Organizing for Entrepreneurship

by

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For my dear family and friends, who encouraged me to fly toward my dream.

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ABSTRACT

Why do start-ups succeed or fail to capture entrepreneurial opportunities? To address this question, my dissertation focuses on the organizational design of start-ups. To provide the intellectual foundations upon which this dissertation builds upon, the first chapter reviews the extant research on the organizational design of start-ups. This review demonstrates that their organizational design, despite its important role in executing business ideas and scaling up businesses, has received relatively little scholarly attention. Although it may seem that this gap can be addressed by simply applying the findings regarding the organizational design of mature firms to start-ups, this chapter suggests that they may not be applicable theoretically because of the unique constraints and problems that start-ups face and empirically because of selection bias. Given this potential gap in our understanding of the organizational design of start-ups, this chapter highlights two promising avenues for future research: (1) empirically test and clarify the opposing predictions in the existing theories on organizational design and (2) revisit the existing theories by exploring the antecedents and consequences unique to start-ups.

Building on this review, the following two chapters each present an empirical study that clarifies how existing theories of organizational design apply to start-ups. The second chapter investigates how start-ups vary in their organizational structure of hierarchy and how their hierarchy influences their performance in terms of creative and commercial success. There has been an ongoing debate over whether start-ups should be "flat" with minimal hierarchical layers. To reconcile this debate, I distinguish between creative and commercial success (i.e., product novelty vs. profitability), and examines how these outcomes are variously influenced by a start-up's hierarchy. This study finds that while a flatter hierarchy can improve ideation and creative success, it can result in haphazard execution and commercial failure by overwhelming managers with the burden of direction and causing subordinates to drift into power struggles and aimless idea explorations. I provide empirical

support for this trade-off using a large-sample of game development start-ups. These findings offer one resolution to the debate by sorting out the conditions under which hierarchy can be conducive or detrimental to start-ups.

The last chapter (joint work with Felipe Csaszar) studies how two key attributes of organizational design—organizational structure and managerial cognition—affect adaptation to disruptive innovations. We do so by analyzing how video game firms adapted to the "free-to-play" business model around the period of disruption (2012–2015). Our dataset (which contains 461 firms, collectively employing 83,157 individuals) allows us to characterize each firm's organizational structure and each employee's experience profile; it also captures the performance of firms under the existing and new technological regimes (that is, firms that do and do not adopt the disruptive innovation). We show that adoption, implementation under the existing regime, and implementation under the new regime are affected by cognitive and structural antecedents in different and often opposite ways. We also point out conditions under which cognitive and structural antecedents can compensate for each other. Overall, our study contributes to a better understanding of how firms should organize to face disruptive innovations.

Taken together, my dissertation disentangles the role of organizational design in the context of entrepreneurship and thus contributes to the broader agenda of how firms organize for adaptation.

CHAPTER I

Literature Review

1.1 Introduction

High growth start-ups—newly established ventures (of any size) that aim to introduce innovations and achieve organizational growth (Carland et al. 1984:354, Wasserman 2012:6)—make up the backbone of the economy (Haltiwanger et al. 2013, Decker et al. 2014). Unfortunately, however, the vast majority of these start-ups fail within the first few years (Stinchcombe 1965, Decker et al. 2014:10). Whether start-ups succeed or fail rests upon not just their business concept and idea, but arguably more so on their execution (Ries 2011:1–2, Zwilling 2012, Howard 2016, Fuld 2018). In this regard, only 12 percent of start-up founders attributed their success to "an unusual or extraordinary idea," while the other 88 percent reported their success was mainly due to "the exceptional execution of an ordinary idea" (Bhide 2000:32).

To successfully execute their ideas and scale up their businesses, start-ups need to establish an appropriate organizational structure to divide the underlying task across their employees and