an opportunity cost to consider – learning is a path-dependent process, and the knowledge, routines, and processes one invests in may foreclose alternative paths of knowledge development (Cohen & Levinthal, 1990). For these reasons, it is crucial for research to establish and characterize who knowledge seekers should target for this effort.

To that end, this dissertation examines the following question: who should knowledge seekers be targeting as ideal sources of new knowledge? I primarily focus on the extent of a source's knowledge relative to the focal knowledge seeker, a dimension that may hold important implications for the literatures on learning and innovation. Specifically, I study the impact of a source's relative level of knowledge – which I term *knowledge distance* – on the recipient's future performance to understand how recipients absorb knowledge possessed by their peers. Scholars have explored this relationship across a variety of settings. Research looking at the performance outcomes of individuals and teams has found that performance is increasing in the quality of peers one engages with (Chan et al., 2014; A. Chatterji et al., 2019; Hasan & Koning, 2019). R&D research in strategy and economics has reached similar conclusions, and suggested that knowledge seekers face greater opportunity for learning when they draw from peers that are more distant – i.e., much more superior – in the extent of their knowledge (e.g., Alcácer & Oxley, 2014; Knott, 2003). Under this view, the more knowledge-rich the peer, the greater the pool of potentially exploitable knowledge the knowledge seeker is exposed to.

In light of this, we may expect knowledge seekers to naturally gravitate to sources situated near the knowledge frontier. However, work examining how individuals endogenously form peer groups suggests a preference for knowledge sources of proximate quality (Carrell et al., 2013). Consistent with this, work anchored in the interorganizational learning school (Cohen & Levinthal, 1990; Lane et al., 2001; Lane & Lubatkin, 1998; Miao et al., 2021) emphasizes the role of dissimilarity between a source and recipient in inhibiting successful knowledge flows. Knowledge possessed by a more dissimilar source may simply be too incompatible with the knowledge seeker's routines and structures, thereby prohibiting successful acquisition and assimilation. In this sense, knowledge recipients may have a greater capacity to successfully learn when they draw from peers that are only marginally or moderately superior in knowledge.

Given these apparently conflicting perspectives, my investigation in this dissertation seeks to explore the tradeoffs pertinent to knowledge distance from potential sources. My inquiry starts in the current chapter with the body of prevailing empirical work across disciplines and builds on it by developing a theoretical model which explores the process of spillover absorption. I characterize a simple computational model of spillover absorption in which two underlying mechanisms jointly drive successful learning: the opportunity presented by a potential source's wealth of knowledge and the knowledge seeker's capacity to effectively assimilate that knowledge. I conceptualize assimilation capacity as either *independent* – meaning a knowledge seeker's ability to successfully learn from a given source is a function of the knowledge seeker's own characteristics and is independent of the source's characteristics – or *relative* – meaning a recipient's ability to learn from a source depends at least in part on characteristics of the source. The former characterization follows Cohen and Levinthal's (1990) concept of absorptive capacity, while the latter reflects an attenuation effect of knowledge distance and draws from Jaffe (1986), Lane et al. (2001), Lane & Lubatkin (1998), and others. My theory suggests these two ways of characterizing the construct generate diverging predictions for this paper's question of interest. In one scenario, knowledge absorption is increasing in knowledge distance, albeit at a diminishing rate. In another, knowledge absorption is increasing in knowledge distance only up to a point, thereafter falling with additional marginal increases in knowledge distance.

In Chapter 2, I empirically test the model's predictions, drawing from the cross-disciplinary literature on individual peer effects. I investigate whether and how the performance of an individual depends on the relative ability of the peers with whom they interact. I exploit granular performance data from a unique team-based eSports setting in which individuals are randomly assigned to peers groups to test how knowledge distance from one's peers impacts knowledge diffusion. This setting offers two key advantages over prior work investigating peer-based learning. First, it approximates an ideal experiment as it is characterized by plausibly random variation in peers. Second, it takes advantage of a uniquely large sample size, which allows for greater internal and external validity. In Chapter 3, I extend my predictions to a firm-level setting, inferring the flow of knowledge across firms by exploring the mobility patterns of workers within the videogame development industry.

To my knowledge, this dissertation is the first research effort to model and empirically test for the non-monotonic relationship between peer quality and knowledge absorption. On account of this, I am able to not only unpack the process of spillover absorption, but also demonstrate that the process may not be as straightforward as it has been empirically modelled in prevailing research. While my primary goal is to characterize this process, my empirical exercises by extension also enable an exploration of assimilation capacity, including what the appropriate functional form for the construct should look like. Consistent with some prior work, my results across all three chapters suggest that knowledge absorption from peers is on average increasing in knowledge distance when the peers in question possess a greater wealth of knowledge than the knowledge seeker. However, I find that this positive association is an incomplete characterization, as evidenced by the presence of an inverted U-shape in the relationship. An implication is that knowledge seekers may benefit from employing a 'Goldilocks' approach to knowledge source selection – eschewing knowledge sources that are too similar or too distant in favor of those from whom they have a moderate extent of knowledge distance. My analysis in Chapter 2 further finds that though knowledge seekers may learning from competitive ties with their knowledge sources, most spillover absorption occurs when knowledge seekers and their peers share collaborative ties.

The three chapters in this dissertation contribute to a large and varied literature on learning in organizations and teams, including research on R&D spillovers (Alcácer & Chung, 2007; Bloom et al., 2013; Jaffe, 1986; Jaffe et al., 1993; Knott et al., 2009; Shaver & Flyer, 2000), interorganizational learning (Argote et al., 1990; Argote & Ingram, 2000; Cohen & Levinthal, 1990; Lane & Lubatkin, 1998; Levin & Cross, 2004), individual peer-effects (Carrell et al., 2013; Chan et al., 2014; Dimitriadis & Koning, 2022; Hasan & Koning, 2019; Mas & Moretti, 2009) and social networks (Borgatti & Cross, 2003; Fleming et al., 2007; Ingram & Roberts, 2000; Liebeskind et al., 1996; Reagans & McEvily, 2003; Sosa, 2011). Specifically, this dissertation has several important implications. To my knowledge, this is the first set of studies to explicitly decompose the strategic value of peer knowledge into the learning opportunity and assimilation capacity, thereby characterizing and testing the tradeoffs of knowledge distance. By consolidating theoretical and empirical insights from the R&D spillovers, organizational learning, and individual peer effects literatures, I provide an important refinement to our understanding of spillover absorption. For practitioners, this research proposes a strategic approach to learning from peers that may encourage optimal knowledge accumulation. More broadly, my findings also build on and inform wide-ranging research into social learning (Gagnon-Bartsch & Bushong, 2023; Heyes, 2012; Kim & Miner, 2007; Park & Puranam, 2023; Rendell et al., 2011), advice-giving and advice-taking (Bonaccio & Dalal, 2006; Brooks et al., 2015; A. Chatterji et al., 2019; Naborn et al., 2023; Tost et al., 2012; Yaniv & Milyavsky, 2007), and team learning (Myers, 2021; Vashdi et al., 2013; Wilson et al., 2007).

The rest of this dissertation is structured as follows. The balance of Chapter 1 draws heavily upon various bodies of work to develop a framework of the antecedents to peer knowledge absorption and to uncover a crucial tension inherent in prior work concerning my question of interest. The chapter explores the tension further by way of a simple computational model and thereby sharpens this framework, advancing testable hypotheses on the relationship between knowledge distance and absorption of peer knowledge. Chapter 2 tests the model's predictions using microdata on individuals interacting in the eSports game *Call of Duty: Warzone*, complementing empirical analysis with qualitative data covering individuals in this eSports setting. Finally, Chapter 3 carries the theoretical predictions from the present chapter and the empirical findings from Chapter 2 to a firm-level setting, examining the knowledge-sourcing behaviors of videogame development firms and the consequent performance outcomes.

1.2 Background

To what extent does prevailing research offer theoretical foundations that may inform this paper's question of interest? I present here a theoretical framework that combines insights gleaned from the learning and R&D literatures, as well as the work on individual peer-based learning, to understand how knowledge distance between a knowledge seeker and a potential knowledge source impacts the knowledge seeker's future performance through spillover absorption.

1.2.1 Knowledge diffusion and performance

The notion that knowledge seekers can improve performance by drawing on the spilled-over knowledge of peers is well established. Research in the interorganizational learning tradition has documented how knowledge diffusion across firm boundaries may generate performance benefits for the recipient (Argote & Epple, 1990). Some early work suggests that knowledge acquired through direct experience transfers across firms to benefit recipients with no prior direct experience themselves (See for instance Argote et al., 1990). Empirical work in the R&D literature has likewise produced evidence that firms in knowledge-intensive industries benefit from the research conducted by their peers through spillovers (Bloom et al., 2013; Griliches, 1991; Jaffe, 1986).

Research into individual-level peer-based learning has also reached consistent findings. Chan et al. (2014) examine collocated salespeople in the cosmetics section of a large department store and find strong evidence for peer-based learning: the productivity trajectory of individual salespeople is more strongly shaped by the peers with whom they work than by own learning-by-doing. The authors find that learning took place through a combination of direct instruction – knowledgeable salespersons showing their more novice counterparts the ropes – and through observation of the behaviors and techniques of better-performing salespersons. In the same vein, Papay et al. (2020) study an intervention on classroom teachers that temporarily pairs low-skilled teachers with more proficient peers and find that the low-skilled teachers experience improved job performance following the intervention, measured by way of students' test score growth.

Prevailing work points to two underlying factors that govern successful knowledge absorption: (1) how much external knowledge exists to be transferred to the aspirant recipient in the first place, and (2) how capable the recipient is to actually acquire and assimilate the knowledge from the source with whom it currently resides. On the one hand, a source endowed with larger quantities of knowledge offers greater *opportunity* for potential knowledge transfer to take place than one endowed with smaller quantities. On the other hand, the recipient's assimilation capacity – that is, the extent to which they can effectively exploit this opportunity– depends on the recipient's base of prior knowledge and how well it fits with the external knowledge to be acquired.

1.2.2 Learning opportunity, assimilation capacity, and spillover absorption

Prevailing research suggests that knowledge-rich peers act as catalysts for performance improvements for knowledge seekers. They possess knowledge, both explicit (patented technologies, trade secrets, blueprints, etc.) and tacit, or process-embodied (routines, processes, human capital, organizational structure, etc.), which generates opportunities for spillover absorption for others whom they encounter (Argote & Ingram, 2000; Kogut & Zander, 1992). The magnitude of these opportunities – which I broadly refer to in the present paper as *the learning opportunity* generated by interacting with a peer and, in particular, with their knowledge – is a direct consequence of the quantity and quality of new and diverse knowledge possessed by the peer (Chan et al., 2014; Knott, 2003; Stuart, 2000).

If the learning opportunity a peer's stock of knowledge represents were the only consideration, then it would naturally follow that knowledge seekers should always seek to draw from the most knowledge-rich peers available to them. However, learning opportunity may not be the only consideration. A peer's surfeit of knowledge may also serve as a barrier for spillover absorption for a knowledge seeker. To successfully leverage external knowledge to their advantage, a knowledge seeker must be able to comprehend and assimilate the knowledge, which requires literacy in both the knowledge itself as well as the routines and processes that govern it. Sources that are sufficiently advanced may be fundamentally different from the knowledge seeker in their routines, structures, and heuristics, such that the very processes in which their knowledge is embedded, and the ways in which it is articulated internally, are far beyond the knowledge seeker's understanding and ability to exploit the knowledge. As a result, the same knowledge-rich peers who present bountiful learning opportunity for a knowledge seeker may also represent relatively inaccessible sources of knowledge. Efforts to assimilate knowledge from such sources are likely to be inefficient and counterproductive, squandering resources that could otherwise have been employed to learn through more effective channels. In the present chapter, I refer to this phenomenon by which spillover absorption attenuates with increasing dissimilarity between a knowledge seeker and their potential source as the knowledge seeker's assimilation capacity relative to that source. That is, a knowledge seeker's assimilation capacity denotes the extent to which they are capable of effectively exploiting the learning opportunity they face when interacting with a knowledge source and their knowledge. A consequence is that, all else equal, source-recipient pairs that are more similar in the extent of their knowledge will be more compatible, and thus better able to learn from each other. The greater the knowledge distance from a potential source – that is, the higher the relative knowledge of the source – the more difficult it will be for a recipient to evaluate, comprehend, and acquire the source's knowledge.

Several concepts across the various disciplines studying individuals, teams, and organizations are consistent with the concept of assimilation capacity. At the individual level, research in developmental psychology posits the idea of a zone of proximal development,[1] which represents the range of knowledge which learners can effectually assimilate given the support of more knowledgeable individuals, such as teachers, mentors, or superior peers (Allal & Pelgrims Ducrey, 2000; Vygotsky & Cole, 1978). See Figure 1.1 for an intuitive illustration of this concept. While learners can independently develop new knowledge in an incremental fashion if the new knowledge is relatively unsophisticated compared to the learners' current knowledge and abilities, the development of more sophisticated knowledge – that which fall under the zone of proximal development – is a much more difficult proposition independently, but can be facilitated by drawing on more knowledgeable others. Beyond the zone of proximal development, however, even the assistance or influence of others with superior knowledge is insufficient for effective learning to take place. This is because the knowledge to be acquired or built in this case is beyond the learner's current ability to understand.

In the organizational learning literature, Cohen & Levinthal (1990) posit the concept of absorptive capacity, which is related but not identical to assimilation capacity. The authors argue that for a knowledge seeker to exploit external knowledge, they must possess the ability to absorb this knowledge in the first place. Successful recognition and valuation of new external knowledge,

[1] Originally introduced by Russian psychologist Lev Semyonovich Vygotsky. See (Vygotsky & Cole, 1978)

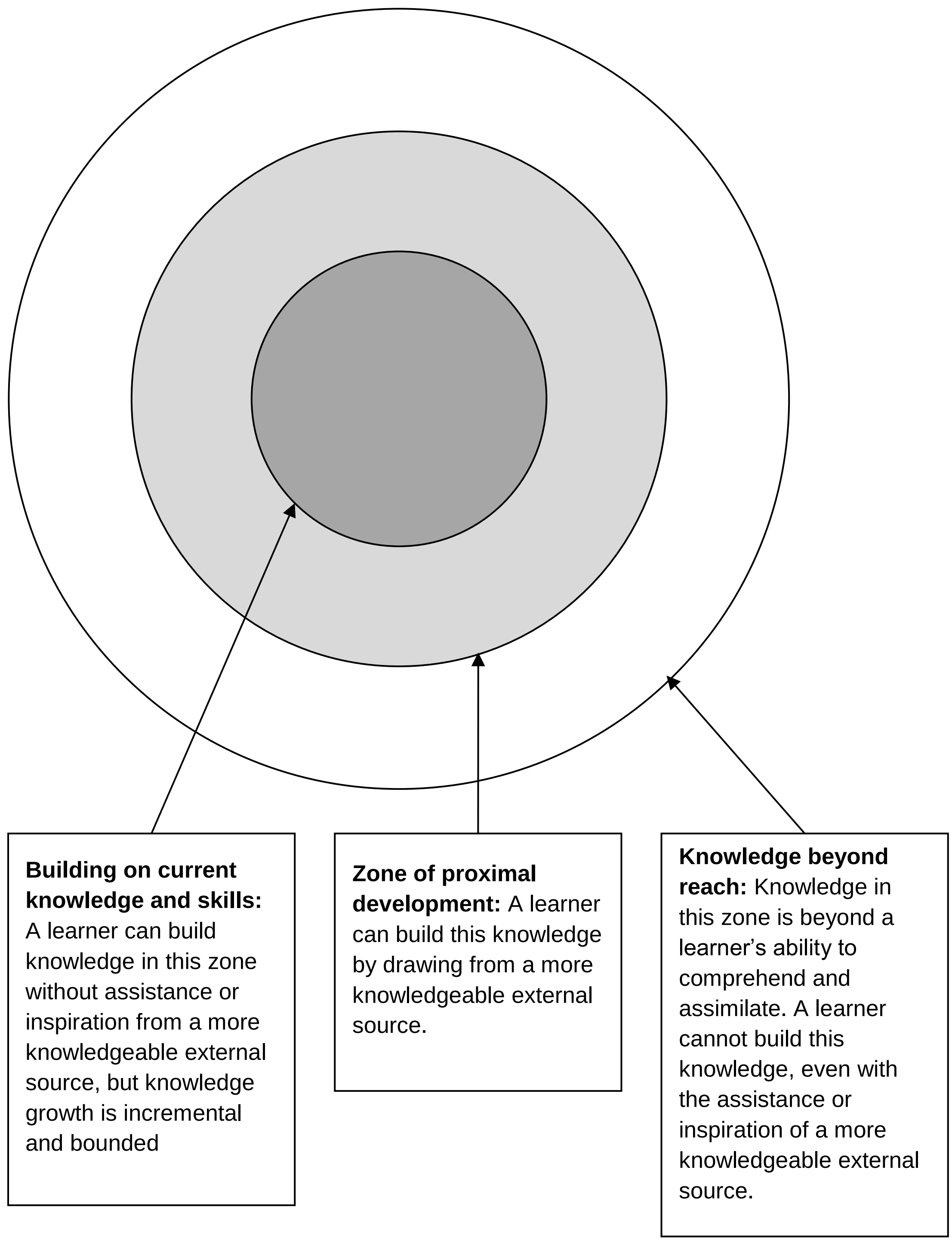


Figure 1.1 Vygotsky's zone of proximal development.

as well as the subsequent assimilation and exploitation, require a strong base of prior knowledge. Further, the authors argue that not all knowledge is equally relevant or easily assimilated. Both the complexity of the knowledge and the degree to which it is targeted to the knowledge seeker's needs and concerns impact the ease of successful assimilation. This reasoning suggests that the opportunity to absorb a peer's knowledge is not sufficient for successful absorption to take place. The knowledge recipient must also possess the capacity to absorb and assimilate such knowledge.

Unlike assimilation capacity, which is informed by the relative characteristics of the knowledge seeker and knowledge source, seminal work on absorptive capacity narrows its attention to the characteristics of the knowledge recipient. Here, the knowledge to be assimilated is taken as being more or less in the air, with little reference made to the relevance of the specific knowledge source.

Related theoretical models in economics posit that knowledge transfer attenuates with distance between a source and knowledge seeker along multiple dimensions, including the extent to which the prior knowledge of the knowledge seeker and potential source are related (Bloom et al., 2013; Jaffe, 1986). Relatedness between a knowledge seeker and a potential source in technology space facilitates both the recognition by the knowledge seeker of exploitable technological opportunities, thereby encouraging spillover absorption efforts, as well as the existence of a shared language between the source and knowledge seeker, which enables effective spillover absorption. Consistent with these models of spillover absorption, some work within the management literature has redefined an organization's absorptive capacity as a source-dependent construct, rather than one that is informed only by the characteristics of the learning organization, as in the construct's original conception. Proponents of this approach argue that since knowledge is often context-specific (Szulanski, 1996; Zahra & George, 2002), shared skills, languages, and cognitive structures between the source and recipient enable knowledge absorption. As a result, a knowledge seeker will be better able to learn from a source when the two have compatible routines, norms, cognitive structures, and dominant logics (Lane et al., 2001; Lane & Lubatkin, 1998). This compatibility, they argue, is fostered by the extent to which the source and recipient are similar (Camisón & Forés, 2010; Lane & Lubatkin, 1998; Mowery et al., 1996).

1.3 Modelling spillover absorption

Taken together, the preceding discussion generates a tension that warrants further exploration. On the one hand, the opportunity for absorption is increasing in knowledge distance. On the other hand, the extent to which a knowledge seeker is able to effectively capitalize on this opportunity is tempered by their assimilation capacity, which may depend on the knowledge distance between the source and recipient.

We can therefore conceptualize this paper's relationship of interest as a tension between two latent or functions which jointly determine how knowledge distance between a knowledge seeker and a potential source impacts the successful diffusion of knowledge from the source to the knowledge seeker (See an illustration in Figure 1.2 below).

To understand how this tension resolves and consequently draw hypotheses on this paper's central question, we must consider the two underlying constructs concurrently. To this end, I develop a simple computational model that approximates the knowledge upgrading process for knowledge seekers. This is a model of learning through random interactions that explicitly considers the influence of both opportunity and assimilation capacity. I conceptualize learning – that is to say knowledge accumulation – as the outcome of a combination of accumulated experience and spillover absorption through one-off interactions with peers. In every period, knowledge seekers engage with peers of varying quality and improve their knowledge position by

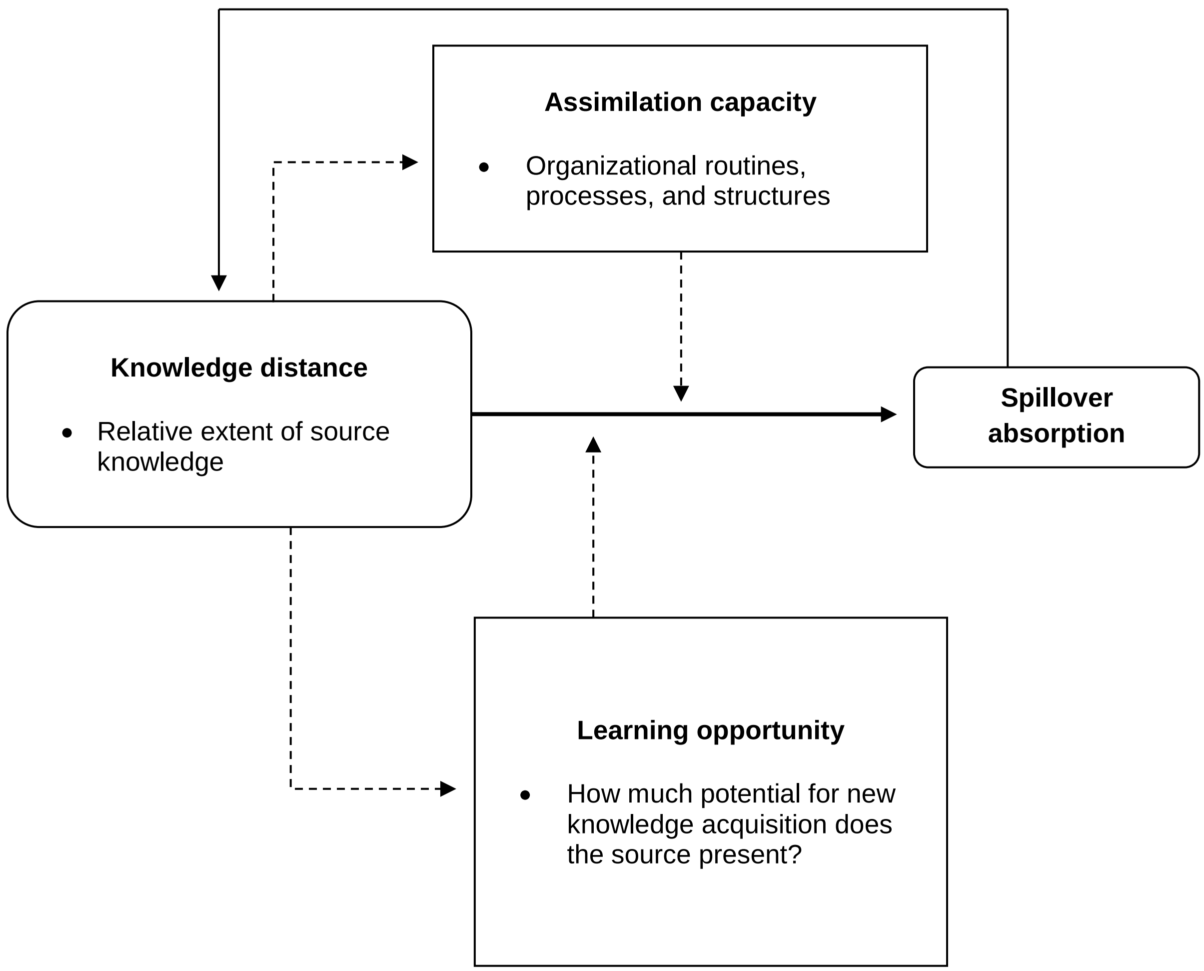


Figure 1.2 Model of spillover absorption with opportunity and assimilation capacity.

Note: This figure illustrates the tension underpinning this dissertation's theory. An increase in learning opportunity naturally follows from any increase in knowledge distance, meaning greater knowledge distance increases the potential for new knowledge to be absorbed by the knowledge recipient. However, for this potential to be effectively realized, the recipient must possess sufficient assimilation capacity, which may also depend on the knowledge distance between the knowledge source and knowledge recipient. Consequently, realized spillover absorption is a product of the tradeoff between learning opportunity and assimilation capacity.

accumulating more experience as well as by drawing on the knowledge of better-endowed peers. A given peer may be further along or behind on the knowledge frontier relative to the knowledge seeker. Additionally, their knowledge distance from the knowledge seeker – the extent to which their knowledge position is superior, or inferior, to the knowledge seeker's – may vary greatly.

Consistent with prior work on learning through spillovers (e.g., Knott & Turner, 2019), I assume knowledge seekers are boundedly rational, in that they can only interact with and potentially learn from a single peer in a given period. Further, they are not able to identify ex-ante which peers offer the greatest likelihood of successful knowledge absorption, and so the model randomly pairs knowledge seekers with peers in every period. Knowledge seekers in this model have identical routines in that they undergo identical knowledge upgrading processes. They differ only in the specific knowledge environments in which they are embedded and in their initial knowledge endowments.

1.3.1 Model parameters

In the model, the knowledge seeker and their interactions are characterized by four basic parameters – the knowledge seeker's innate ability or learning rate, their initial endowment of knowledge, the extent of knowledge in their environment, and the extent to which the nature of their interaction with a given peer is conducive to successful spillover absorption. The first three are fixed and the fourth may be viewed as peer-dependent.

The first parameter, the knowledge seeker's innate ability, $\delta_i \in [0, 1]$, specifies the extent to which the experience they accrue in any period results in the creation of new knowledge. This parameter captures the notion that knowledge seekers are heterogeneous in their ability to effectively learn from their own experience: , $\delta_i = 0$ corresponds to a complete inability to learn from one's experience, and $\delta_i = 1$ corresponds to the ability to perfectly translate a unit of experience into a new unit of knowledge. The inclusion of δ_i is consistent with findings that suggest that individuals, organizations, and even industries vary greatly in the rates at which they learn, as well as in the rates at which they are able to convert effort into innovations (Argote et al., 1990; Balasubramanian & Lieberman, 2010; Knott, 2008; Lieberman, 1984; Salomon & Jin, 2010).

The second parameter, the knowledge seeker's initial endowment of knowledge is defined by $y_{i,t=0}$.While one's stock of knowledge in each period is determined by their cumulative experience and spillover absorption in prior periods, their initial endowment$y_{i,t=0}$, is exogenously drawn from a uniform distribution in the range $[0, 50]$. The third parameter, the extent of knowledge in a knowledge seeker's environment, $\overline{y}_{-i}$, defines the average quality of the mix of peers with whom the knowledge seeker may interact. The intent behind this parameter is to reflect heterogeneity in the opportunity environments knowledge seekers may find themselves in, and its inclusion follows research highlighting the importance of knowledge-rich environments as prime sources of new knowledge for aspiring knowledge recipients (See for example Alcácer & Chung, 2007; Almeida, 1996; Roche, 2020; Saxenian, 1994; Shaver & Flyer, 2000)

The population of peers one interacts with is specified by independently drawing values of peer knowledge endowment from a normal distribution with a mean equal to $\overline{y}_{-i}$. Finally, the extent to which the nature of an interaction between the knowledge seeker and their peer is conducive to successful knowledge absorption, $\varphi_{i,j,t} \in [0, 1]$, is intended to reflect several otherwise unaccounted for conditions of the interactions with one's peers that make knowledge diffusion more likely in one way or another. These may include how involved the interaction is, or the extent to which it is collaborative as opposed to hostile. Note that a description of all parameters and characteristics employed in the model is summarized in Table 1.1.

Table 1.1 Model characteristics

Parameters	
Learning rate, or innate ability (δ_i)	Knowledge seeker's learning-by-doing capability
Knowledge endowment ($y_{i,t=0}$)	Knowledge seeker's initial stock of knowledge
Mean peer knowledge ($\bar{y}_{-i}$)	Extent of knowledge spillovers available in a knowledge seeker's environment
Learning context ($\varphi_{i,j,t}$)	Extent to which the nature of a knowledge seeker's interaction with a potential source fosters spillover absorption
Other characteristics	
Opportunity ($\xi_{i,j,t}$)	Amount of potentially exploitable knowledge a knowledge seeker is exposed to in an interaction with a potential knowledge source
Assimilation capacity ($\alpha_{i,j,t}$)	Knowledge seeker's ability to comprehend and effectively absorb peer knowledge
Knowledge stock ($y_{i,t}$)	Knowledge seeker's knowledge stock
Peer knowledge stock ($y_{j,t}$)	Stock of knowledge held by knowledge seeker's peer
Knowledge gain ($\Delta y_{i,j,t}$)	Knowledge accrued by knowledge seeker

1.3.2 Opportunity and assimilation capacity

In addition to the parameters just described, knowledge seekers and their interactions in the model are also defined by two key characteristics: learning opportunity, $\xi_{i,j,t}$, and assimilation capacity, $\alpha_{i,j,t}$. As these two are central to the present paper's research question, and their specific functional forms are pivotal determinants of the propositions the model generates, it is important to be intentional about how the constructs are assembled. Learning opportunity is simple enough to conceptualize, given the extent of potentially exploitable knowledge a knowledge seeker is presented with in a specified peer interaction can be readily conceived of as the quantity of excess knowledge the peer possesses. Thus, I define $\xi_{i,j,t}$ as follows: a knowledge seeker, i, interacting with potential knowledge source j in period t faces a learning opportunity that takes the form:

$$\xi_{i,j,t} = \begin{cases} y_{j,t} - y_{i,t}, & \text{if } y_{i,t} - y_{j,t} < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{1.1}$$

where:

$\xi_{i,j,t}$ represents the learning opportunity presented by an interaction with j in period t,

$y_{i,t}$ represents i's prior knowledge stock in period t, and

$y_{j,t}$ represents peer j's prior knowledge stock in period t.

In keeping with prior research (e.g., Knott et al., 2009; Stuart, 2000), Equation (1.1) embodies the key assumption that opportunity is weakly positive – that is to say the flow of knowledge is unidirectional, from superior to inferior peers, and when the knowledge seeker's stock of knowledge is greater than the potential source's, no valuable new knowledge is available for the knowledge seeker to exploit. It is important to note that realized values for $\xi_{i,j,t}$ in the model are influenced by $\overline{y}_{-i}$, the extent of knowledge present in the knowledge seeker's environment. Larger values of $\overline{y}_{-i}$ mean the knowledge seeker is more likely to interact with peers offering greater opportunity for knowledge absorption, in much the same way a firm located in a highly agglomerated and knowledge-intensive locale will experience greater opportunity to exploit spillovers.

Knowledge seekers are also characterized by their assimilation capacity, $\alpha_{i,j,t}$, whose specific form is a more complex consideration. $\alpha_{i,j,t}$ is governed primarily by the knowledge seeker's own prior knowledge level, $y_{i,t}$, but depending on how one conceptualizes assimilation capacity, it may also depend on $y_{j,t}$, the prior knowledge level of the peer. The manner and extent to which assimilation capacity and knowledge distance might relate is likewise a subtle matter warranting greater exploration. As it happens, the precise way in which we conceptualize assimilation capacity is key in determining this relationship. In a broad sense, assimilation capacity may be conceptualized as being similar to absorptive capacity in its original Cohen & Levinthal (1990) conception, where it is solely informed by the learning unit's prior knowledge level and is not context-dependent, or as being more akin to a distance-based attenuation of knowledge transferability, similar to the redefined conception of absorptive capacity by Lane & Lubatkin (1998), where a learning unit's ability to draw from external knowledge sources is informed by the *relative* knowledge between the learning unit and their sources and attenuates with greater dissimilarity. I define the former as *absolute assimilation capacity* and the latter as *relative assimilation capacity.* I characterize the absolute assimilation capacity of a knowledge seeker, i, interacting with knowledge source j in period t as:

$$\alpha_{i,j,t}^{Absolute} = y_{i,t}, \tag{1.2}$$

where *Absolute* indexes the absolute form of assimilation capacity. In the model, the measure is normalized by the theoretical upper bound of $\overline{y}_{-i}$. 'Absolute' in the context of our model refers to the notion that the knowledge seeker has a given level of assimilation capacity that does not change based on where the spilled-over knowledge has originated. Another way to think about this is to say that the knowledge itself is independent enough from its original creator, and perhaps discrete enough, that its successful diffusion from one individual to the next – or one firm to the next – can occur without consideration of the routines, processes, complementary knowledge, and idiosyncrasies of the creator.

A hypothetical omnipotent observer attempting to increase a given knowledge seeker's assimilation capacity can thus achieve this end simply by increasing the extent of the knowledge seeker's prior knowledge; altering the extent of the potential knowledge source will have no effect on the aspiring recipient's ability to assimilate the source's knowledge.

I characterize, a knowledge seeker's relative assimilation capacity with regard to a given potential source as increasing proportionally with its own prior knowledge level and, likewise, inversely proportional with the source's level of knowledge. This form of assimilation capacity may be characterized for a knowledge recipient i interacting with a potential source j in period t as:

$$\alpha_{i,j,t}^{Relative} = \frac{y_{i,t}}{y_{j,t}}, \tag{1.3}$$

where *Relative* indexes the relative form of assimilation capacity.

This chapterr's model takes a conservative approach and separately employs each of the two characterizations of assimilation capacity while remaining agnostic on the question of which one is most appropriate. I construct the model of spillover absorption in two alternative ways, each differing from the other only in how I characterize the functional form for the construct. The empirical estimations, presented in Chapter 2 and 3, serve as critical tests of these functional forms and provide suggestive evidence on how researchers should conceive assimilation capacity.

1.3.3 Knowledge accumulation through spillovers and own experience

Now we may turn to a discussion of the model's outputs. The goal of the computational exercise is to understand how the extent of a knowledge seeker's knowledge evolves as a function of the characteristics of the peers with whom they interact. I therefore take as the primary output of interest the knowledge accumulated by a knowledge seeker in their peer interactions. The model assumes that knowledge seekers can amass new knowledge through two basic mechanisms – by accumulating direct experience or by drawing on the accumulated knowledge of better-endowed peers. The amount of knowledge gained in a given period through direct experience is a function of the knowledge seeker's ability to convert experience into expertise. That is, normalizing the amount of experience accrued in a given period to 1, for knowledge seeker, i, in a given period, t, knowledge gained through direct experience is characterized as:

$$\Delta y^E_{i,t} = \delta_i, \tag{1.4}$$

where E indexes direct experience. The amount of knowledge accumulated through absorbing peer knowledge is characterized as:

$$\Delta y^S_{i,j,t} = \begin{cases} \varphi_{i,j,t}\alpha_{i,j,t}\xi_{i,j,t}, & \text{if } y_{i,t} - y_{j,t} < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{1.5}$$

Where S indexes spillover absorption. Total knowledge gained is thus equivalent to:

$$\Delta y_{i,j,t} = \begin{cases} \delta_i + \varphi_{i,j,t}\alpha_{i,j,t}\xi_{i,j,t}, & \text{if } y_{i,t} - y_{j,t} < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{1.6}$$

1.3.4 Analysis procedure

The model is analyzed using a Monte Carlo simulation programmed in Mathematica. The simulation procedure begins with defining the knowledge seeker and their environment by initializing the time-invariant parameters learning rate, δ_i, knowledge endowment, $y_{i,t=0}$, and mean peer knowledge, $\overline{y}_{-i}$. With these initial conditions set, the following sequence of events is repeated for fifty periods. The knowledge seeker engages with peers in their environment. In each period, they are able to interact with a single peer from whom they may or may not successfully learn. The simulation defines the player's peer in a given period by drawing the extent of the peer's knowledge from a normal distribution with exogenously defined mean equal to $\overline{y}_{-i}$ and a standard deviation of 200. A lower bound of 1 is set for the distribution to avoid instances where a peer possesses negative knowledge, as well as instances where a peer possesses 0 units of knowledge, which would result in undefined values for the relative form of assimilation capacity. The values of an individual interaction's $\varphi_{i,j,t}$ are uniformly distributed in the range 0 to 1 and are independently drawn for each knowledge seeker-peer pairing. The simulation then defines the values in a given period for opportunity and assimilation capacity following the rules outlined in Equations (1.1) to (1.3). All characteristics and parameters, as well as the knowledge generated in a period according to Equations (1.4) to (1.6) are recorded and stored in a comma-delimited data file. Following this, the knowledge seeker may proceed to the next period and to their next interaction, carrying with them their potentially updated stock of knowledge.

At the end of the fifty-period run, the procedure terminates, and a new set of initial conditions is drawn, allowing for a new knowledge seeker and peer population. For the sake of robustness, the simulation is run for four thousand unique knowledge seekers, each engaging with a different randomly set population. The model is analyzed under two separate assimilation capacity regimes defined according to Equations (1.2) and (1.3), with two thousand knowledge seekers for each of the two functional forms of assimilation capacity. The resulting data are summarized in Table 1.2 and are analyzed in the following subsection.

1.3.5 Model analysis and hypothesis

The data from our simulation are analyzed using panel regression. Recall that the wider goal of this exercise is to form testable hypotheses on how opportunity and assimilation capacity jointly influence the relationship between knowledge distance and realized absorption of peer knowledge. A collateral but no less important goal is to more directly examine the different functional forms of assimilation capacity that have been presented and utilized extensively in management research.

In particular, I believe it is fundamental to understand in a more definite sense what predictions the different forms of assimilation capacity compel.

Table 1.2 Simulation data summary

	Mean	Std. dev	Min	Pctl(25)	Median	Pctl(75)	Pctl(95)	Maximum
Parameters								
Learning rate, or innate ability (δ_i)	0.502	0.293	0	0.244	0.506	0.760	0.953	1
Knowledge endowment ($y_{i,t=0}$)	25.041	14.789	0	12	25	38	48	50
Mean peer knowledge ($\bar{y}_{-i}$)	251.143	143.815	0	500	251	376	474	500
Learning context ($\varphi_{i,j,t}$)	0.501	0.289	0	0.252	0.501	0.750	0.950	1
Other characteristics								
Opportunity ($\xi_{i,j,t}$)	99.669	162.121	0	0	0	157.434	460.626	1256.16
Assimilation capacity ($\alpha_{i,j,t}$)	1499.271	12295.920	0	0.606	3.759	283.552	907.049	549498
Knowledge stock ($y_{i,t}$)	290.971	238.640	0	73.745	237.637	467.428	731.773	1182.27
Peer knowledge stock ($y_{j,t}$)	270.712	214.712	0	81.671	250.616	420.737	655.519	1284.27
Knowledge gain ($\Delta y_{i,j,t}$)	9.292	22.771	0	0.431	0.826	6.203	50.805	531.484

Observations = 300,000; Knowledge seekers = 6,000.

Figure 1.3 plots a binned scatter of the relationship between knowledge distance between knowledge seekers and their peers in the model and the knowledge gained from period-to-period. The two panels present basic predictions on the joint impact of opportunity and capacity on this relationship. Knowledge growth is on average increasing in knowledge distance under both assimilation capacity regimes, reflecting the positive impact of opportunity. A difference emerges between the two as knowledge distance continues to increase. While the link between knowledge distance and knowledge accumulation under an absolute assimilation capacity regime, though diminishing, appears to persist even with peers approaching the knowledge frontier, the same cannot be said for the relative regime. In the latter, the relationship is characterized by an inverted

U shape – knowledge accumulation appears to increase in knowledge distance only for peers from whom the knowledge seeker has low to moderate knowledge distance, while decreasing for peers approaching the knowledge frontier.

Table 1.3 presents a clearer look at these relationships. I use a fixed effects quadratic model of knowledge accumulation on knowledge seeker and peer characteristics. Model 1, which presents results for the absolute assimilation capacity regime suggests that knowledge accumulation is largely an increasing function of knowledge distance. There is also a modest but significant effect on the quadratic knowledge distance term, suggesting the relationship is diminishing and possibly even inverted U-shaped. Model 2 present results for the relative capacity regime and suggests both a positive linear knowledge distance term and a negative quadratic term, once again pointing at either a diminishing or inverted U-shaped relationship. Both models also suggest that own experience and learning context are important considerations for knowledge accumulation.

I conduct a further test to explore the two assimilation capacity regimes. Quadratic regressions, though useful, are a notoriously insufficient tool for reliably diagnosing non-monotonic relationships. They are vulnerable to both Type I and Type II errors. For instance, under certain circumstances, a clearly monotonic relationship may be significantly detected as inverted U when relying primarily on quadratic regression. Figure 1.4 presents an example – the monotonically increasing function $f(x) = 10 + \log(x)$, which is illustrated here for the values of $x \in [0, 200]$, yields both a positive linear and negative quadratic coefficient, with a plot of the fitted values intimating an inverted U relationship (see panel (b) of the figure). However, as panel

(a) *Absolute Assimilation Capacity*

(b) *Relative Assimilation Capacity*

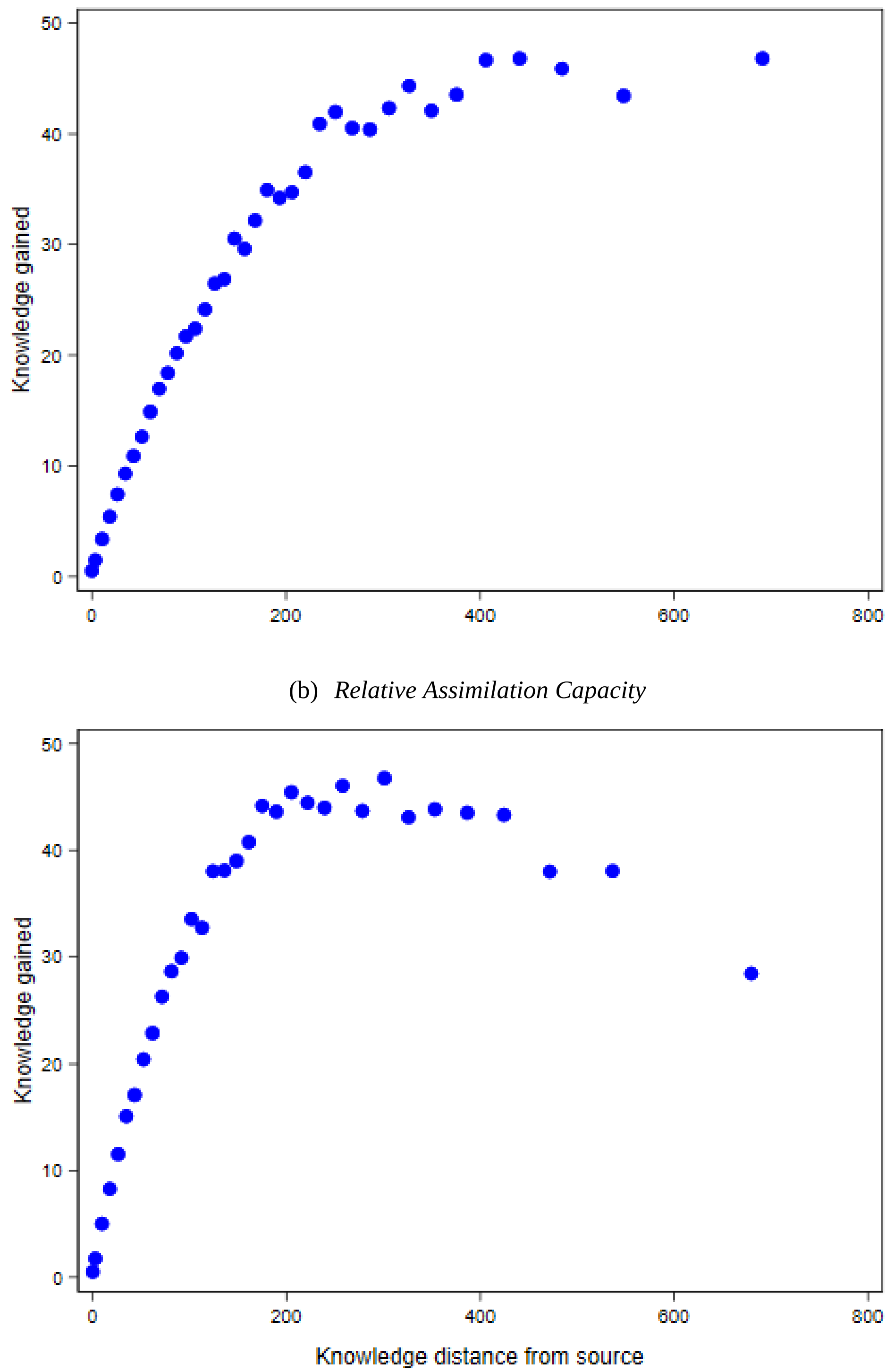
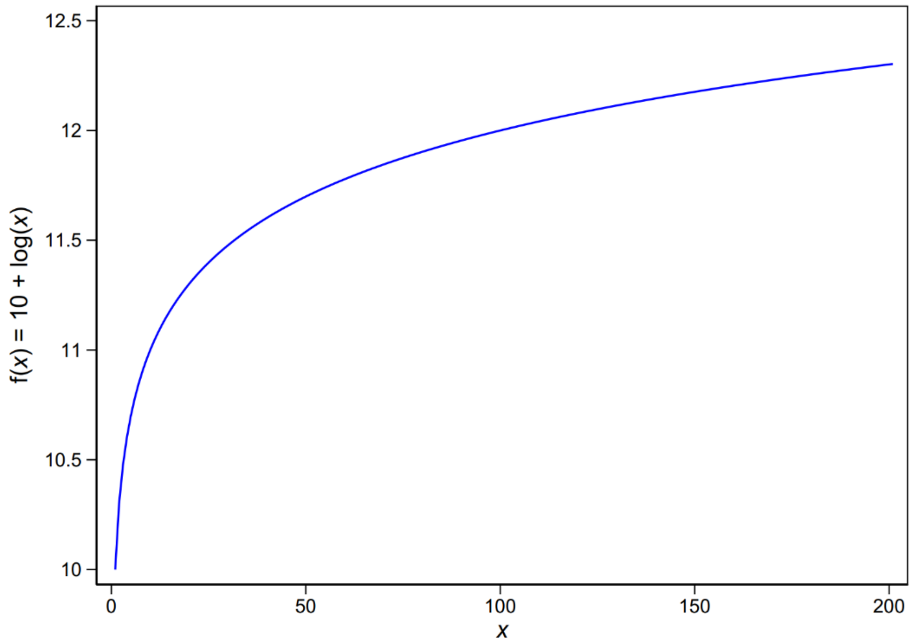


Figure 1.3 Knowledge distance and spillover absorption.

Note: This figure plots for the two forms of assimilation capacity binned scatters for knowledge distance from peers and the knowledge gained in a period by a knowledge seeker.

(a) *True relationship:* $f(x) = 10 + \log(x)$



(b) *Fitted values from quadratic regression*

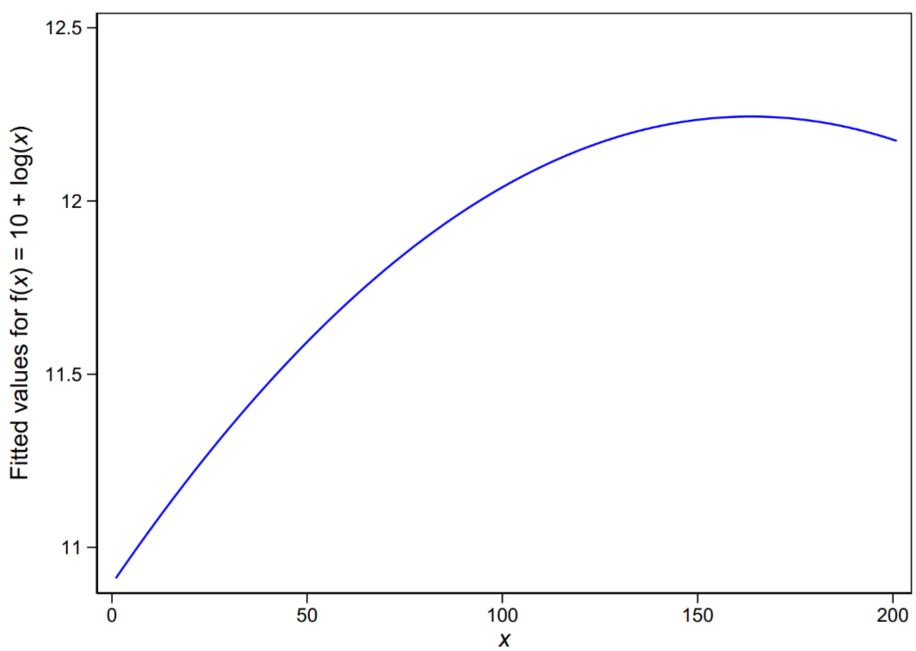


Figure 1.4 Example of a non-inverted U-shaped relationship.

Note: This figure plots the relationship $f(x) = 10 + \log(x)$. Panel (a) plots the true shape of the relationship in the range $x \in [0, 200]$, showing a monotonic but plateauing relationship. Panel (b) plots the shape of the relationship according to a quadratic regression, which misdiagnoses the existence of an inverted U.

(a) – or, in fact, a quick back-of-the-envelope calculation – would suggest, at no values of x is this function decreasing.

In light of this, I carry out the two-lines test interrupted regression using break points set according to the Robin Hood algorithm outlined in (Simonsohn, 2018). Results are shown in Table 1.4. A brief primer on the two-lines test: the intent is not to pin down a line of best fit, but rather to diagnose the existence – or not – of an inverted U anywhere within the range of values present in the data. This is done by segmenting the data at carefully selected thresholds, or 'break points', and estimating two regression lines – one for low values of the regressor and one for high values – so as to identify the average effect within each segment. The subscript *low* in Table 1.4 denotes values of knowledge distance below the break point and the subscript *high* denotes values greater than the break point.

Table 1.3 Knowledge distance and knowledge accumulation

	Absolute assimilation capacity (1)	Relative assimilation capacity (2)
Dependent variable: log(*Knowledge gain*)		
log(*Knowledge distance*)	0.976***	1.430***
	(0.006)	(0.005)
log(*Knowledge distance*)^2	-0.039***	-0.116***
	(0.001)	(0.001)
Experience	0.017***	0.009***
	(0.000)	(0.000)
Learning context	0.925***	0.864***
	(0.009)	(0.008)
Knowledge seekers	2,000	2,000
Number of observations	100,000	100,000

Knowledge-seeker FEs in all models.

The results for model 1 suggest that knowledge accumulation in our model's absolute assimilation capacity regime is increasing in knowledge distance – insofar as the coefficient on

$\log(Knowledge\ distance_{low})$ is positive and significant. However, as the coefficient on $\log(Knowledge\ distance_{high})$ is insignificant, there is no indication of an inverted U-shaped relationship in this case. These results suggest that under a regime where assimilation capacity is absolute, the amount of knowledge a knowledge seeker may successfully absorb from a potential source is an increasing function of the relative knowledge of the source. Knowledge-rich sources offer greater opportunity for learning but do not appear inaccessible to knowledge recipients. Thus:

> **Absolute assimilation capacity hypothesis.** *The extent of a knowledge recipient's knowledge absorption is increasing in the recipient's knowledge distance relative to the peers from whom they learn.*

Table 1.4 Two-lines test for inverted U

	Absolute assimilation capacity (1)	Relative assimilation capacity (2)
Dependent variable: log(*Knowledge gain*)		
log(*Knowledge distance*)$_{low}$	0.878***	1.140***
	(0.006)	(0.007)
log(*Knowledge distance*)$_{high}$	-0.170	-0.772***
	(0.111)	(0.044)
Knowledge seekers	2,000	2,000
Number of observations	100,000	100,000

Controls and knowledge-seeker FEs in all models.

The picture is different when we consider the relative assimilation capacity regime, the results for which are presented in Model 2 of Table 1.4. Here, the linear and quadratic coefficients are significant and markedly similar in magnitude, though opposite in direction, indicating that an inverted U not only exists but is particularly appreciable. The results are consistent with the notion that a peer that is too near to the knowledge recipient presents little opportunity for new knowledge to be acquired, while one that is too distant, though offering greater opportunity, is too dissimilar from the aspiring knowledge recipient for the recipient to effectively acquire and integrate their knowledge. A model of knowledge absorption that conceptualizes capacity as being relative therefore prescribes a 'Goldilocks' approach to knowledge source targeting: peers that are too near or too distant should be eschewed in favor of those that are only moderately distant. Thus:

> **Relative assimilation capacity hypothesis.** *The extent of a knowledge recipient's knowledge absorption has a curvilinear (inverted U-shaped) relationship with the recipient's knowledge distance relative to the peers from whom they learn.*

Chapter 2

LEVERAGING PEER KNOWLEDGE: EVIDENCE FROM THE INTERACTIONS OF ESPORTS PLAYERS

In Chapter 1, I developed a theoretical framework that outlines the tradeoffs inherent in knowledge distance, and thereby formed testable predictions on the impact of knowledge distance from peers on spillover absorption. In the present chapter, I conduct an empirical test of the framework, evaluating both the impact of knowledge distance and the appropriate functional form for assimilation capacity. Chapter 2 is structured as follows. Section 2.1 outlines my research setting; Section 2.2 describes my methodology; Section 2.3 presents empirical results using microdata on the interactions of individuals embedded within eSports teams; Section 2.4 employs qualitative data to explore the mechanisms for knowledge absorption in my setting; finally, Section 2.5 offers a brief discussion and conclusion.

2.1 Empirical setting

In this section, I lay out my research setting as well as my empirical approach to investigating the relationship between knowledge distance and spillover absorption. In addition to gaining a better understanding of this relationship, my empirical exercise also acts as a critical test of the two functional forms of assimilation capacity that have been proposed and utilized in prevailing research.

Examining knowledge absorption—in particular, which of one's peers one should attempt to learn from—is an empirically challenging endeavor. First, it is often difficult to observe which peers have served as a knowledge recipient's reference group, barring a context where an externally observable direct link exists. At the firm level, prior work has often leveraged strategic alliances (Mowery et al., 1996), acquisitions or mergers (Ahuja & Katila, 2001), supply relationships (Alcácer & Oxley, 2014), and other such arrangements. The balance of existing research on peer-based learning or spillover absorption can generally only infer learning by way of indirect links between firms, like shared geography or patent citations. A second challenge, which holds even in the instances where a direct link can be observed by the researcher, is that who one learns from is typically endogenous: firms, business units, and even individuals often make active choices on who to draw knowledge from. As a result, it is difficult to disentangle treatment effects from self-selection effects. Third, studies of knowledge diffusion through peer interactions at the individual level are often characterized by small samples, undermining their internal and external validity.

Electronic Sports (eSports), or competitive online multiplayer games, offer a potential solution to these limitations. The professional eSports sector is a rapidly growing industry and has a worldwide audience of over four hundred million,[2] generating yearly revenues topping a billion dollars, according to 2022 estimates.[3] In many ways, eSports may be compared to other competitive sports settings such as basketball (Chen & Garg, 2018) and motorsport racing (Bothner et al., 2012; Hoisl et al., 2017), which have previously been employed to address questions relevant to management research. The industry has earned lucrative sponsorships from global brands like PepsiCo, Comcast Xfinity, and Adidas, and attracted large investments like Amazon's billion-dollar purchase of Twitch Interactive Inc., an online video streaming platform where players can broadcast and monetize gaming content for a global audience (MacMillan &

[2] *Source:* Statista (https://www.statista.com/statistics/1109956/global-esports-audience/), accessed January, 2022.
[3] *Source:* Newzoo (https://newzoo.com/resources/blog/the-esports-audience-will-pass-half-a-billion-in-2022-as-revenue-engagement-esport-industry-growth), accessed June, 2022.

Bensinger, 2014). Top professional eSports broadcasters – referred to as 'streamers' – can earn millions of dollars through tournament participation and broadcasting. Most recently, Félix Lengyel, known professionally as xQc, made headlines for signing a two-year $100 million dollar broadcast deal with online broadcasting platform, Kick, a contract that places him in the same conversation as top-ranking traditional professional athletes in sports such as basketball, football, and American football.[4]

Despite the growing prominence of this nascent industry though, studies exploring different aspects of eSports remain relatively scarce. In a heartening turn in recent years, scholars have called for more attention on this setting as an emerging context for management research, and have argued that the context offers a natural laboratory for testing theories of organizations (See for instance Clement, 2017). To this end, Ching et al. (2021) use eSports player data to study the performance of specialist project teams. Künn et al. (2021) use online tournament data from the internet chess platform *chess24* to study the effect of remote work policies on performance. Likewise, Clement, (2017) uses player data to examine how firms adapt to architectural change.

ESports settings are often characterized by thousands – and at times several millions – of individuals and teams interacting dynamically through a combination of collaborative and competitive linkages, making them a promising venue for studying team dynamics, among other things. Many, though not all, of the interactions are usually centered on achieving some defined objective, or set of objectives, for which individuals and teams accrue pecuniary or nonpecuniary rewards.

[4] *Source:* New York Times (https://www.nytimes.com/2023/06/16/business/twitch-kick-xqc.html/), accessed August, 2023.

This study will exploit a unique eSports dataset in which potential knowledge recipients are exogenously assigned to peers of varying ability. As the data allows for observation of interactions with both teammates and opponents, it bears some similarity to Chan et al. (2014), in which salespeople learn from both intra-firm and competing peers. The nature of interactions and learning in this setting may also be viewed as qualitatively comparable to interorganizational learning through cooperative links (e.g., joint ventures or acquisitions, where partners must coordinate extensively for the success of the joint enterprise) and competitive links (e.g., competition within industry clusters).

2.1.1 Call of Duty: Warzone

I test this paper's hypotheses using match-level data from the online game *Call of Duty: Warzone*, a leading strategy-based military simulator in which multiple small teams compete in a series of zero-sum altercations. The game was developed by the game studios Infinity Ward and Raven Software and published in March 2020 by Activision and later updated in November 2022. It boasts an estimated player base of 100 million, according to media sources,[5] with up to 300,000 concurrent players at a time and over 28.8 billion matches played at the time of writing.[6]

In each match, multiple teams are assigned to compete in a tournament-style manner, with only one team emerging as the ultimate victor. Engagements between opposing players and teams are zero-sum. The goal for each team is to use skill, game knowledge, in-game resources, and careful strategy to outmatch and eliminate as many opponent teams as possible. The more opponents and opponent teams your own team eliminates, the greater your team's chances of

[5] *Source:* VentureBeat (https://venturebeat.com/2021/04/20/call-of-duty-warzone-hits-100-million-downloads/), accessed January, 2022.
[6] *Source:* CallOfDuty.com (https://www.callofduty.com/content/atvi/callofduty/blog/web/en/home/2021/04/Incredible-Warzone-and-Game-Sales-Milestones.html/), accessed January, 2022.

emerging as the victor in the given match. One participant I interviewed encapsulated the format of a typical match quite concisely:

> The whole idea with *Warzone* is you drop into a battlefield. It's meant to simulate a battlefield on a bit of a massive scale. So you basically jump off a plane and you're parachuting into a battlefield…Teamwork and team coordination is paramount to succeeding. If you're not in a well-coordinated team, you are not going to do well, you're going to get eliminated pretty early on… [S]o, being able to communicate and share information with everybody on the team and respond very quickly is the strategy…Once we decide where we're going to land and we've stocked up on weapons and gear, the next thing that we decide is how do we want to position for the rest of the game. And if you understand the mechanics of *Warzone*, the battlefield continuously shrinks over certain time intervals. The battlefield will keep getting smaller and smaller and smaller, which forces all of the different teams into confrontations until only one team remains…So, a key decision we make early on is basically how we want to position for the rest of the game. That usually involves picking a strategic location where we might hide out, or deliberately getting into confrontations with other teams, or setting traps for other teams. (Participant 12)

Teams can adopt a slew of different strategies. A more brazen team may choose the high-risk strategy of directly confronting opponents. While this approach is more likely to lead to elimination, it also increases the likelihood of eliminating other teams, whose resources you can then loot and utilize, potentially resulting in having an upper hand in future confrontations. Alternatively, a more conservative team may shun confrontations altogether, positioning themselves in hidden locations to prolong their chances of making it further through the match. Other teams may also choose to position themselves carefully in strategic locations, such as high traffic areas, allowing them to engage other teams while holding the proverbial higher ground.

As with most strategy-based sports, performance in *Warzone* is based on a combination of factors: careful strategy, innate ability, and knowledge of the game and its intricacies. Differences across players in their knowledge of game mechanics, tactical engagements, and resource combinations are key factors defining heterogeneity in player outcomes. A given player's task can be viewed as the selection of a combination of resource-resource and resource-action bundles that maps onto the player's chance for a successful outcome in any given altercation with an opponent or opponent team. Prior to and during each match, players equip their in-game avatars with a collection of resources—weapons, specialized equipment, and abilities. A key consideration for players is that the "currency" with which one attains these resources is limited. For example, a player may only equip their in-game avatar with so many weapons. Similarly, though a player is able to customize their firearms with different equipment and attachments with the aim of optimizing performance, they are limited in the quantity and mix of equipment and attachments they may carry. Strategic trade-offs are an unavoidable part of the process of picking resources. As a result, a player's knowledge of the combinative advantages of specific resource bundles in specific tactical situations – in particular, how specific resource combinations complement their own skill level and playstyle – is key.

The relative advantages of individual resources and in-game actions, as well as the relative advantages of the various ways in which these resources and actions may be combined are typically unknown to new players. Such a player may uncover this knowledge through a steady process of trial-and-error, not unlike local search on a rugged landscape. They may try different combinations across matches, switching out individual elements until they arrive at a combination of resource-resource and resource-action bundles that approximates an optimum. More effectively, a player may also uncover this knowledge by observing peers within the game itself, drawing upon the peers' accumulated knowledge.

Match-making—the assignment of teammates and opponents—is exogenously carried out by the game's algorithm. When a given player chooses to play a match, they are placed in a queue with the approximately 300,000 concurrently active players. The game's match-making algorithm, which is designed to primarily minimize network connection delays between players, then assigns the player to a match with several dozen other players. This also involves assigning the player to a specified set of teammates, with the balance of players in the match assigned to distinct opponent teams. Teams range in size from one to four players, depending on the specific match type, and individual matches may have as many as 150 total players. Players cannot under any circumstance choose their opponents in the match-making queue; this is assigned by the game, with no input from players. Similarly, they typically do not choose their teammates. They may, however, opt to "party-up", meaning to form one's own team with online or offline colleagues prior to joining the match-making queue. For example, a player may party-up with a sibling playing on a separate gaming device before joining the match-making queue, which would allow the two to be placed in the same match and team. However, it is typical that only a small minority of players party-up, and given that the data (discussed below) allows for a detailed view of a player's match history, such players can be easily identified, and are omitted in all of my analysis.

2.2 Data and methods

2.2.1 Sample and data collection

My analysis draws on unique, match-level data available through Activision's Application Programming Interface (API).[7] For each individual player, *Warzone*'s system records and stores exhaustive information across every match played, including the player's performance, teammates, and opponents, allowing for analysis of a player's learning trajectory. This data is then made available to third parties through the API. Figure 2.1 illustrates the data-assembly process. I engaged in a comprehensive data collection effort that loosely follows Ching et al. (2021) and begins by generating a random list of 1,000 players from the population of players who have

[7] An API is a first-party software interface that allows third-party programs and software applications to retrieve game statistics through a defined set of call and request procedures.

participated in at least one match in *Warzone*. While the API does not offer a direct way to generate a random sampling of players, I utilized a workaround which takes advantage of *Call of Duty*'s 'leaderboard' system. Leaderboards are a series of lists that rank-order all players by certain performance metrics. I developed a Python script that randomly and independently draws individual players from these leaderboards to approximate a random sampling from the population of all players. Next, I manually identified for each of the sampled players all matches on record. Comprehensive data on these matches, including the list of teammates and opponents across all matches, were then collected and assembled into a single repository. Finally, I iterated this process to collect match-level performance data for the list of teammates and opponents. All data were then combined and aggregated to the player-match level for analysis.

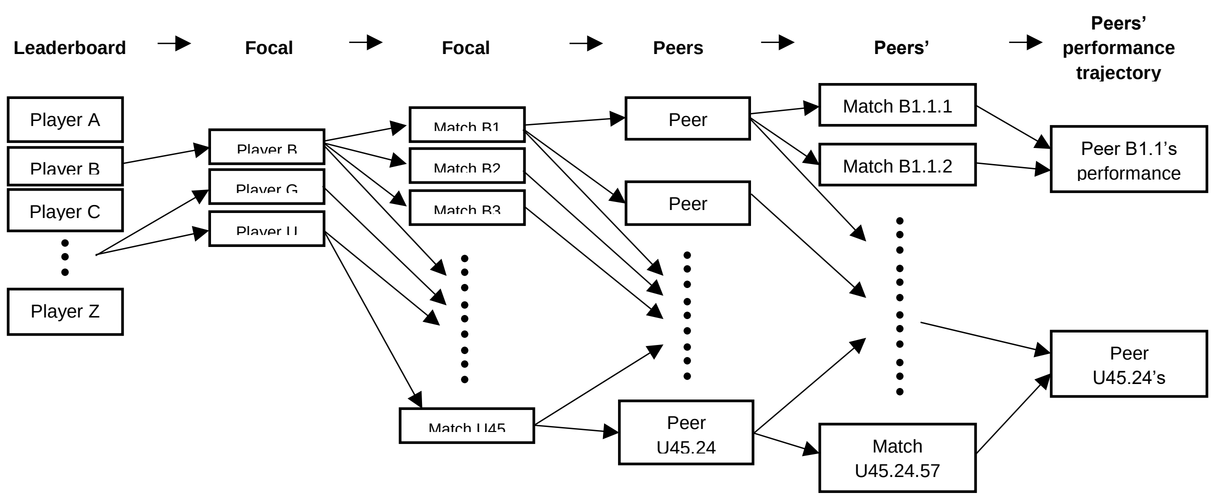


Figure 2.1 Data collection procedure

Data collection was limited to the first sixteen weeks following *Warzone*'s public release, for several reasons. Firstly, the computational burden imposed by the quantity of data even for a limited sample of players necessitated that I work with a relatively modest sample. Though the final data cover about 1,000 focal players, collecting a comprehensive account of their matches and peers, as well as those peers' matches would exponentially increase the quantity of raw data required. Even with a coverage of just sixteen weeks, I collected and processed data on over 12 million peers – or, close to half a billion matches. Secondly, as empirically comparable work has previously shown (See for example Chan et al., 2014), much of the learning of interest in these contexts occurs near the beginning of subjects' careers. As such, the additional insights to be gleaned by increasing the size of our coverage window is diminishing. It is therefore not necessary to obtain a full account of a player's matches throughout their career – only those in their first few weeks or months playing the game. Lastly, following January 2021, *Warzone*'s publisher introduced a key change to its data policy which rendered most player statistics after this period difficult to track reliably and comprehensively.

Nevertheless, I believe sixteen weeks of data is more than sufficient to observe our effect of interest. My final dataset contains fine-grained information on players, including their performance, experience, match history, peers, and a large number of additional key characteristics. The data cover just under 1,000 unique players across 200,000 unique player-match observations and are summarized in Table 2.1.

2.2.2 Threats to identification

To isolate the causal effect of the knowledge distance from potential sources on a recipient's knowledge absorption, and by extension, their future performance, the ideal experiment would randomly assign firms or individuals to knowledge sources of varying levels of knowledge and record how knowledge distance from the source affects subsequent performance. Because such a treatment would be independent of a focal knowledge recipient's prior characteristics, the hypothetical researcher would be able to attribute to the knowledge sources observed differences in outcomes for the focal recipient. Such an experiment may, however, be prohibitively expensive and, in some ways, infeasible. As the goal of my exercise is to identify the existence of and potentially characterize the non-monotonic relationship between my variables, a randomized experimental setup with a simple treatment-control procedure would fall short. Instead, a more appropriate experiment would divide participants into multiple treatment pools of increasing knowledge distance – an approach that would necessitate both a large slew of subjects and research assistants as well as a correspondingly handsome research grant.

Table 2.1 Summary statistics

	Mean	Std. dev	Minimum	Pctl(25)	Median	Pctl(75)	Pctl(95)	Maximum
Performance								
Opponent eliminations in match t	3.169	2.355	0	1.549	2.991	4.070	7.073	30.096
Player characteristics								
Player's own ability in t - 1	1.535	0.648	0	1.118	1.464	1.835	2.583	20.667
Number of matches played up to t - 1	397.571	450.204	16	89	203	513	1493	1855
ln(*Number of matches played up to t* - 1)	5.358	1.167	2.773	4.489	5.313	6.240	7.309	7.526
Total matches played by player	245.443	346.715	19	71	143	266	657	1855
Knowledge distance								
Distance from high-type teammates in t - 1	1.496	2.110	0	0	0	2.860	5.622	12.819
Distance from high-type opponents in t - 1	0.628	1.997	0	0	0	0	5.208	23.631
Distance from low-type teammates in t - 1	-2.815	2.680	-10.567	-5.243	-3.567	0	0	0
Distance from low-type opponents in t - 1	-3.175	2.009	-9.146	-4.652	-3.649	-1.901	0	0
Controls								
Deaths	2.472	1.955	0	2	2	3	7	21
Current match difficulty	1.039	0.158	0.535	0.949	1.040	1.134	1.288	1.984

If we are to climb down from this utopian hypothetical and settle instead for a second-best alternative – as I do in this paper – we must consider two major threats to identification that might bias analysis results: reflection and self-selection. The reflection problem in the context of peer effects research, perhaps best characterized by Manski (1993), results from reflection, or simultaneity, in social networks – that is to say, an inherent interdependence and reciprocal influence across individuals in a group. Resultantly, it is difficult to tease apart the influence a given individual's characteristics or behaviors have on their peers from the influence that those peers' characteristics or behaviors have on the individual. My empirical approach mitigates this concern through several means. First, I employ a lagged model where a focal subject's performance in the present period is measured as a function of the characteristics and behaviors of peers in a previous period, while controlling for the peers with whom the subject interacts in the present period. Second, as my setting comprises an atomistic population of hundreds of millions of players from which individuals are selected into one-off engagements, the potential influence of subjects on their peers is dispersed broadly such that it is unlikely for simultaneity to bias the results to an appreciable degree.

Closely related to the reflection problem is the selection problem. It is typical in social settings that individuals self-select into their social networks. They actively choose the peers with whom they interact based on shared preferences or characteristics. For instance, at the firm level, we can expect high technology entrepreneurial firms to locate their operations near regions of concentrated knowledge and human capital such as universities or industry clusters. As a result, they are likely to share suppliers, customers, and even employees. Though greater proximity may indeed lead to knowledge diffusion between them, the preexisting similarities between the firms will likely manifest in terms of comparable behavior and outcomes. It would be erroneous to attribute this comparability solely to the diffusion of knowledge between the firms. This endogeneity concern is minimal in my empirical exercise as my setting approximates a randomized control trial. Individuals in my sample do not select into their interactions, but rather are assigned exogenously to teammates and opponents by the games matchmaking system. In this way, my empirical approach is able to isolate peer influence from self-selection.

2.2.3 Measures

Dependent variable: player performance

Successful opponent eliminations are key to a player and team's performance in *Warzone*, and they depend strongly on a player's knowledge. For this reason, I operationalize a player's performance in given match, $y_{i,t}$, as the number of successful opponent eliminations by the player in a given match, normalized by the theoretical maximum possible eliminations – the total number of opponents in the match. A count of opponent eliminations is the most suitable performance measure in my setting for two reasons. First, unlike possible alternatives, such as a team's rank placement at the end of a match, elimination count depends principally on the behavior of the focal player, not their teammates. Second, maximizing the number of opponent eliminations is the main objective for a given player in a match. It essentially defines a player's objective function. While winning a match or team placement is the broader goal, because the game is tournament-esque in its design, these are generally achieved through the more direct action of challenging and eliminating individual opponents and opponent teams. In this sense, you can imagine a player as a firm that can maximize its profits by running its competitors out of business.

Focal independent variable: knowledge distance from superior peers

I characterize knowledge distance between a player and their superior peers in my empirical setup as:

$$\overline{KD}_{i,j,t} = \frac{\sum_{j \in N_{r,t-1}: a_{j,t-1} \geq a_{i,t-1}; j \neq i} (a_{j,t-1} - a_{i,t-1})}{\sum_{j \in N_{r,t-1}} 1_{(a_{j,t-1} \geq a_{i,t-1}; j \neq i)}}, \tag{2.1}$$

where $a_{i,t-1}$ is player i's observed *ability* during period $t-1$, measured as her average per-match *performance* in the five-match window leading up to but not including match t. The expression $(a_{j,t-1} - a_{i,t-1})$ captures the knowledge distance between the focal player i and their peer j who is embedded in team r in match $t-1$, and so $\overline{KD}_{i,j,t}$ represents the average knowledge distance between i and all superior peers in $t-1$.

Other independent variables

While my primary relationship of interest concerns interactions with superior peers, I also examine the effect of interactions with inferior peers. *Knowledge distance from inferior peers* is operationalized as:

$$\underline{KD}_{i,j,t} = \frac{\sum_{j \in N_{r,t-1}: a_{j,t-1} < a_{i,t-1}} (a_{i,t-1} - a_{j,t-1})}{\sum_{j \in N_{r,t-1}} 1_{(a_{j,t-1} < a_{i,t-1})}}. \tag{2.2}$$

A player's *experience level* at the time of match t, $m_{i,t}$, is operationalized as the cumulative count of their matches up to but excluding t.

2.2.4 Econometric specification

My empirical approach draws from the cross-disciplinary literature on peer effects. I investigate whether and how the performance of an individual depends on the relative ability of the peers with whom they interact. My core test is for the effect of knowledge distance – measured as the observed ability of a focal player's peers, relative to the focal player's – on the focal player's subsequent performance. I estimate the following equation, at the player-match level, with standard errors clustered at the level of the player:

$$y_{i,t} = \beta_1 m_{i,t} + \beta_2 \overline{KD}_{i,j,t}^{Teammates} + \beta_3 \overline{KD}_{i,j,t}^{Opponents} + \beta_4 \left[\overline{KD}_{i,j,t}^{Teammates}\right]^2 + \beta_5 \left[\overline{KD}_{i,j,t}^{Opponents}\right]^2 + \beta_6 \underline{KD}_{i,j,t}^{Teammates} + \beta_7 \underline{KD}_{i,j,t}^{Opponents} + \gamma Z_t + \varphi_t + \delta_i + \varepsilon_{i,t} \tag{2.3}$$

The term Z_t is a vector controlling for characteristics of match t and o i f's peers in match t, and includes match size, match mode, averaged teammate ability, and averaged opponent ability. φ_t and δ_i are fixed effect terms, with the former representing the week in which t was played and the latter representing player i. Finally, $\varepsilon_{i,t}$ is the error term.

We follow Chan et al. (2014) in several ways. First, like that of the earlier paper, our approach does not impose symmetrical peer effects: we do not assume that the performance effect of interactions with superior peers is the same, or even the reverse of that of interacting with inferior peers. Our model includes separate terms for superior and inferior peers, allowing for, but not assuming, different coefficients. Second, our setting is similar to that of the earlier paper as it allows for the observation of both cooperative and competitive interactions. In the earlier paper, salespeople interact with same-brand peers within the same counter, as well as peers in competing counters working for competing brands. In our setting, players interact with peers in their own team as well as those in competing teams.

To leverage these dynamics, we follow the earlier paper and separately model the effects of teammate and opponent interactions. Our approach differs from the earlier paper, however, in our respective objectives. As our primary intent is to test for the existence of nonlinear effects of distance, we explicitly incorporate nonlinearity into our model, where the earlier paper does not. Additionally, where the earlier paper examines contemporaneous peer effects – that is, how distance from peers in the current period affects performance in the current period – we are primarily concerned with inter-temporal effects.

2.3 Empirical results

I begin with investigating the main effect – whether individuals' performance in *Warzone* increases with the extent of their experience. Figure 2.2 gives a glimpse of the distribution of player performance by experience level in the data for the top and bottom quintiles of players. The illustration points at the existence of experiential learning in this setting. Panel (a) suggests that on average players experience performance improvements the more they play. Panels (b) and (c), which break down the top and bottom quintile, respectively, suggest that players do not appear to learn at the same rate, however – players in the top ability quintile are characterized by markedly better experiential learning than those in the bottom quintile, consistent with the inclusion of the inclusion of the heterogeneous learning capability term, δ_i, in the model in Chapter 1. This intuition is formally confirmed in the analysis in Table 2.2.

The paper's first preliminary empirical analysis is a baseline regression of the link between performance in the current period and knowledge distance in the preceding period, as well as other factors that have been shown in prevailing work to influence performance improvement through knowledge accumulation. Our hypotheses for the effect of knowledge distance on knowledge absorption under both regimes of assimilation capacity suggest a diminishing relationship. We should therefore expect a positive linear knowledge distance effect and a corresponding negative quadratic effect, regardless of which form of assimilation capacity is reflective of the true state of the world. Results for this analysis are presented in Table 2.2, with basic controls for characteristics of the player and their competitive environment. Player dummies are included as unobserved time-invariant heterogeneity across players may influence performance; in particular, as the model in

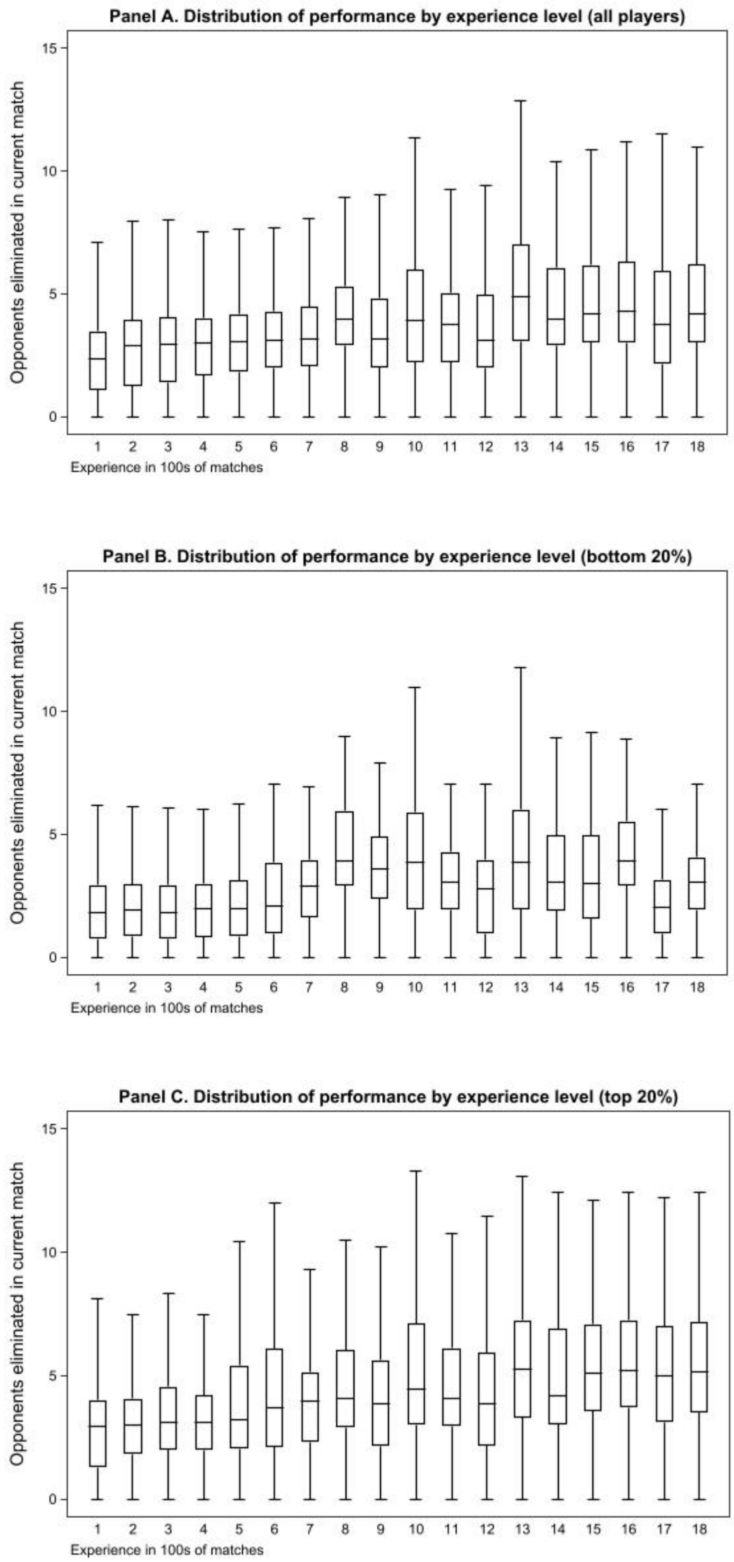


Figure 2.2 Performance over experience, by quintile.

Chapter 1 suggests, players are likely to be innately heterogeneous in their learning capabilities, and thus performance improvements may be concentrated among a select group of players. I also include time dummies at the week level to address any potentially confounding events that may have occurred during our study period that could bias analysis results. The analysis across all models covers 193,242 player-match observations for 854 unique players and utilizes a fixed effect panel specification.

Table 2.2 Baseline results for peer learning

	Learning-by-doing	High-type peers only	Teammates only	Opponents only	All-in
	(1)	(2)	(3)	(4)	(5)
Dependent variable: *Opponent eliminations in match* t *(normalized)*					
ln(*Number of matches played up to* t - 1)	0.262***	0.288***	0.286***	0.266***	0.287***
	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)
Distance from high-type teammates in t - 1		0.213***	0.284***		0.279***
		(0.010)	(0.015)		(0.015)
(*Distance from high-type teammates in* t - 1)^2		-0.026***	-0.033***		-0.032***
		(0.002)	(0.002)		(0.002)
Distance from high-type opponents in t - 1		0.004**		0.005**	0.004**
		(0.002)		(0.002)	(0.002)
(*Distance from high-type opponents in* t - 1)^2		0.001***		0.001***	0.000
		(0.000)		(0.000)	(0.000)
Distance from low-type teammates in t - 1			-0.034***		-0.036***
			(0.005)		(0.005)
Distance from low-type opponents in t - 1				0.026***	0.014***
				(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Player fixed effects	Yes	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes	Yes
Players	854	854	854	854	854
Number of observations	193,242	193,242	193,242	193,242	193,242

Robust standard errors in parentheses, clustered at the player level.

Column (1) shows the relationship between experience and performance with robust errors clustered at the player level. Column (2) adds linear and quadratic knowledge distance terms for high-type peers – peers of greater ability than the focal player. Column (3) focuses on knowledge distance from teammates – peers with whom a player has collaborative ties. Column (4) focuses on opponents. Finally, Column (5) includes all knowledge distance terms to the analysis. Consistent with the illustration in Figure 2.2, Column (1) reveals a strong positive relationship between a player's experience level and a lagged performance term, supporting the existence of learning-by-doing in this setting. This effect persists in magnitude and significance even after accounting the various knowledge distance terms. The consistency of effect size across specifications suggests that learning-by-doing in this setting occurs independent of, and in addition to, peer-based learning.

Column (2) suggests that in addition to direct experience, player performance is also positively linked to knowledge distance from high-type peers. Though I find an average positive link for both teammates and opponents, the magnitude of this effect is markedly stronger for teammates than for opponents. This may point to a greater learning effect from collaborative as opposed to competitive interactions, consistent with the learning context term, $\varphi_{i,j,t}$in the model in Chapter 1. In addition to the positive effect on the linear terms for both high-type teammates and opponents, I find a negative quadratic effect for teammates, consistent with both the absolute and relative assimilation capacity regimes, as well as a modest but positive quadratic effect for opponents. The quadratic effect for teammates is robust in both magnitude and direction across specifications. For opponents, the quadratic effect does not persist across specifications and disappears entirely in the exhaustive model of Column (5). If a quadratic effect does exist for high-type opponents, it appears too small in magnitude to reliably detect. For superior peers with whom players interact collaboratively, the results suggest the presence of a positive but diminishing relationship between knowledge distance and performance. Figure 2.3 plots this predicted relationship and hints at the existence of an inverted U-shaped relationship. However, I encourage caution against drawing such strong inferences from the results in Table 2.2 alone.

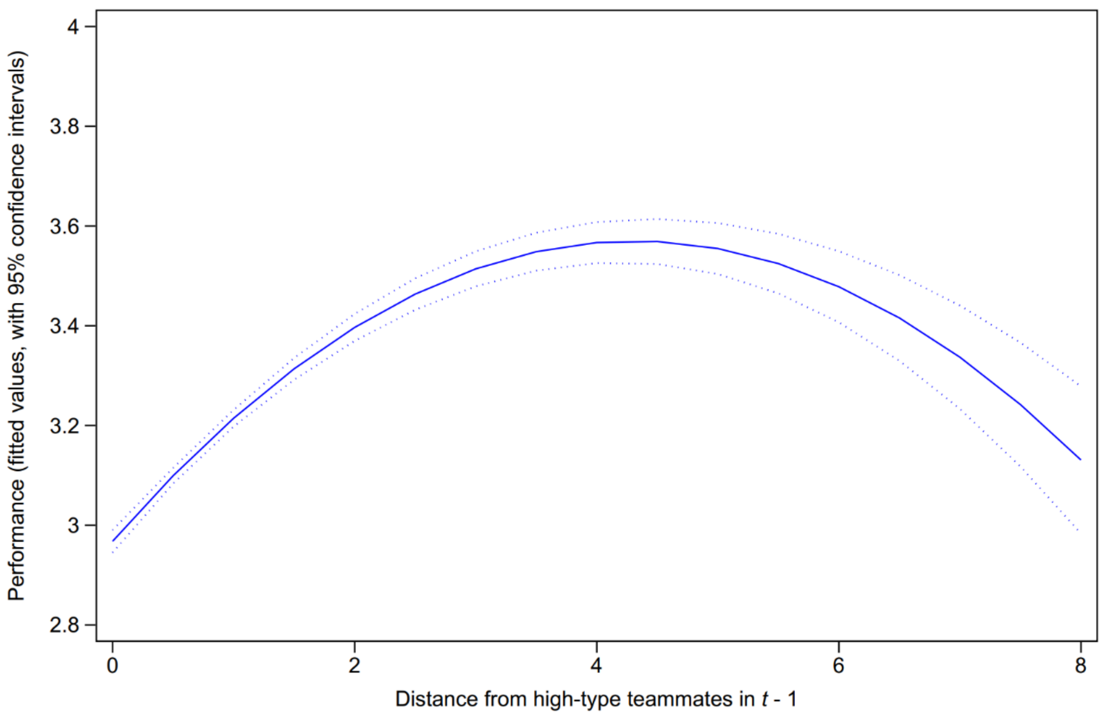


Figure 2.3 Predicted performance for high-type teammates.

Note: This figure plots the fitted values for performance against knowledge distance from high-type peers, which suggest the presence of an inverted U-shaped relationship. Fitted values are from Table 2.2, Column 5.

Column (3) largely presents consistent outcomes for teammates as Column (2). The additional knowledge distance term for low-type teammates points to a small but negative effect – playing with teammates of inferior quality appears to inhibit, even hurt, performance improvement in successive matches. Results in Column (4), which includes both high- and low-type opponents, are consistent with Column (2)'s results with results, excepting the added term for knowledge distance from low-type opponents. I find a positive effect for distance from low-type opponents. Interestingly, there appears to be greater performance improvement in successive matches from having engaged with inferior as opposed to superior peers. Column (5), which is my preferred model, includes all regressors in the analysis. For most regressors, results are consistent with those in previous models. Exceptions include the quadratic knowledge distance term for superior opponents from Columns (2) and (4) as well as the knowledge distance term for inferior opponents from Column (4).

I next investigate the effect of knowledge distance from high-type peers plotted in Figure 2.3. Both the absolute and the relative assimilation capacity hypotheses predict a positive but diminishing effect of knowledge distance, as a consequence of the joint effect of opportunity and assimilationcapacity. The results from Table 2.2 are consistent with both hypotheses, at least for peers with whom individuals share collaborative ties. At first glance, it is tempting to take the results from Table 2.2 and Figure 2.3 as suggestive of an inverted U-shaped relationship, which would rule out the absolute assimilation capacity hypothesis in favor of the relative absolute capacity hypothesis. However, as previously outlined in Chapter 1, a quadratic estimation procedure is hardly sufficient for diagnosing the existence of an inverted U. I carry out a two-lines test using Simonsohn's (2018) Robin Hood procedure to more precisely unpack this relationship. Results for the test are reported in Table 2.3.

Similar to the models in Table 2.2, the dependent variable for Table 2.3 is a count of a opponents eliminated in the current match, normalized by the number of opponents in the match. The key variables of interest are $Distance\ from\ hightype\ teammates\ in\ t-1_{low}$ which reflects the average effect of knowledge distance for values of knowledge distance below the break point, and $Distance\ from\ hightype\ teammates\ in\ t-1_{high}$, which reflects the average effect for values above the break point. The goal of the test is to establish whether there is a region of superior teammate knowledge distance for which the relationship between the regressor and our dependent variable is positive as well as a region for which this relationship is negative. There is a robust positive effect for $Distance\ from\ hightype\ teammates\ in\ t-1_{low}$, confirming that performance is initially increasing in superior teammate knowledge distance. I also find a negative effect for $Distance\ from\ hightype\ teammates\ in\ t-1_{high}$, suggesting that for extreme values of superior teammate knowledge distance there is an inversion in the direction of our relationship of interest. Given this evidence, results in my setting are consistent with the absolute assimilation capacity hypothesis, and the notion that though a peer from whom a knowledge seeker has very little knowledge distance provides minimal chance for acquiring new knowledge, a peer who is approaching the knowledge frontier, despite providing greater opportunity, is too dissimilar to the knowledge seeker, making it challenging for them to effectively grasp and incorporate the peer's knowledge.

I turn now to an exploration of the heterogeneity in our results for players across the spectrum of ability. Table 2.4 segments our sample of players into five quintiles by ability and replicates the analysis from Table 2.2. Players' relative positions on the ability distribution improve from Columns (1) to (5), with Column (1) focusing on the lowest ability players and Column (5) focusing on the highest ability players. Column (6) includes all players. A marked trend to note in this analysis is the link between experience and performance. Results for the experience term, ln(*Number of matches played up to* t – 1), across the models highlight great heterogeneity in the players' learning rates. Low-ability players are markedly inferior to their counterparts in learning from own experience. Surprisingly, however, this learning heterogeneity is not reflected in players' ability to draw knowledge from peers. There is little variation in effect size for most measures of knowledge distance across player groups. This may imply that the processes of learning from own experience and learning from peers involve distinct capabilities, and though there might be some overlap between the two, excelling at one does not necessarily imply a capability to excel at the other. Knowledge seekers may therefore benefit from separately investing in improving both their ability to learn by doing δ_i, as well as their ability to effectively draw knowledge from external sources $\alpha_{i,j,t}$.

Table 2.3 Two-lines test interrupted regression

	Dependent variable: *Opponent eliminations in match* t
Distance from high-type teammates in $t-1_{low}$	0.311*** (0.066)
Distance from high-type teammates in $t-1_{high}$	-0.026*** (0.004)
ln(*Number of matches played up to* t - 1)	0.347*** (0.008)
Distance from high-type opponents in t - 1	0.004* (0.002)
(*Distance from high-type opponents in* $t-1)^2$	0.000 (0.000)
Distance from low-type teammates in t - 1	-0.011** (0.005)
Distance from low-type opponents in t - 1	0.012*** (0.003)
Controls	Yes
Player fixed effects	No
Week dummies	Yes
Players	854
Number of observations	193,242

Standard errors in parentheses.

Table 2.4 Learning heterogeneity by ability

	Lowest ability players	20th - 39th pctl	40th - 59th pctl	60th - 79th pctl	Highest ability players	Full sample
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: *Opponent eliminations in match* t *(normalized)*						
ln(*Number of matches played up to* t - 1)	0.127***	0.124**	0.122***	0.303***	0.553***	0.351***
	(0.023)	(0.040)	(0.014)	(0.022)	(0.056)	(0.025)
Distance from high-type teammates in t - 1	0.142***	0.212***	0.132***	0.111**	0.120***	0.260***
	(0.022)	(0.022)	(0.020)	(0.037)	(0.033)	(0.015)
Distance from high-type opponents in t - 1	0.004	0.004	0.004	0.007	-0.001	0.003*
	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.002)
(*Distance from high-type teammates in* t - 1)^2	-0.028***	-0.025***	-0.014***	0.017**	0.021***	-0.032***
	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)	(0.003)
(*Distance from high-type opponents in* t - 1)^2	0.001	0.000	0.000	0.000	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Distance from low-type teammates in t - 1	-0.087***	-0.070***	-0.031***	-0.024***	-0.014	-0.043***
	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)	(0.005)
Distance from low-type opponents in t - 1	-0.014**	0.011*	0.009*	0.012*	0.021***	0.011***
	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Player fixed effects	No	No	No	No	No	No
Week dummies	Yes	Yes	Yes	Yes	Yes	Yes
Players	177	177	172	168	160	854
Number of observations	18,634	29,173	42,274	43,659	59,502	193,242

Robust standard errors in parentheses, clustered at the player level.

2.4 Qualitative results

To gain a richer understanding of the channels through which learning occurs in this setting, I turn now to qualitative evidence. I conducted fifteen hours of interviews with active participants in *Call of Duty: Warzone*. All interviews were IRB-approved and were carried out over the video-conferencing platform *Zoom*, after which they were transcribed using *Parrot AI* and manually double-checked for fidelity. Each interview was semi-structured – while a pre-planned set of questions guided the discussions, I leaned heavily on extemporary prompts to extract nuances and detail from the interview participants. The list of guiding questions is detailed in Table A1 in the

Appendix. Broadly speaking, the qualitative evidence is consistent with my empirical findings and suggests the following. Players continually adapt and improve through their experience and interactions in the game, and the role of peers as sources of knowledge and motivation is crucial in this process. However, there are limitations to how much can be learned from peers, especially when engaging with highly skilled peers.

2.4.1 The role of knowledge

My interview participants offered several useful insights. Perhaps most fundamental were their thoughts regarding the relative importance of knowledge and innate ability in this setting. As this study is primarily focused on the transferability of knowledge within a competitive team setting such as *Warzone*, it is pertinent to establish whether active *Warzone* players view knowledge as being a salient factor in one's performance. Establishing the influence of knowledge on performance also clarifies the ways in which the dynamics in this setting are analogous to those in team settings within organizations.

With one exception, the participants were in accord that knowledge is of first-order importance in *Warzone*. While some competencies that one might think of as being innate or non-transferable – such as a player's motor skills or hand-eye coordination – play a part in performance, participants generally agreed that knowledge of different elements of the game itself and the different strategies opponents may employ was the primary driving factor behind performance. When prompted on what aspects they thought made the greatest difference for a player's performance, one participant said:

> Essentially what you know about the game...how to adapt and how to basically counter different play styles, and also how to change your own play style based on how the game is going is...paramount because it allows you to capitalize on your natural abilities, where you can pick locations, for example, where, you know, that, 'I'm really good at this certain plays style and, and you know, this location serves that best.' For example, if you're a

> sniper, you might look for locations with high buildings or mansions where you can engage with players from a further distance because you know that you're better off at that. So that's an aspect where you're using knowledge and what you're learning from other players. And you can find those locations from confrontations with other players. If you've ever been in a confrontation with another sniper who took you out and you're also a sniper, you could be like, 'Well, they did something that I didn't do. What was that?' (Participant 12)

Similarly, when prompted on how they would weigh the relative importance of knowledge and natural ability, another participant stated:

> I'll probably put it at like forty-percent natural ability, sixty-percent knowledge – or maybe even more like thirty-percent natural ability, seventy-percent knowledge. Mostly because your natural ability is only useful in those confrontations where you're evenly matched with your opponent, where you both happen to be using the best [weapons] for that particular situation, you both happen to be in locations that perfectly suit your natural ability. And that's kind of hard to get right all the time. It's really impossible to get it right all the time. (Participant 1)

In contrast to this, one participant felt that while a player's knowledge is certainly influential, its role was only secondary. When prompted further, they commented:

> I think knowledge plays a pretty good part…you can…know all these things about how to move, how to rotate, weapons and stuff, but then when it comes to you winning gun fights against [other] players, if you lose a gunfight…it doesn't matter at all what you know…So I think having good gun skill will help you more. (Participant 4)

2.4.2 Team coherence

Relatedly, several participants interviewed also felt that a key determinant for one's performance in a given match is the extent to which they are able to effectively collaborate with teammates. Participants' responses suggested that the interactions with peers in this setting aren't generally inconsequential, but can be both meaningful and rather structured. Participants noted the need to establish a de-facto leader in any given match – someone who can coordinate the team's efforts and lead the strategy-making process, soliciting contributions from the members of the team. Without a structured and coordinated approach to a team's actions, participants argued a team would meet with very little success in a match.

Some participants also underscored the importance of understanding early on in the match the idiosyncrasies of individual team members, so as to center the team's overall strategy on the team members' play styles and competencies. For instance, participants described how some players can be more risk averse, which necessitates a more conservative and deliberate approach. As part of their response to a question on what they believed was most important toward a player's success, one participant cited instances where tailoring the team's strategy to team members' play styles proved effective:

> [I]f you have a team member who is a little bit more risk averse, they might let you play conservatively, which sometimes is the best way. You can win a game without firing a single shot. I think we might have played a few games where we either fired no shots, or we fired the least amount of shots without actually killing off any opponents, but still won the game. And so the teammates that you have and how complimentary your skills are [decide your success]. (Participant 13)

2.4.3 Experiential and peer-based learning

Participants unanimously agreed that learning was typical in this setting. Most cited not only the extent to which their performance had evolved over time, but also the growth in their knowledge of the complex and often interconnected elements of the game. Consistent with research on learning, both at the individual/team and organizational levels, participants suggested their rates of learning were correlated with how often they played, with some participants stating they played the game multiple times a week, and sometimes even every day. Further, they also suggested that forgetting was a key concern – when participants underwent prolonged periods without playing, their performance suffered as a result. According to some participants, this effect is not only a result of losing one’s accumulated knowledge, but also being left behind by a constantly-advancing knowledge frontier. One participant described this as:

> [At some point] I ended up not playing the game as much, and that also definitely reflected on my performance…I’d get into the game and I’m playing with a playstyle that I used…a while ago, and it’s just not working. And from taking a look at what my opponents are doing…I noticed that apparently there was a whole new movement style where if you move in the game in a certain way, you’re just a harder target to hit. And that allows you to land more shots while avoiding getting shot. And that actually increases your odds of success…And because I hadn’t learned that new skill, but everybody had already picked up on it, it was reflecting on my performance. (Participant 12)

Sixty-five percent of participants also described in some fashion how their experiential learning was not an automatic process, but rather the result of intentional effort. One stated: “…when I’m playing, I’m always trying to improve my knowledge…so I always test myself…because sitting there, just sitting there…it’s not going to help you get better at the game.”[8] Participants detailed how a player needs to make deliberate efforts to understand the weapons, equipment, and possible strategies in the game, and how different combinations of these elements may work better than others. Constant experimentation is therefore necessary.

Beyond experiential learning, the interviewed participants also had much insight to offer on the role their peers play in one’s performance trajectory. Peers lead to both a motivational and learning effect. Two participants confided how a fear of “disappointing” superior teammates often provides a motivational push to improve one’s performance through increased effort.[9] My empirical analysis recognizes the likelihood for such an effect and controls for intra-temporal peer effects to isolate the learning effect of one’s peers.

[8] Participant 4
[9] Participants 4 and 15

On the question of learning from peers, the qualitative evidence points to two central mechanisms: observation and directed learning. Participants unanimously identified observation of peers' behaviors, strategies, and resources as a key avenue for learning. This was true for both teammates and opponents. One participant, who described themselves as partial to a more conservative game style, explained how playing with superior teammates who take a more aggressive approach to opponent engagements allows them to observe and pick up useful tactics for engaging opponents without directly experiencing such engagements themselves. This sort of experience was common across my participants, many of whom described in a similar fashion how observing their teammates or opponents had impacted their own behaviors in subsequent matches.

Similarly, participants described how engaging with opponents, even when the engagements end in defeat, may sometimes yield new insights. One participant, for example, describes the following:

> Sometimes after [opponents] take you out, you can notice the equipment they were using, and why they chose it. Because sometimes you can clearly tell that, well, [in] this engagement they won because they clearly had the better equipment or they were better positioned. And basically that gives you a wealth of knowledge…on just how the game works and on the different ways to play the game, and also on what other players are doing. And that also allows you to go like, "You know what, I think I like what those guys were doing. I think it's actually a smart strategy. Let me try that in my next game. (Participant 7)

A second participant described a nearly identical phenomenon:

> Say somebody takes you out and knocks you out of the game, you might actually see the exact weapon that they were using to do that. And if you've been playing the game a while, you can tell just based on how the gunfight went that, 'Well, I know that my skills were not the problem, because I was landing as many shots as I could but their gun just happened to kill a lot faster than mine could. Or their gun allowed them to move and be a lot more nimble than mine did.' Things like that, and you can notice it from the gun fight itself. (Participant 12)

Another common example of this which featured across participants involved learning about superior resource combinations by collecting and experimenting with weapon combinations and equipment combinations assembled and unintentionally left behind by opponent teams. A participant described the following illustrative scenario:

> When you take out a team, one of the best things about [*Warzone*] is that you can take on whatever equipment or resources…they have. That's very useful, because oftentimes for me…I believe it's usually the primary weapon that is the most effective tool. And if you can get hands [on] a primary weapon you…haven't used, or haven't configured in that way, it may change everything. I remember a while ago – I mean, this happens all the time when you encounter a [weapon] from an enemy team that has an impressive fire rate, or the attachments that you need to be mobile, to be effective, to be elusive. And to hit your target every single time, or at least the majority of the time. And once you learn something like that, it can improve your game significantly. Because sometimes you might have all these challenges, but you just don't have the weapons to execute, to execute it. So…if you go scavenge from the people that you have taken down, then you can learn some things about the guns that they're using, how they're using them. (Participant 13)

A second avenue through which participants described learning from peers was direct instruction. As players in Warzone are only able to directly communicate with peers on their own team, this mechanism for learning was only reported to apply in interactions between teammates. Participants described such teammate instruction as consisting of either the teammate simply encouraging a particular course of action, which the participant only later realized was superior to the way they would have done things otherwise, or the teammate intentionally choosing to instruct the participant on a given superior activity or element of the game that they were previously unaware of. In the former camp, a participant gave the following example:

> I am less aggressive as a player. So I will pick the safest place to land. But again, not confronting enemies leaves you with no real opportunity to learn how to tactically fight in a game. And so, when a teammate suggests that we land at a place where I think, 'Why are we doing this? This is not a good idea. We won't have any weapons. We're just landing

> with a pistol and would have to make do with that.' When I'm forced to go into that scenario…even if I approach it as…the person who is in the air and takes about a minute to land by surveying the space first. I get to understand that, you know, playing it safe isn't going to win us this game. But going out there and having experiences where you come into a fight, even if you're defeated, that really isn't the objective, but the objective is to go there and learn how to confront a player in a different circumstance. (Participant 3)

In the latter camp, a participant described experiences in which a superior teammate directly instructed them on how to play the game in a better way:

> [U]sually somebody discovers something and they share it with their team. It could be a new strategy…[It] might be based on some interaction they had in a previous game, something they learned from other players…It's like you're able to learn more of the game from a team than you ever would on your own. (Participant 12)

Another participant described a recent interaction they had had with a teammate:

> Recently, one dude I played with actually told me about a setting that I didn't even know that was in the game. And ever since I put that setting on, I'm winning more gun fights, because I didn't know that was there. (Participant 4)

After some prompting, the participant exposited on this particular instance, describing the setting in question as a game mechanic involving a specific weapon scope attachment which allowed him to be more accurate in engagements with opponents.

2.4.4 Limitations to learning from peers

Participants also described different factors that limit the extent to which they can learn from their peers. Of particular note was the role played by a peer's relative competence. While participants almost unanimously agreed that peers superior to them often served as the most useful sources of learning, several expressed that this was only up to a point. As part of a detailed account of instances where interacting with different players has influenced their own behavior and performance, one participant described their experience in the following manner:

> Sometimes if I run into a very good player…and they take me out, I might just find that discouraging. I might not actually learn a whole lot from that player, because they'll be doing things that I just don't even understand. (Participant 8)

Another participant similarly described the following experience from their peer interactions:

> So, you know, your teammate could use this one gun. You see they're going crazy with it, and you're like, 'Wow, I want to put that gun on," right? You put it on, but what they're doing with that gun you're not doing at all. You need to find out the right tunes for it, the attachments for it, so you can perform like them. But that doesn't come easy. (Participant 4)

A third participant exposited on the extent to which they are able to learn from the opponents they interact with and detailed how much easier it is sometimes to learn from teammates. They described how one can observe opponents from a distance, or from engaging directly with them and noticing specific strategies they employ in one's engagements with them. Similarly one can also gain some information from getting one's hands on their weapons and equipment. However, more often than not, engagements with opponents begin and end really quickly, and it is difficult for a player to gain an understanding of the actual strategic decision-making employed by a team. As the participant described:

> You only see how they execute, but you can't really see all the planning that went into it, or how they were moving around to get themselves in place…You won't be able to pick up on how they're communicating, their styles of play. (Participant 13)

These insights may explain both the magnitude and shape of the relationship between knowledge distance and performance in my empirical analysis. It may be the case that though opponents can serve as a source of useful knowledge to players, the types of knowledge that can be effectively transferred through these competitive interactions is limited. More complex and tacit elements, for instance, may not be so easily transferred across members of opposing teams through observation alone.

2.4.5 Mechanisms in summary

I will conclude this subsection with a synthesis of the key themes and findings from my qualitative data. First and foremost, the interviews reveal that knowledge is considered by players to be a primary factor influencing performance in *Warzone*. Players believe that understanding various aspects of the game – such as strategies, resource combinations and resources-sourcing tactics, as well as key defensible locations and lines of attack – is crucial for success. Knowledge allows players to adapt their playstyle, acquire optimal resources, choose advantageous locations, and counter different opponents effectively. Most participants emphasized the significance of knowledge over innate ability. While natural ability like motor skills and hand-eye coordination plays a role, knowledge of the game's mechanics and strategies is the primary driver of performance. Coupled with that, players emphasized the importance of effective collaboration with teammates, highlighting the need for a structured and coordinated approach within the team, including the designation of a leader who can coordinate roles and leverage team members' strengths. In this way, the activities of individuals and teams in this setting are a relevant analog to those of individuals, teams, and organizations, and likewise, the learning processes may inform our understanding of learning processes in these other settings.

On the question of how individuals learn, players agreed that learning is a ubiquitous experience, with rates of learning linked to one's cumulative experience. Players emphasized the need for deliberate efforts to understand game elements, resources, and strategies through experimentation, and noted that extended breaks from the game lead to a decline in performance, due to both a loss of accumulated knowledge and falling behind in the evolving game meta. In addition to experiential learning, players also learn from their peers through observation and directed learning. Observing teammates and opponents allows them to pick up strategies and superior resource combinations. Direct instruction from teammates complements this observational learning and also significantly impact a player's performance by introducing new and more effective approaches to the game. However, players may struggle to learn from exceptionally skilled peers, whose strategies may be too advanced to understand.

2.5 Conclusion

This study has leveraged a dynamic and competitive eSports setting to provide empirical insights that enhance our understanding of the factors driving successful knowledge diffusion among peers.

The findings presented shed light on the interplay between knowledge distance and absorption of peer knowledge and contribute to a more comprehensive understanding of knowledge absorption. More precisely, my investigation in this chapter is consistent with the model of spillover absorption with relative assimilation capacity from Chapter 1 (See the Relative Capacity Hypothesis) and reveals that the relationship between the quality of knowledge sources and realized knowledge absorption is not as straightforward as previously assumed. It is true that knowledge seekers tend to benefit from engaging with peers possessing a greater wealth of knowledge relative to themselves. This outcome aligns with and builds upon perspectives in the literature on R&D spillovers where accessing highly knowledgeable peers is perceived as an opportunity-rich strategy for knowledge acquisition. My findings suggest, however, that there is more to this story: while some degree of greater relative knowledge possessed by one's peers enhances learning, there exists an optimal point beyond which increasing the source's relative wealth of knowledge might actually hinder the effective absorption of knowledge. This important refinement complements the organizational learning perspective, emphasizing the role of assimilation capacity and the potential challenges associated with learning from peers who are significantly dissimilar.

The practical implication is that knowledge seekers may optimize their learning by targeting peers who are only moderately superior in knowledge. This ‘Goldilocks’ approach to knowledge source selection encourages the cultivation of learning environments that strike a balance between familiarity and novelty, fostering more effective knowledge transfer.

A few limitations are worth highlighting. First, my research setting is one in which knowledge is applied toward solving a single well-defined problem. In this sense, it may not be perfectly representative of the sorts of open-ended and multidimensional problem-solving efforts typical within most organizations. Nevertheless, my interviews with *Warzone* players suggest that this is a sufficiently complex and strategic setting to, at the least, approximate the real-life interactions that workers within organizations undertake. Second, as my empirical setting primarily centers on learning at the level of the individual, the results may not readily generalize to teams and organizations. In the following chapter, I make efforts to address this limitation by extending the empirical and qualitative findings from this chapter to a more traditional organizational setting.

Chapter 3

CTRL+SHIFT+INNOVATE: LEVERAGING KNOWLWEDGE SPILLOVERS IN THE VIDEOGAME DEVELOPMENT INDUSTRY

3.1 Introduction

In the preceding chapter, I provided the first set of empirical tests of the 'Goldilocks' model of spillover absorption outlined in Chapter 1. My results, using microdata on the interactions and performance trajectories of individuals in a competitive eSports setting, were consistent with my theoretical framework and pointed to the existence of an optimal knowledge distance aspiring knowledge recipients should target to maximize learning outcomes. While that empirical exercise is useful as a laboratory test of sorts of my phenomenon of interest, as it takes advantage of pseudo-random assignment, it remains unclear how generalizable the findings in Chapter 2 are.

The current chapter aims to remedy this limitation and extend the theory and findings to a more typical organizational setting and does so by addressing two questions. First, does the knowledge-sourcing behavior of firms mirror the dynamics characterized in the first two chapters of this volume? Second, conditional on firms' behavior, are performance outcomes consistent with the Relative Capacity Hypothesis in the first chapter? That is, do firms realize performance premiums from sourcing knowledge in a manner that mirrors the 'Goldilocks' approach – eschewing sources with whom they have either very low or exceedingly large knowledge distance in favor of those from whom they are moderately distant?

To address this question, I follow previous research and use employee mobility to infer the flow of knowledge across firms (See e.g., Corredoira & Rosenkopf, 2010; Lacetera et al., 2004). My study is set in the computer and videogame industry, a knowledge-intensive industry offering a comprehensive and uniquely translucent view of project-level teams and firm-level worker mobility. To address the first question, I carry out a descriptive investigation of the relationship between a firm's knowledge distance from its peers and its inward worker mobility. To address the second, I follow the empirical approach from the second chapter and test for the realized performance implications of firms' knowledge distance from the peer firms whose employees they hire. My results are largely consistent with the relative assimilation capacity framework in the first chapter of the dissertation, as well as the empirical and qualitative findings from the second chapter, and support the existence of an optimal knowledge distance for knowledge sourcing.

The rest of this chapter is structured as follows. The following section draws on the employee mobility literature and this dissertation's theoretical framework to generate hypotheses for my empirical tests; Section 3.3 introduces and offers institutional details on my research setting; Section 3.4 describes my data, sample, and methods; Section 3.5 presents my results; and Section 3.6 concludes the dissertation with a brief summation of the dissertation's findings and a discussion of potential contributions.

3.2 Employee mobility and knowledge spillovers

Among the many mechanisms that have been identified in the various literatures studying knowledge spillovers across firm boundaries, the mobility of workers is perhaps the most central (Argote & Ingram, 2000; Grant, 1996). Management scholars have argued that employees act as knowledge reservoirs – a great deal of the routines and capabilities that create value and generate competitive heterogeneity across firms reside in the workers within those firms (a consequence of their accumulated knowledge, skills, and expertise) and in the interactions between them (Agarwal et al., 2009; Almeida & Kogut, 1999; Corredoira & Rosenkopf, 2010; Felin & Hesterly, 2007). This is perhaps best exemplified by the body of work establishing the link between networks of skilled individuals and macro-level innovative outcomes. Carlino et al. (2007), Roche (2020), and others have shown, for instance, that the density of workers in urban areas increases the per capita invention rate, by influencing the organization of knowledge exchange between individuals. Similarly, Zucker et al. (1998) have anchored the proliferation of inventive activity to the movements and interactions of skilled individuals.

Research has also linked the mobility of workers across firms to firm-level outcomes for the firm receiving the worker. In entrepreneurship studies, the mobility of workers has been shown to increase the likelihood of startup formation (Carnahan, 2017; Elfenbein et al., 2010; Klepper & Thompson, 2010), as well as the post-entry performance of these new firms (Agarwal et al., 2004; Elfenbein et al., 2010)); when they leave an existing firm, ex-employees often carry with them the knowledge – technological, market-relevant, regulatory, and even managerial – generated in the firm and use it as a bedrock on which to found the new venture (A. K. Chatterji, 2009; Gambardella et al., 2015). Researchers who study mobility and organizational outcomes for established firms have likewise shown that firms hiring away another's employees benefit from the knowledge, skills, and experience accumulated at their previous job (Almeida & Kogut, 1999; Arrow, 1962; Singh & Agrawal, 2011; Song et al., 2001, 2003), and that inward mobility, or learning-by-hiring, is particularly effective for enhancing exploration of knowledge domains new to the hiring firm, rather than exploitation of the firm's existing expertise (Boeker, 1997; Rosenkopf & Almeida, 2003; Song et al., 2003; Tzabbar, 2009).

A substantial portion of the knowledge of specialized routines, processes, and technologies that underpins a firm's innovativeness and competitive outcomes is tacit (Dokko et al., 2009; Grant, 1996; Kogut & Zander, 1992; Polanyi, 1966), meaning it defies codification or explicit articulation, and is instead deeply ingrained in the individuals and processes within a firm. It is for this reason the mobility of workers proves such an effective vehicle for knowledge spillovers across firms, as it allows for extensive personal contact in the form of collaborations between the newly hired worker and the existing workers within the hiring firm.

It is worth highlighting that the employee mobility story is not just one of acquiring the knowledge already possessed by the individual mobile worker, but also one of building relational capital for the hiring firm. In addition to acquiring the workers' skills, when a firm hires workers away from another, it also alters the patterns of interaction with their previous employer (Dokko & Rosenkopf, 2010), which may generate opportunities for further knowledge spillovers. As mobile workers may maintain their networks with colleagues in their previous firm post-mobility, they may effectively connect their new network at the hiring firm to their original network at the previous firm (Agrawal et al., 2006; Corredoira & Rosenkopf, 2010; Somaya et al., 2008). This, in turn, impacts the amount and types of information that is shared between the two firms post-mobility.

The upshot of this research is that if we assume firms are behaving optimally, we may expect them to actively use the inward mobility of employees as a channel by which to access and take advantage of not only the skills of the mobile workers, but also the former employers' unprotectable information. If such is the case, following previous research highlighting the directionality of knowledge spillovers (Alcácer & Chung, 2007; Knott et al., 2009; Posen et al., 2013; Shaver & Flyer, 2000), I argue that firms will generally look to hire workers away from their peers when the peers in question possess superior knowledge. Thus:

> **Hypothesis 1.** *The rate of inward mobility of employees from a peer is, all else equal, increasing in the knowledge distance between the peer and the hiring firm.*

To understand the performance implications of firms' hiring decisions in the context of this dissertation's theoretical framework, the discussion above may be combined with the predictions from the model in Chapter 1, as well as the empirical findings in Chapter 2. In order to successfully access and exploit the knowledge from a hired worker's former employer, the hiring firm must have the ability to effectively comprehend and integrate that knowledge. That is, the hired worker must complement the existing routines and structures of hiring firm (Lacetera et al., 2004). As Chapter 1 argues, this complementarity will be greater when the knowledge distance between the knowledge source and knowledge recipient – in this case, the worker's former employer and the firm hiring them away from that former employer – is modest. This will result in the existence of an 'optimal' knowledge distance between the hiring firm and the worker's former employer; therefore, to maximize learning outcomes, the hiring firm must follow a 'Goldilocks' approach to knowledge source selection. Thus:

> **Hypothesis 2.** *All else equal, there is an inverted U-shaped relationship between knowledge distance from the peers from whom a focal firm hires employees and the focal firm's post-hiring learning.*

3.3 Research setting

This chapter focuses on the transfer of knowledge across firm boundaries by way of worker mobility. The empirical context for this inquiry is the computer and videogame industry. Since the industry's emergence with *Spacewar!*, developed in 1961 by Steve Russell and his colleagues for the PDP-1 minicomputer at MIT (Graetz, 1981), and the subsequent 1972 commercial release of *Pong*, videogames have bloomed from nonexistence into a cultural staple and a leading entertainment industry. In 2023, five decades after *Pong*, annual videogame revenues in the U.S. had reached $68 billion; globally, this figure stood at over $249 billion, reflecting an 11.8% year-on-year growth rate from the previous year. The videogame industry now rivals and often dwarfs comparable entertainment industries such as film, television, print, and music – for instance, videogames boast annual revenues two to nine times those of recorded music and film (See Table 3.1 for a detailed comparison). Unlike those industries, however, the videogame industry is relatively nascent, and is predicted to continue growing at a compound annual growth rate of 13.1% between 2023 and 2030.[10]

In addition to eclipsing other forms of entertainment, videogames now increasingly serve as a source of intellectual property for tent-pole projects in both film and television.[11] For instance, *The Super Mario Bros. Movie*, based on a series of videogames developed by Japanese developer and publisher, Nintendo, pulled $1.36 billion at the global box office in 2023, becoming the second-highest grossing motion picture released that year. Similarly, *Arcane*, an animated series produced for Netflix in 2022 based on the *League of Legends* series of videogames by Riot Games, earned the streaming service four Emmy awards,[12] while competing television and streaming giant HBO's *The Last of Us*, based on a videogame of the same name by developer Naughty Dog, brought in up to 8.2 million viewers and received eight Emmy awards from twenty-four

[10] *Source:* Fortune Business Insights (https://www.fortunebusinessinsights.com/gaming-market-105730, accessed March, 2024).
[11] *Source:* The Wall Street Journal (https://www.wsj.com/arts-culture/television/hollywood-finds-fresh-characters-and-new-worlds-in-videogames-7358864a, accessed March, 2024).
[12] *Source:* The Television Academy (https://www.emmys.com/shows/arcane, accessed March, 2024).

nominations.[13] It is almost self-evident that the computer and videogame industry represents an important and increasingly impactful sector of the global economy. Despite this, the industry has attracted little attention from strategy researchers.[14]

Table 3.1 Annual revenue and growth comparison, 2018 - 2023

GAME DEVELOPMENT						
	2018	*2019*	*2020*	*2021*	*2022*	*2023*
U.S.	$31.8B	$38.7B	$47.7B	$58.2B	$60.4B	$68.3B
Global	$131.6B	$153.4B	$192.9B	$227.3B	$223.2B	$249.6B
CY Change, *Global*	+15.8% ▲	+16.6% ▲	+25.7% ▲	+17.8% ▲	-1.8% ▼	+11.8% ▲

MOVIE AND VIDEO PRODUCTION						
	2018	*2019*	*2020*	*2021*	*2022*	*2023*
U.S.	$37.6B	$37.7B	$26.2B	$31.5B	$31.3B	$31.6B
Global	$124.9B	$122.5B	$79.5B	$96.4B	$93.4B	$92.5B
CY Change, *Global*	-3.9% ▼	-2.0% ▼	-35.1% ▼	+21.3% ▲	-3.2% ▼	-0.9% ▼

RECORDED MUSIC						
	2018	*2019*	*2020*	*2021*	*2022*	*2023*
U.S.	$9.7B	$11.1B	$12.2B	$15.0B	$15.9B	$17.1B
Global	$17.4B	$18.8B	$20.1B	$23.8B	$26.0B	$28.6B
CY Change, *Global*	+10.1% ▲	+8.0% ▲	+6.9% ▲	+18.4% ▲	+9.2% ▲	+10.0% ▲

This table reports revenue and growth figures for the game development, film, and recorded music industries for the period 2018 - 2023. All revenues in nominal USD. **SOURCES: IBISWORLD, INTERNATIONAL FEDERATION OF THE PHONOGRAPHIC INDUSTRY GLOBAL MUSIC REPORT, RECORDING INDUSTRY ASSOCIATION OF AMERICA U.S. MUSIC REVENUE DATABASE, STATISTA MARKET INSIGHTS.**

[13] *Source:* The Television Academy (https://www.emmys.com/shows/last-us, accessed March, 2024); Variety (https://variety.com/2023/tv/news/the-last-of-us-season-1-finale-ratings-viewers-1235551465/, accessed March, 2024).

[14] Recent exceptions include Lee (2022), Miric et al. (2023), Mollick (2012), Ozalp et al. (2023), and Tschang & Ertug (2016).

This study focuses on game development, the upstream segment of the videogame industry, which involves the actual creation of videogame software for consoles, personal computers, and handheld devices. Videogame development is a knowledge-intensive industry, and reflects the features of both a high-technology and a creative industry. Like software development, game development requires highly technical and complex computer programming skills, with some game projects requiring the services of hundreds of programmers. Likewise, game development also incorporates a great deal of creative work – similar to Hollywood film productions or television shows, many games heavily rely on the skills and creativity of teams of writers, visual artists, animators, music composers, performers (actors, motion capture performers, voice actors, etc.), and editors. This dual nature of videogames is not incidental, but is intrinsically tied to how the industry emerged and evolved: the early videogame industry was fueled by a pool of skilled creators from the comic book and animated film industries, combined with the cutting-edge technology and expertise of veterans in the consumer electronics industry (Aoyama & Izushi, 2003; Graetz, 1981). Nowadays, advances in gaming are intrinsically tied to the evolution of artificial intelligence and electronic circuitry (both of which allow for greater complexity and fidelity of games) as well as increasingly immersive designs and novel in-game narratives.

Figure 3.1 illustrates the organization of firms in the industry. A typical game is developed by one or more videogame development studios (hereafter *studios*) working with or under a publisher. While it is common for a studio to be a subsidiary of a given publisher (e.g., Naughty Dog, which was initially independent but is now under the Sony Computer Entertainment umbrella), many studios also exist independently, either publishing their games unilaterally (e.g., Epic Games with their 2017 release *Fortnite*) or through arm's length arrangements with publishers (e.g., CD PROJEKT RED, whose 2007 game *The Witcher* was co-published by Atari).

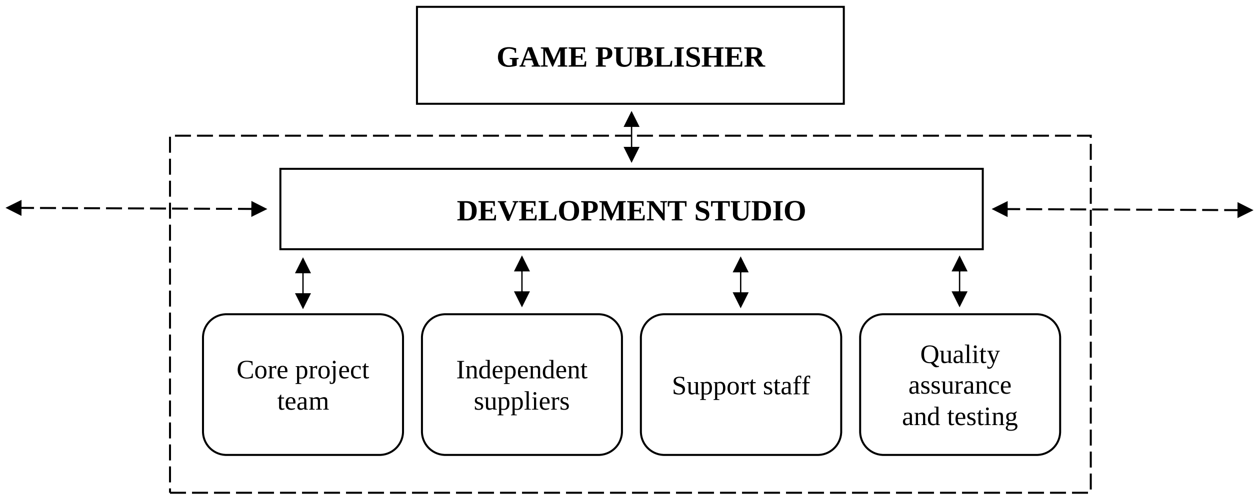


Figure 3.1 Organization of firms in videogame development.

Note: This figure describes the organization of firms in the videogame industry. Game development in carried out by upstream firms known as development studios, and distribution is carried out by game publishers. Studios may be subsidiaries of publishers, or they may be independent, engaging in arm's length partnerships with publishers not unlike those typical between production companies and distributors in Hollywood. Central within a development studio is the core team for a given videogame project, which is structured into different role-based sub-teams. Roles include production and project management, game design, programming, concept art and animation, sound design, and quality assurance.

Individual projects vary substantially in scope and scale, but they frequently represent large investments for studios, with so-called 'Triple-A' projects costing up to a high of over $300 million.[15] Studios are composed of project teams assembled around a given game or series of games, each including a mix of technical and creative workers. While there is considerable variation across studios and across individual projects, the core team of developers for a given game will typically include writers, artists, programmers, software engineers, and other creative and technical workers central to the creation of the game (Irish, 2005). Studios also frequently engage the services of outside suppliers, including performers, concept artists, and composers. See

[15] *Source:* VentureBeat (https://venturebeat.com/business/red-dead-redemption-2-could-hit-20-million-in-sales-and-turn-a-profit-by-december/, accessed March, 2024).

Table 3.2 for a detailed description of the organizational structure of large game studios, and Figure 3.2 for an illustration of the typical project timeline.

Table 3.2 Organizational structure of a typical development studio

ROLE	**DESCRIPTION**
Executive producer	The overall project manager for a given game, responsible for planning, scheduling, monitoring game development, and ensuring project delivery. Producers are less involved in the day-to-day development process, but instead oversee and manage all aspects of the game, including development costs, revenue generation, and overall game quality.
Directors	The creative heads for a given project, responsible for day-to-day decision-making, as well as for defining and directing the project's creative and technical vision. A project may have one or more directors, depending on its scale. As directors are principally in charge of many of the decisions that customers readily notice (such as the graphical fidelity of a game, or the novelty and cohesion of a game's narrative), many directors are likely to be known by players. Examples of prominent directors in the industry include Shigeru Miyamoto (*Super Mario Bros.*), Ed Boon (*Mortal Kombat*), Neil Druckmann (*The Last of Us*), David Vonderhaar (*Call of Duty: Black Ops 2*), and Hideo Kojima (*Metal Gear Solid*).
Leads	On large projects, leads oversee distinct aspects of a project that require senior leadership. For instance, a 'lead artist' helps execute the director's vision by overseeing the combined talents of team members in charge designing characters, environments, lighting, and so on.
Sub-leads	Similar to leads in that they oversee the day-to-day tasks of their team, but more heavily involved in the actual game development process.
Contributors	The vast majority of team-members, responsible for executing on the day-to-day development process. Examples include animators, gameplay engineers, programmers, sound designers, and visual effects artists. Contributors vary substantially in the extent to which their roles on a project are technical or creative, with many roles marrying both technical and creative skills.

The information presented in this table was sourced from Irish (2005), as well as from a lead designer at Blizzard, a leading development studio and publisher responsible for Triple-A titles such as *World of Warcraft*, *Overwatch*, and *Diablo*. While there is substantial variation in structure across studios, the information in this table is typical for large gaming companies like Blizzard.

Videogame development offers a particularly suitable setting for a large-sample study of knowledge flows for several reasons. First, studios typically disclose all project-level accreditation information for published games, including information on the specific roles individual contributors have undertaken on a project. As a result, researchers can longitudinally trace with great accuracy the careers of workers in this industry, including instances of mobility across firm boundaries. Second, as previous studies have noted (e.g., Mollick, 2012), videogame development is an industry principally characterized by knowledge work, with both the innovativeness of studios and the success of individual projects largely dependent on the technical and creative expertise of the individuals studios employ. Third, the industry is characterized by constant cycles of technological and creative evolution, stemming from the introduction every few years of new console platforms, electronic circuitry, and game development engines. This evolution creates opportunities for knowledge-based differentiation across firms, and, consequently, for knowledge diffusion.

3.4 Methods

3.4.1 Data and measures

My theory concerns how firms draw knowledge from their peers within an industry via the inward mobility of employees. Accordingly, I construct a comprehensive dataset of the within-industry employment histories of most workers in the videogame development industry, for both private and public firms. The primary data utilized in this effort are sourced from *MobyGames* (https://www.MobyGames.com), a near-exhaustive online repository of gaming information. *MobyGames*, which is owned by the gaming giant Atari and operated by Jeremiah Freyholtz, Tracy Poff, Jim Leonard, Brian Hirt, and others,[16] describes its mission as the meticulous cataloging of

[16] See https://www.mobygames.com/leaderboard/ for a live listing of top contributors to *MobyGames*' catalog.

"all relevant information about electronic games (computer, console, and arcade) on a game-by-game basis."[17]

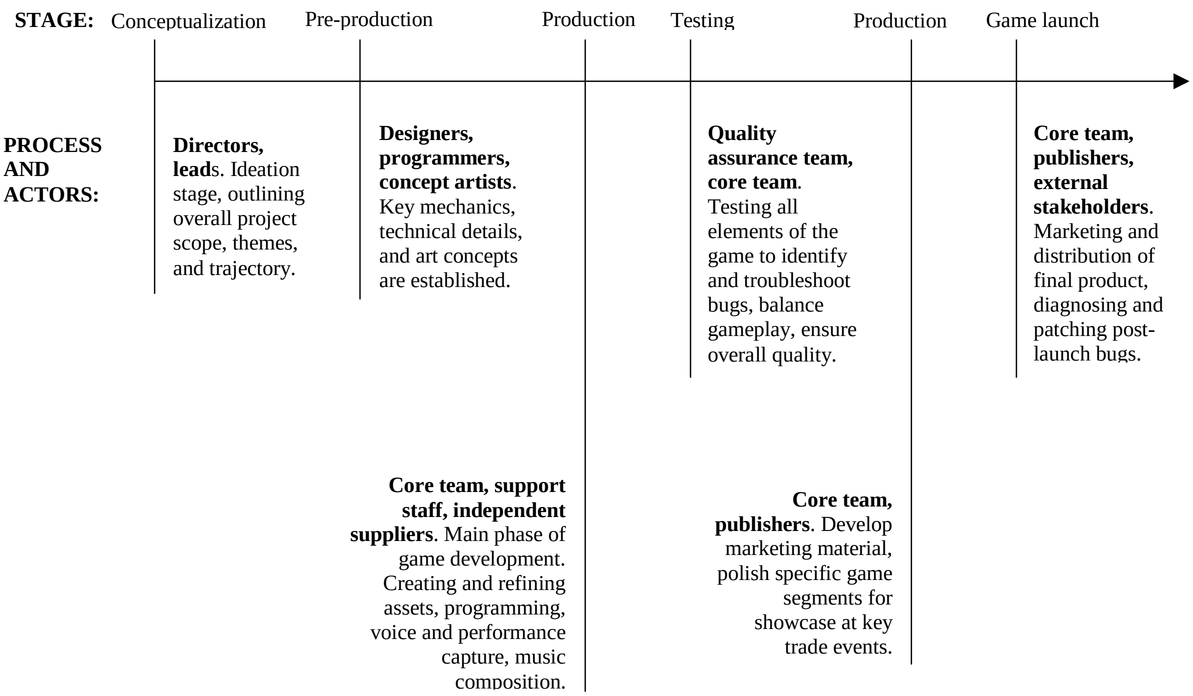


Figure 3.2 Project development timeline

Note: This figure outlines the game development timeline for a typical project. Game development is by its nature an iterative process, so many of the stages described may occur more than once, or co-occur within a game's development. For instance, while the bulk of testing occurs near the tail-end of the development process, game developers commonly test discrete segments of a game as throughout the process, iterating repeatedly between testing and production

The catalog contains crowdsourced and peer-reviewed microdata on over 270,000 commercially published game projects, including the 1.2 million unique individuals involved in their creation across 51,000 firms. See Figure 3.3 for an illustration of some of the information available in the front-end interface for a typical game. Data for each game project includes accreditation, development studio, publisher, genres, aggregated reviews from critics and

[17] *Source:* https://www.mobygames.com/info/about/, accessed April, 2024.

customers, publication information, platform information, and technical specifications. Of particular note, *MobyGames*' accreditation for each project allows for the linking of individual developers to the studios they worked for at the time of each project – this includes a clear understanding of the role each developer played on a given project.

The catalog's accreditation information is hand-sourced from game manuals and from the credits section of a game (similar to the end credits section in a movie or television program) by independent *MobyGames* contributors, after which it is verified and added to the catalog by *MobyGames* administrators.[18] *MobyGames* is the largest and most comprehensive database of its kind, and has been employed and validated in recent empirical work within the management literature (See for instance Lee, 2022; Mollick, 2012; Piezunka & Grohsjean, 2023; Storz et al., 2015). All *MobyGames* data for this chapter were collected using call requests to the catalog's API service developed and executed in Python.

My second data source was an archive of the videogame review aggregator *GameRankings.com*, which contains project-level Bayesian average critic review scores for all videogames that have accumulated six or more reviews from critics. Finally, the geographic information for firms in my sample was hand-collected from multiple sources including *LinkedIn* and *Compustat*, as well as from company websites, and was geocoded using *Google*'s Geocoding API tool.

The dataset used for my analysis is constructed as follows. I begin at the project level, with an exhaustive list of all game projects available in the *MobyGames* catalog, from 1972 to 2023. I track all instances of worker mobility for the studios behind each of these projects, identifying

[18] See https://www.mobygames.com/info/standards/ for a detailed manual of *MobyGames*' data collection standards.

both the worker's origin and destination firms. I follow Mollick (2012) and Storz et al. (2015) and focus on workers in the 'core team' for a given project. These are the individuals – designers, artists, programmers, producers, and managers – principally involved in the project's development, and excludes those only peripherally involved such as voice actors, testers, musicians whose songs were used in the game, and individuals listed in the game's acknowledgments section. I then merge this data with all available information on the origin and destination firm, as well as all information on the workers themselves. Finally, I follow Storz et al. (2015) and narrow my attention to games released for console platforms or computers (or both),[19] and for which complete information is available across all my data sources. In total, the final dataset for testing H1 contains information on 434,515 focal studio-peer studio-year observations covering 11,660 focal studios, and the dataset for testing H2 contains 60,543 studio-year observation for 10,107 focal studios. Both datasets cover the period 1979–2015. You may refer to Table 3.3 for a summary of all measures used; detailed descriptions of their construction are provided below.

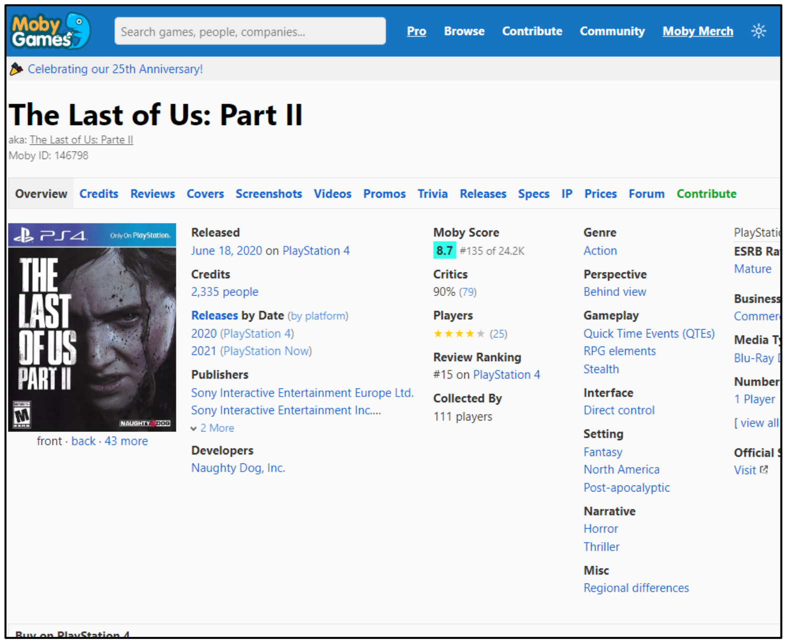
Measures for Testing H1

Dependent Variable

H1 concerns the hiring decisions of development studios. The goal is to establish whether the mobility patterns in this industry are consistent with the premise that firms strategically hire away each other's employees in order to gain access to each other's knowledge. *Inter-studio mobility* captures the rate of mobility between firms by identifying and counting instances when workers moved to a studio *i* from some other studio *j* in a given calendar year. I identify these mobility eve-

[19] Note that my approach differs slightly from Storz et al. (2015) – where the previous paper focused exclusively on console games, I include both computer and console games. Advances in microchip technology have made it such that many games in recent years are just as compatible for consoles as they are for computers, meaning many of the same studios and game designers making computer games are also making console games. Focusing my attention on one or the other would omit important within-firm dynamics.

(a) *Main page*



(b) Accreditation

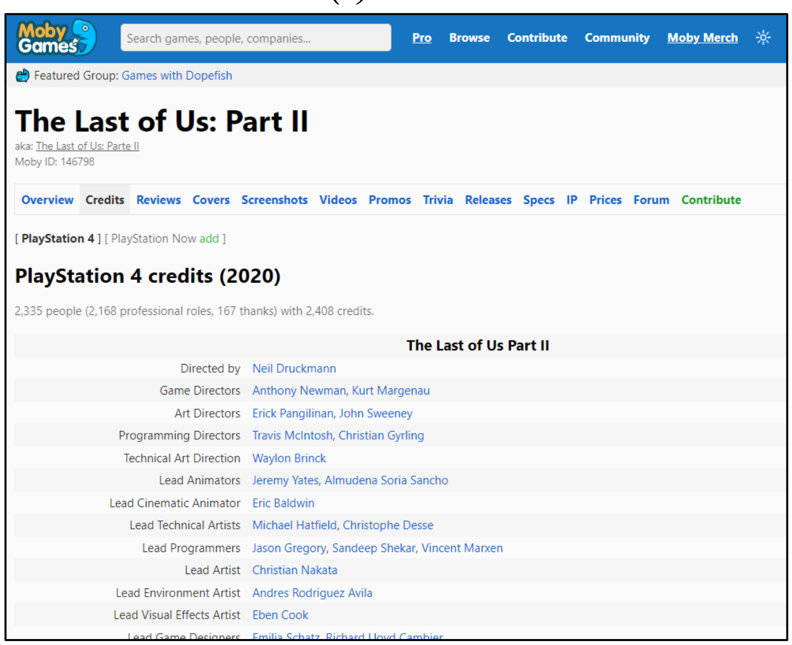


Figure 3.3 A typical entry in the *MobyGames* catalog.

Note: This figure illustrates the front-end user interface for a typical game on MobyGames.com. Panel A shows the landing page for a given game, which includes all basic information about the game, including release information, critic and user reviews, and genre information. Panel B shows accreditation information, which includes both the names and roles of all individuals involved in the project. Accreditation is categorized in accordance with the game's manual or credits section, and so may differ slightly across games. Some individuals are credited more than once on a given game – this suggests they occupied multiple roles on the project. For example, it is not uncommon for a project's principal director to also be credited as the writer or narrative lead. For the game illustrated in this figure, 2,335 unique creators were credited across a total of 2,408 roles.

nts by tracking instances when a worker identified in *MobyGames* on a project belonging to studio *j* subsequently appears on a project belonging to studio *i*. While it is not possible to precisely identify the timing of such instances, I follow Corredoira & Rosenkopf (2010) and others in the mobility literature and code the timing of a given instance of mobility as the year before the employee was credited on a project by firm *i*. The unit of analysis for *Inter-studio mobility* is the dyad-year – each observation represents a unique pairing of destination studio *i* and source firm *j* for a given year.

Independent Variables

To test H1, I construct my measure of knowledge distance two alternative ways. I first characterize knowledge distance as *Superiority of peer studio j*, following the construction of the variable *Knowledge distance* in the second chapter of this dissertation – that is, *Superiority of peer studio j* infers the difference in the extent of knowledge for a focal studio and an alter studio using their observed capabilities, based on the cumulative performance of their past projects. I take the difference in the quality of products by firm *i* and firm *j*, with quality measured as the weighted average of *GameRankings* scores received by all their prior games.[20] The weighting is based on vintage, and increasingly discounts games the older their vintage. For example, if a studio has previously made three games over a period of ten years, the most emphasis is placed on the most recently released of the three, and the least emphasis is on the oldest. I include vintage-based weighting for this variable to reflect organizational forgetting – due to labor turnover, technological and environmental changes, and overall knowledge decay, a firm's pool of knowledge may depreciate rapidly over time (Argote et al., 1990; Argote & Epple, 1990; David &

[20] The construction of *Superiority of peer studio j* for this chapter loosely follows Piezunka & Grohsjean's (2023) construction of their independent variable *Superiority of peers*.

Brachet, 2011). A prominent, albeit dramatic, example is NASA's ongoing Artemis program. Artemis aims to reestablish the space agency's moon-landing missions, which were abandoned in 1972 following Apollo 17. Despite significant advances in technology since, NASA is having to re-learn how to successfully undertake a crewed mission to the moon. As one NASA flight controller explains: "When the Apollo program ended, the factories that assembled those vehicles were re-tasked or shut down. The jigs were disassembled. The molds were destroyed. The technicians, engineers, scientists, and flight controllers moved on to other jobs. Over time, some of the materials used became obsolete."[21] Resultantly, a firm's most recent products will more closely reflect its current capabilities than will its older products. *Superiority of peer studio j* is constructed for each dyad-year in my data and can take values in the range [-100, 100]. A negative value reflects a superior *focal* studio and inferior *alter* studio, while a positive value inversely reflects a superior *alter* studio and inferior *focal* studio. Following the approach in the second chapter, my analysis for H1 decomposes this measure in order to separately account for knowledge distance form superior peer studios and knowledge distance from inferior peer studios.

For robustness, I alternatively construct knowledge distance using the amount of experience accrued by studios to infer the relative extent of their knowledge. *Distance in experience depth*, which builds on Ozalp et al.'s (2023) *Experience depth* measure, is operationalized as the genre-weighted difference between development studios *i* and *j* in the total volume of experience each studio has accumulated, with volume measured as the number of previous projects the studio has successfully developed and commercially released. Positive values of *Distance in experience depth* reflect the *alter* studio is superior and negative values reflect the

[21] *Source:* Newsweek (https://www.newsweek.com/nasa-discarded-hardware-apollo-missions-moon-1739500), accessed April, 2024.

opposite. As with *Superiority of peer studio j*, my analysis using *Distance in experience depth* separately accounts for knowledge distance from superior versus inferior alter studios.

Control Variables

In order to account for confounding effects and increase confidence in the results, I control for several factors across levels. At the most granular level, which is the workers moving from firm *j* to firm *i*, I include multiple measures to reflect both the quality and tendencies of the mobile workers: *Employee industry tenure* is a count of previous projects a mobile employee has previously worked on, averaged across employees moving from *j* to *i* in a specified year. *Employee experience breadth* is an indicator equal to 1 if any of the mobile employees between *i* and *j* has previously served in both creative and technical roles, and zero otherwise. *Employee technical experience* is a count of projects on which a hired employee has held a technical role, averaged across mobile employees. *Employee creative experience*, *Employee leader experience (director)*, *Employee leader experience (writer)*, *Employee leader experience (producer)* are constructed in the same fashion just described, but reflecting a mobile employee's experiences in creative and leadership positions. *Employee job-hopping propensity* is defined as the average number of different videogame firms for which mobile employees have worked in the past, divided by the total number of years since they joined the industry.

At the dyad level, I include controls for alternative factors that may increase the likelihood of firms hiring from each other. *Extent of genre overlap* reflects the proportion of all genres in which development studio *i* was active in the preceding five-year window that studio *j* was also active in. For example, if the studio Infinity Ward had games in ten genres in the previous five years and another studio, Blizzard, was active in three of those genres, then the extent of genre overlap, assuming Infinity Ward is the focal firm, would be 0.3. *Shared publisher* is an indicator equal to 1 if the two studios share the same game publisher. *Shared gaming engine* is an indicator equal to 1 if the two studios use the same gaming engine on any of the games they released in the preceding five-year window. Gaming engines, which are akin to software engines, are middleware software environments that some development studios may use as foundational frameworks on which to build their games. Engines may be developed by a third party for licensed use by other developers, or they may be developed in-house for a development studio's in-house use. *Same MSA* is an indicator equal to 1 if studios *i* and *j* are located in the same metropolitan area.

I also include controls specific to the focal studio. *Hiring studio size* is the logged count of core team workers across all the studio's current projects. *Hiring studio industry tenure* is the number of years since the studio's first game release.

Measures for Testing H2

H2 focuses on the performance implications of development studios' hiring decisions in order to establish whether there exists a 'Goldilocks' effect in this setting. My analysis examines whether there exists an inverted U-shaped relationship between knowledge distance and subsequent performance in this setting, as in the results from the previous chapter using data on individuals embedded in competing teams. In other words, do firms realize any performance premiums from making hiring decisions that approximate the 'Goldilocks' approach?

Dependent Variable

The variable *Performance* is constructed for each firm-year and follows extant research on videogame development, measuring a development studio's performance as the average critic reviews across all games it released in a given year (Katila et al., 2022; Lee, 2022; Storz et al., 2015; Tschang & Ertug, 2016). I employ *GameRankings*' Bayesian average score, normalized from 0 to 100 for each game – a score approaching 100 represents an exceptional game, while one approaching 0 represents one of lackluster quality and minimal novelty. Previous research has argued that critic reviews are a particularly pertinent gauge of project-level performance within creative industries. Not only do they reflect the overall novelty, or innovativeness, of a project, but they are also authored by industry insiders, drawing on their wealth of specialized knowledge. As a result, they offer a comprehensive picture of new products, framing them within the broader context of existing products in the market (Storz et al., 2015). The videogame industry is no exception.

Independent Variables

I employ the measure *Superiority of peer studio j*, defined above, as the independent variable in my tests of H1, and it is meant to reflect the knowledge distance between a focal studio and its peers.

Control Variables

My analysis includes multiple controls for potential confounds at the studio level. *Studio size* is the logged count of core team workers across all the studio's current projects. *Studio industry tenure* is the number of years since the studio's first game release. To account for variation in the ability of a publisher to effectively market and distribute a studio's products, I include *Publisher*, a series of indicator variables identifying any third-party publishing firms that may have marketed and distributed the games developed by a focal studio. Similarly, *Genre* and *Platform* are series of dummies identifying the genres and platforms under which a studio's games are categorized in *MobyGames*, and are included to account for potential variation across genres and gaming platforms. Following the approaches of Mollick, (2012), Ozalp et al. (2023), and Storz et al. (2015), I also control for the *Proportion of games that are licensed* and the *Proportion of games that are sequels*. Licensed games are based on third-party properties, such as movies, books, or television shows – for instance, entrants in the *Batman: Arkham* series of games were developed by Rocksteady and WB Games Interactive, based on the DC Comics and Warner Bros. character Batman. I expect games based on licensed properties to vary substantially from original properties. Similarly, I expect sequel games, which are games based on previous games, usually by the same studio, to vary from original properties as they benefit from the reputation (typically positive) of their predecessor. Examples of sequels include *FIFA 22*, developed by EA Vancouver, and *Far Cry 3,* developed by Ubisoft Montreal.

Finally, I control for the *Proportion of games that are multiplatform* – while it is common for games to be released for a single family of platforms (e.g., games by the Santa Monica-based developer Naughty Dog are released exclusively on Sony PlayStation devices), it is more typical for games to be released across platforms. Studios that develop games for single platform families may vary in unobservable ways from those that develop multi-platform games. I therefore account for the proportion of a studio's games that are released across platform families.

3.4.2 Econometric specifications

The goal of my empirical analysis is to examine (H1) whether firms behave 'optimally' when they hire workers from their peers, based on the model from the first chapter and the results in the second chapter which use individuals embedded within teams, and (H2) whether that behavior is also optimal at the firm level.

Table 3.3 Variable descriptions

(a) FOR TESTING HYPOTHESIS 1	
VARIABLE	**DESCRIPTION**
Inter-studio mobility (DV)	A count of workers moving from firm *j* to firm *i*.
Superiority of peer studio j	The distance in the extent of knowledge between studios *i* and *j*, measured using critic reviews. Positive values represent superiority of studio *j*, negative values represent superiority of studio *i*.
Distance in experience depth	The genre-weighted difference between studios *i* and *j* in in their cumulative volume of experience developing games.
Employee industry tenure	A count of previous projects on which a mobile worker has previously worked.
Employee experience breath	A dummy equal to 1 if any of the mobile employees between *i* and *j* has previously served in both creative and technical roles.
Employee experience	A series of measures accounting for mobile employees' technical, creative, and leadership experience.
Employee job-hopping propensity	An average ratio of the number of previous videogame firms for which mobile employees have worked and the number of years since they joined the industry.
Extent of genre overlap	The proportion of genres in which studio *i* is active in which studio *j* is also active.
Shared publisher	A dummy equal to 1 if the two studios share the same publisher.
Shared gaming engine	A dummy equal to 1 if the two studios use the same gaming engine on any of their games released in the preceding five years.
Same MSA	A dummy equal to 1 if the two studios are located in the same metropolitan area.
Hiring studio size	A logged count of core team workers across a focal hiring studio's current projects.
Hiring studio industry tenure	The number of years since the focal hiring studio's first game release.

(b) FOR TESTING HYPOTHESIS 2

VARIABLE	DESCRIPTION
Performance	The average critic review scores across all games a focal studio in a given year.
Studio size	A logged count of core team workers across a focal hiring studio's current projects.
Studio industry tenure	The number of years since the focal hiring studio's first game release.
Publisher	A series of dummies identifying publishers that distributed games developed by a focal studio.
Genre	A series of dummies identifying the genres into which a focal studio's games are categorized.
Platform	A series of dummies identifying the platform families on which a focal studio's games are available.
Proportion of games that are licensed	The proportion of games developed by a focal studio that are based on licensed properties.
Proportion of games that are sequels	The proportion of games developed by a focal studio that are sequels to previosuly released games.
Proportion of games that are multiplatform	The proportion of games developed by a focal studio that are available across platform families.

Panel (a) of this table describes the variables used for testing Hypothesis 1. Except for the controls for size and industry tenure, all variables are recorded at the dyad level, with each observation representing a unique destination studio-source studio-year. Panel (b) describes variables used for testing Hypothesis 2. All variables are recorded at the studio-year level.

My unit of analysis for testing H1 is each dyad in which at least one employee is mobile across development studios. While multiple observations of a focal dyad are permitted if the dyad repeats across years, I treat my sample as pooled cross-sectional as opposed to panel. This is because most dyads occur either once or a small handful of times in my sample, making panel estimation untenable. My dependent variable, *Inter-studio mobility*, is a count measure that can only assume nonnegative integer values, with most observations concentrated close to zero. The recommended approach for outcome variables of this sort is the Poisson regression (Greene, 2003). A key assumption of such a model is that the data are distributed according to the Poisson distribution, such that the mean and variance of the dependent variable are equal; if this distributional assumption is violated, then the likelihood function would be misspecified. My data, however, are characterized by overdispersion – that is, the variance of *Inter-studio mobility* is substantially larger than the mean. Consequently, I employ a negative binomial model, as it accounts for such excess variance (Hausman et al., 1984). My model for testing H1 has the form:

$$\lambda_{i,j} = \exp(\beta_1 \overline{x}_{i,j} + \beta_2 \underline{x}_{i,j} + \gamma Z_{i,j} + \varepsilon_{i,j}) \tag{3.1}$$

where $\lambda_{i,j}$ represents the expected number of workers moving to studio i from studio j, $\overline{x}_{i,j}$ represents the variable *Superiority of peer studio j* for superior peer studios, $\underline{x}_{i,j}$ represents *Superiority of peer studio j* for inferior peer studios, $Z_{i,j}$ is a vector controlling for dyad, studio, and worker traits, and $\varepsilon_{i,j}$ is the unobserved error term.

The unit of analysis for testing H2 is the studio-year – each row of data represents a unique studio and year combination. Similar to the main analysis in the second chapter, my core test is for the effect of knowledge distance on subsequent performance. I employ panel a fixed effects regression model of the form:

$$\begin{aligned} y_{i,t} = {} & \beta_1 Knowledge\ distance\ from\ superior\ peers_{i,j,t-1} \\ & + \beta_2 Knowledge\ distance\ from\ inferior\ peers_{i,j,t-1} \\ & + \beta_3 \left(Knowledge\ distance\ from\ superior\ peers_{i,j,t-1}\right)^2 \\ & + \gamma Controls_{i,t} + \phi_t + \delta_i + \varepsilon_{i,t} \end{aligned} \tag{3.2}$$

where $y_{i,t}$ represents a studio's *Performance*, *Knowledge distance* is constructed using *Superiority of peer studio j*, ϕ_t is a year fixed effect term, δ_i is a fixed effect term identifying each development studio i, and $\varepsilon_{i,t}$ is the error term.

3.4.3 Comparison with Chapter 2

As the empirical analysis reported in the following section is an extension of sorts of the analysis from the second chapter, it is worth outlining, before proceeding to a discussion of my results, how the analysis in the present chapter differs from the second chapter's. This is especially relevant given these differences may inform the possibility of diverging results across the two chapters. At a high level, the primary point of divergence between the two sets of empirical tests is the unit of analysis: where the second chapter's analysis focuses on peer-based learning at the individual level, examining the linkages between individuals embedded within teams and competing across teams, the present chapter's analysis focuses on this phenomenon at the firm level, examining the linkages between development studios embedded within a single industry. A second point of difference between the two sets of analyses is the hypothesized channels for knowledge flows across units. In the second chapter, knowledge is hypothesized to flow across individuals through a combination of observing peers' behaviors and modeling own behavior after the observed peer behavior as well as directed learning. In the present chapter, I hypothesize that knowledge flows across development studios through the mobility of workers across studios.

A further difference is the way peer groups for a focal unit are chosen. A key advantage of the second chapter's analysis is that individuals are exogenously assigned to their peer groups by the game's matchmaking system, which removes selection-related endogeneity concerns. The setting thus lends itself well to generating normative predictions on how knowledge seekers *ought* to be learning from their peers. In contrast, peer group selection in the present chapter is endogenously determined: development studios actively select the peers whose knowledge they potentially learn from by way of hiring away their employees. Resultantly, this warrants a descriptive exploration of who firms are actually hiring from in this setting, which is the primary function of the analysis of H1.

In addition to the question of peer group selection, linkages and interactions between units across the two chapters also differ in the breadth of interactions observed. The data in the second chapter allow for the separate observation of peer interactions governed by cooperative and competitive ties. In the present chapter, units share competitive ties in product market space. Though some potentially cooperative ties may exist – between studios owned by or working with the same publisher, for instance – they are few and far between and therefore don’t lend themselves to a systematic analysis of the differences between cooperative and competitive linkages, as was done in the second chapter. Further, it is not a given that being under the same publisher necessarily implies cooperation between studios; it may just as likely lead to enhanced competition for the shared publisher’s resources. My analysis, reported in the following section, includes a control term to account for instances where two studios share a publisher.

The analyses also differ in the specific model specifications and variable measures for key constructs of interest. While both chapters infer knowledge distance from a focal unit’s ability, which is observed from the unit’s past performance, the specific performance variables that form the basis for ability differ. In the second chapter, ability is measured using a rolling average of past match-level performance, with performance measured as the per-match opponent eliminations. I separately account for knowledge distance from superior, inferior, collaborative, and competitive peers. In the present chapter, ability is measured using the cumulative performance of their past projects, with performance measured using critics' review scores from *GameRankings*. My analysis includes separate terms for superior and inferior peers, but not for collaborative and competitive peers. Relatedly, the outcome variable for performance in the previous chapter is constructed using opponent eliminations in a focal match, while the present chapter employs critics' review scores across a studio's projects released in the focal year. Finally, the previous chapter's empirical tests rely on quadratic and interrupted fixed effects regressions, while the analogous analysis in the present chapter relies on quadratic fixed effects and instrumental variable regressions, with the tests for H1 employing negative binomial regressions.

3.5 Results

Summary statistics are presented in Table 3.4. The dyad-level sample, shown in Panel (a) and used for testing H1 has 434,515 observations. The studio-level sample, shown in Panel (b) and used for testing H2 has 60,543 observation, covering 10,431 development studios. Each observation is a unique studio-year combination.

My empirical tests begin in Table 3.5, which shows the core results for my examination of H1. Recall, H1 proposes that development studios will make strategic hiring decisions with the goal of sourcing knowledge generated by knowledge-rich peer studios. I use negative binomial regressions to examine the relationship between the knowledge distance[22] between a focal studio and its peers and the inward mobility of workers from those peers, with robust standard errors clustered at the studio level. Control variables are suppressed in my results table, for readability.

[22] Knowledge distance is measured using the variable *Superiority of peer studio j*. See Table 3.3 for a description of the variable.

Model (1) shows regression results using a single measure for the independent variable which captures knowledge distance from both superior and inferior peers – that is both positive and negative knowledge distance values – and excludes all control variables and fixed effects. In this model, knowledge distance has shows a positive but statistically insignificant relationship with inter-studio mobility. Model (2) is identical to model (1), but introduces the control variables across the dyad-, firm-, and mobile employee-levels, as well as fixed effect terms at the focal hiring studio and year levels. The estimated coefficient on knowledge distance is positive and highly significant.

In models (3) and (4), I decompose my knowledge distance measure, as was done in my tests in Chapter 2, to separately capture knowledge distance from superior peers and from inferior peers. The goal of this decomposition is to relax the assumption – implicit when using a single measure – that the effect of superior peers is identical to, or an exact mirror of, that of inferior peers. In so doing, I avoid potentially confounding the two effects in my regressions. Like model (1), model (3) does not include any controls or fixed effects, while model (4) follows model (2) in including all controls and fixed effects. The coefficient on knowledge distance from superior peer studios is positive and significant in the preferred estimation in model (4), which includes all controls and also separately accounts for superior and inferior peers (*coef*: 0.008; *s.e.*: 0.002). Taking the exponent ($e^{0.008} = 1.008$), gives the marginal contribution of a unit change in the independent variable for superior peers: controlling for other factors, every unit increase in the superiority of a peer studio – with superiority measured according to aggregated review scores of previously released game projects – is associated with a 0.8% increase in the number of employees hired from that partner. The estimated coefficient on the analogous knowledge distance term for

Table 3.4 Summary statistics

(a) FOR TESTING HYPOTHESIS 1

VARIABLE	N	MEAN	STD. DEV.	MIN	MAX
Inter-studio mobility (DV)	434,515	3.44	2.934	1	20
Superiority of peer studio j	434,515	7.873	9.256	-13.2	57.2
Distance in experience depth	434,515	0.998	2.169	-8.7	11.6
Employee industry tenure	434,515	11.98	2.593	1.6	25.086
Employee experience breath	434,515	0.252	0.434	0	1
Employee technical experience	434,515	7.53	4.356	0	16.5
Employee creative experience	434,515	4.935	2.011	2	13.333
Employee leader experience (director)	434,515	0.744	1.356	0	3.5
Employee leader experience (writer)	434,515	1.925	0.988	0	6
Employee leader experience (producer)	434,515	0.22	0.445	0	3
Employee job-hopping propensity	434,515	4.501	2.926	1	13
Extent of genre overlap	434,515	0.602	0.166	0.125	0.95
Hiring studio size	434,515	396.279	87.333	33	817
Hiring studio industry tenure	434,515	7.16	6.081	5	38

(b) FOR TESTING HYPOTHESIS 2

VARIABLE	N	MEAN	STD. DEV.	MIN	MAX
Performance	60,543	84.762	5.137	11.942	95.025
Proportion of games that are licensed	60,543	0.062	0.117	0	1
Proportion of games that are sequels	60,543	0.096	0.139	0	1
Proportion of games that are multiplatform	60,218	0.210	0.171	0	1

This table provides summary statistics for the variables used in testing Hypotheses 1 and 2. Panel (a) describes the variables used for testing Hypothesis 1. Panel (b) describes the variables used for testing Hypothesis 2.

Table 3.5 The relationship between knowledge distance and inward worker mobility

	Dependent variable: *Inter-studio mobility*			
	(1)	(2)	(3)	(4)
Knowledge distance from studio j in t - 1 (all)	0.004	0.007***		
	(0.003)	(0.002)		
Knowledge distance from superior studio j in t - 1			0.005*	0.008***
			(0.003)	(0.002)
Knowledge distance from inferior studio j in t - 1			0.004	0.003
			(0.005)	(0.005)
Controls	N	Y	N	Y
Studio FEs	N	Y	N	Y
Year FEs	N	Y	N	Y
Observations	434,515	434,515	434,515	434,515
Number of studios	11,660	11,660	11,660	11,660

This table reports negative binomial regression results examining how knowledge distance between a focal studio and its peer studios relates to the inward mobility of workers from the peer studios. Knowledge distance is measured using the variable *Superiority of peer studio j*. The dependent variable across all models is the measure *Inter-studio mobility*. All variables used are described in Table 3.4. The symbols ***, **, and * denote two-sided p-values less than 0.001, 0.01, and 0.05 levels, respectively. Robust standard errors are reported in parentheses, clustered at the studio level.

inferior peers is insignificant. The results in model (4) of this table (which are qualitatively similar in all but the first model), are consistent with H1 and suggest that all else held equal, videogame development firms hire employees primarily from peers in possession of superior capabilities. It should be highlighted that these results are only descriptive and ought to be interpreted as such – though I make efforts to control for endogeneity, controlling for observable characteristics across units of analysis, the results do not reflect conclusive causal evidence.

A final point of note in Table 3.5 regards the relative effects when controls are omitted from the analysis. The difference in magnitudes and significance between models (3) and (4), as well as between models (1) and (2), suggests that the characteristics of mobile employees, as well as those of their origin and destination studios account for enough of the variation in the dependent variable, *Inter-studio mobility*, that without accounting for these factors, the relationship between the dependent variable and knowledge distance is obscured. In particular, I argue without accounting for the characteristics of mobile employees, it would be difficult to understand the potential influence of their origin firm – and how it relates to the destination firm – on hiring decisions.

I turn next to the analysis of H2, whose baseline results are shown in Table 3.6. I use quadratic fixed effects panel regression to explore the degree to which hiring workers peers from whom a development studio has varying levels of knowledge distance impacts subsequent performance. I employ two-way clustering at the studio-year level in both models presented, with 10,431 development studio clusters and 37 year clusters. The two models are identical, excepting the inclusion of controls and fixed effects at the studio, publisher, and year levels in model (2). The estimated coefficient on the first independent variable, *Knowledge distance from superior peers*, is consistent in direction and significance across both models. Conditional on controls, the coefficient is 0.643 and has a p-values less than 0.01, suggesting a positive link between the dependent variable, performance, and the linear knowledge distance term. The estimated coefficient for the quadratic knowledge distance term for superior peers is significant across both models, and negative in the second model. Taken together with the positive coefficient on the linear term, this result points to an inverted U-shaped relationship between our dependent and independent variables for superior peers. Intuitively, the results from model (2) imply that development studios face an average increase in subsequent performance when they hire workers from peer studios of increasing superiority; however, this positive relationship is not linear but rather diminishes and eventually inverts as the superiority of the peer studios continues to increase. This is consistent with H2, as well as with the empirical results from the previous chapter for interactions with superior teammates and with the theoretical predictions of the spillover absorption model with relative assimilation capacity from the first chapter. Finally, the results for inferior peers point to a small negative relationship between knowledge distance and subsequent performance. It should be noted however, that this finding is not statistically significant in model (1) and is only marginally significant (p = 0.1) in model (2)..

Taken together, the tests presented in Tables 3.5 and 3.6 appear in congruence with H1 and H2.

Table 3.6 The effect of knowledge distance on performance

	Dependent variable: *GameRankings score*	
	(1)	(2)
Knowledge distance from superior peers	1.408***	0.643***
	(0.048)	(0.036)
(*Knowledge distance from superior peers*)^2	0.023**	-0.042***
	(0.010)	(0.007)
Knowledge distance from inferior peers	-0.010	-0.020*
	(0.010)	(0.011)
2SLS	N	N
Controls	N	Y
Studio FEs	N	Y
Publisher FEs	N	Y
Year FEs	N	Y
Observations	60,543	60,218
Number of cluster (development studios)	10,431	10,107
Number of clusters (years)	37	36

This table reports quadratic fixed effects regression results examining how knowledge distance between a focal studio and the peer studios whose workers it hires affects performance outcomes. The dependent variable across both models is the measure *GameRankings score.* All variables used are described in Table 3.4. The symbols ***, **, and * denote two-sided p-values less than 0.001, 0.01, and 0.05 levels, respectively. Standard errors are reported in parentheses, two-way clustered at the studio-year level.

3.5.1 Selection issues

The coefficients on the three primary independent variables in Table 3.6 may be biased in the baseline fixed effects regressions just discussed due to selection. In other words, development studios may select the workers they hire based on traits that are unobservable to this researcher but are correlated with subsequent performance. If such is the case, we may erroneously attribute performance premiums or discounts to one's knowledge distance, when they are in fact only an artifact of underlying unobserved traits. The problem of potential endogeneity is not one that is easily solved, but I take steps to tackle this issue by bringing in additional data on the geographic distribution of development studios.

I consider the geographic distance between a focal studio and alter studios as an instrumental variable for the variable *Superiority of peer studio j*, which forms the basis for both linear knowledge distance terms in Table 3.6 as well as the quadratic knowledge distance from superior peers term. As numerous previous studies have shown (Almeida & Kogut, 1999; Ellison et al., 2010; Saxenian, 1994), labor networks tend to be geographically concentrated, facilitating the interfirm mobility of workers within an industry. When workers and employers are in the same localized network, it is easier for both a would-be mobile worker and an employer looking to hire a mobile worker to evaluate the other party and accurately assess their quality. As a result, when a worker and a hiring firm are geographically localized, it is easier for instances of mobility to be primarily informed by the quality match between the hiring firm and the worker.

In contrast, when the would-be mobile worker and the hiring firm are geographically more distant, there are fewer overlaps between the worker's network and the firm's, leading to information asymmetries in the hiring process. In such instances, hiring firms receive only noisy signals about the quality of the worker, and are thus less likely to be able to accurately assess the quality of a worker. As a consequence, considerations of the worker's source firm are likely to be more salient in hiring decisions, primarily because they can serve as signals of the worker's quality.

I therefore posit that the geographic distance between a source firm and hiring firm will be positively correlated with the knowledge distance between the two firms, with source firm superiority serving as substitute signals for the information on would-be mobile workers that would otherwise be available to hiring firms through localized networks.

I employ the logged geographic distance between a hiring firm and the firm whose employee they hired away as an instrument for the potentially endogenous variable *Superiority of peer studio j*. Table 3.7 presents two-stage least squares first-stage regressions as a simple test for the relevance of the instrument. The two models presented are identical but for the inclusion of controls and fixed effects in model (2). The coefficients for the instrument log(*Geographic distance*) are positive and highly significant across both models.

Table 3.7 2SLS first-stage results for testing H2

	DV: *Superiority of peer studio j*	
	(1)	(2)
log(*Geographic distance*)	2.530***	2.243***
	(0.087)	(0.121)
Controls	N	Y
Studio FEs	N	Y
Publisher FEs	N	Y
Year FEs	N	Y
Observations	60,543	60,218
Development studios	10,431	10,107

This table reports the results of the 2SLS first-stage regression to evaluate the validity of the instrument. The dependent variable is the knowledge distance between a focal studio and the peer studios whose workers it hires, measured using *Superiority of peer studio j*, and the independent variable is the instrument, the logged value of the geographic distance between a focal studio and its peers. The symbols ***, **, and * denote two-sided p-values less than 0.001, 0.01, and 0.05 levels, respectively. Robust standard errors are reported in parentheses.

Table 3.8 presents second-stage results. As with previous results, the models in this table are identical but for the inclusion of controls in the second model. Additionally, the two models directly replicate the analysis presented in Table 3.6, except for the independent variables, which are formed for this analysis using the instrumented version of *Superiority of peer studio j*. Model (2) is the preferred estimation, as it includes fixed effects. My core findings for this analysis appear robust to the inclusion of the instrumental variable in my analysis. The estimated coefficient on the linear knowledge distance term for superior peers is comparable in magnitude and significance to the uninstrumented results, albeit slightly smaller (-0.510, compared to -0.643 in Table 3.6).

The quadratic term, likewise, is similar in magnitude and direction (-0.038, compared to -0.042), with a p-value less than 0.05. As with the results in Table 3.6, the results presented in Table 3.8 point to the existence of inverted U-shaped relationship, suggesting that there is an optimal knowl-

Table 3.8 2SLS second-stage results for H2

	Dependent variable: *GameRankings score*	
	(1)	(2)
Knowledge distance from superior peers	1.830***	0.510***
	(0.177)	(0.146)
(*Knowledge distance from superior peers*)^2	0.026	-0.038**
	(0.020)	(0.019)
Knowledge distance from inferior peers	-0.004	0.012
	(0.012)	(0.013)
2SLS	Y	Y
Controls	N	Y
Studio FEs	N	Y
Publisher FEs	N	Y
Year FEs	N	Y
Observations	60,543	60,218
Number of cluster (development studios)	10,431	10,107
Number of clusters (years)	37	36

This table reports second-stage instrumental regression results examining how knowledge distance between a focal studio and the peer studios whose workers it hires affects performance outcomes. The dependent variable across both models is the measure *GameRankings score*, and the independent variable is the instrumented form of *Knowledge distance from peers*. The symbols ***, **, and * denote two-sided p-values less than 0.001, 0.01, and 0.05 levels, respectively. Standard errors are reported in parentheses, two-way clustered at the studio-year level.

-edge distance where spillover absorption by a focal development studio is maximized, consistent with H2.

3.5.2 Robustness

I carry out two robustness exercises for the tests of H1 presented in Table 3.5. In the first, I employ an alternative measure of knowledge distance. My core results employ the measure *Superiority of peer studio j*, which is designed to mirror the analogous independent variable in my regressions in Chapter 2. *Superiority of peer studio j* infers the knowledge possessed by a given studio from their realized performance outcomes, using critics' review scores adopted from the *GameRankings* archive. To ensure the results for my tests of H1 are not an erroneous artifact of the measure's specific construction, I alternatively construct the variable *Distance in experience depth from studio j* which employs development studios' accumulated project experience to infer their knowledge position. You may refer to Table 3.3 for a description of both measures of knowledge distance, or to Section 3.4.1 for detailed discussion of their construction. Table 3.9 below presents the results from replicating Table 3.5 using the alternative measure of knowledge distance. Results are largely consistent with those in Table 3.5.

In the second alternative specification for my tests of H1, I employ alternative employee-level control variables. Where the tests in Table 3.5 controlled for characteristics of the mobile employees, the tests presented in Table 3.10 control for the population of employees at the source firm. I include controls for capturing the number of technical workers in the source firm, then number of creative workers in the source firm, the average employee industry tenure across all employees at the source firm, and the average employee job-hopping propensity. The empirical

Table 3.9 Replicating Table 3.5 with alternative distance measure

	DV: *Inter-studio mobility*	
	(1)	(2)
Distance in experience depth from studio j in t - 1 (all)	0.081***	
	(0.005)	
Distance in experience depth from superior j in t - 1		0.090***
		(0.007)
Distance in experience depth from inferior j in t - 1		0.058***
		(0.014)
Controls	Y	Y
Studio FEs	Y	Y
Year FEs	Y	Y
Observations	434,515	434,515
Number of studios	11,660	11,660

This table replicates Table 3.5 and reports negative binomial regression results examining how knowledge distance between a focal studio and its peer studios relates to the inward mobility of workers from the peer studios. Knowledge distance is measured using the alternative measure *Distance in experience depth from peer studio j*. The symbols ***, **, and * denote two-sided p-values less than 0.001, 0.01, and 0.05 levels, respectively. Robust standard errors are reported in parentheses, clustered at the studio level.

specifications are otherwise identical to those in Table 3.5. Results of these alternative specifications are consistent with those presented in Table 3.5.

3.6 Conclusion

This dissertation examined how the extent of a knowledge source's knowledge advantage relative to an aspiring knowledge recipient impacts realized spillover absorption for the aspiring recipient. I proposed a theoretical framework to evaluate the strategic value of potential sources and evaluated it across two empirical contexts. The framework, which brought together theories and assumptions from the literatures on R&D spillovers and interorganizational learning, was designed to highlight and explore the tradeoff presented by sources of varying levels of superiority relative to the knowledge seeker. I argued that both opportunity and assimilation capacity play a crucial role in shaping how well a knowledge seeker can tap into the knowledge of the sources with whom they interact, as emphasized in the framework in Chapter 1 and demonstrated in the results in Chapter 2 and 3.

Table 3.10 Replicating Table 3.5 with origin studio worker controls

	DV: *Inter-studio mobility*	
	(1)	(2)
Knowledge distance from studio j in t - 1 (all)	0.005*	
	(0.003)	
Knowledge distance from superior studio j in t - 1		0.007**
		(0.003)
Knowledge distance from inferior studio j in t - 1		0.004
		(0.005)
Controls	Y	Y
Studio FEs	Y	Y
Year FEs	Y	Y
Observations	434,515	434,515
Number of studios	11,660	11,660

This table replicates Table 3.5 and reports negative binomial regression results examining how knowledge distance between a focal studio and its peer studios relates to the inward mobility of workers from the peer studios. Studio- and dyad-level controls are included, as in Table 3.5. Worker-level controls are recorded for all employees of source studio *j*, instead of for the mobile workers, as in Table 3.5, and include counts of technical and creative workers, average employee industry tenure, and average employee job-hopping propensity. The symbols ***, **, and * denote two-sided p-values less than 0.001, 0.01, and 0.05 levels, respectively. Robust standard errors are reported in parentheses, clustered at the studio level.

Knowledge seekers are presented with knowledge of limited value when they interact with peers at, or just above, their own knowledge level, but at the same time, they are bounded in their ability to copy knowledge leaders. The relationship between knowledge distance and learning is, as a consequence, more nuanced than previous work has suggested – indeed, my results in the second and third chapters show that while superior peers are undoubtedly useful sources of new knowledge, there is a limit to how useful they can be when they are too far advanced for the knowledge seeker. This important refinement complements the organizational learning perspective, emphasizing the role of absorptive capacity and the potential challenges associated with learning from peers who are significantly dissimilar, and has real implications for managers, knowledge workers, and entrepreneurs, given the extent to which external knowledge can influence performance.

Most directly, this paper offers potentially useful prescriptions for knowledge workers. Scientists, engineers, academics, and other knowledge workers regularly need to form short-term and often boundary-spanning collaborative ties to achieve pre-specified nonpermanent goals. This could be running a research study, creating a new software product, or diagnosing and solving a problem an organization or group of organizations faces. While the primary purpose is usually the pre-specified goal itself, such arrangements often also generate knowledge exchange for the collaborators (Liebeskind et al., 1996; Reagans & McEvily, 2003). This paper proposes a strategic approach to the formation of such collaborations that may be useful in optimizing knowledge transfer between collaborators.

A knowledge worker seeking to build their own knowledge may be tempted to look to superstars within the relevant knowledge domain, however such sources may not be optimally conducive to effective learning. Instead, a knowledge seeker should pay attention not only to how much knowledge a potential source possesses, but to how accessible the knowledge is to them. My results are equally relevant for informing managers in R&D-oriented organizations on a useful criterion to consider when organizing workers in project teams. More generally, this research also has implications for learning at the organizational level, and may shed light on and inform the knowledge-sourcing behaviors of both entrepreneurial and established firms.

This study also contributes to the management literature by not only exploring the joint influences of opportunity and absorptive capacity but also by characterizing and evaluating absorptive capacity’s functional form. Furthermore, this paper aligns seemingly disparate strands of literature, unifying them under an overarching theme of knowledge-seeking behaviors. This integration serves to amplify the coherence and applicability of these theories across domains and provides practitioners with a more nuanced approach to peer-based learning. As organizations and individuals continue to navigate the evolving landscape of knowledge acquisition, this study offers valuable guidance for making informed decisions regarding knowledge source selection and maximizing the benefits of their social environments.

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Appendix

Table A1 Participant interview questions

Background

- What’s your age and gender?
- Where do you live?
- How frequently do you play the game? How many hours, how many times per week?
- How long have you been playing it? Relatedly, how long have you been playing this kind of video game?
- If you had to guess, where would you place yourself in terms of your ability in this game relative all other players?
- Could you describe what a typical match looks like for you?

Antecedents to performance

- Can you tell me about what elements you think are key to success in the game? In other words, what, in your opinion, makes someone successful at the game?
- Do you think natural ability plays a major role in one’s performance in the game?
- Do you think one’s knowledge of different aspects of the game plays a major role in one’s performance in the game?
- How would you weigh the relative importance of one’s natural ability and one’s knowledge of different aspects of the game?
- Would you say both elements are important? Or you can definitely be successful with just one or the other?

Knowledge and performance trajectory

- When you are playing a given match, how motivated are you to improve your overall long-term skill versus just playing to enjoy the game in the moment?
- Would you say your performance in the game has changed since you started playing it?
- If so, how (better or worse)?
- What do you think has been most useful toward improving your performance?
- What sources of information have you generally drawn on to improve your knowledge of different aspects of the game?

Teammates and opponents

- Would you say you’re generally able to tell whether your teammates and opponents are skilled or not while in a game with them?
- Do you find you enjoy the game more when you're playing against more skilled opponents versus ones that are not quite as skilled as you or ones that are more or less at your level?
- How about teammates?
- In your experience have you found the teammates you play with to be a useful source of any knowledge or information that changed or improved the way you play?
- How do you typically learn from your teammates?
- What kinds of teammates have you found you learn best from?
- How about opponents?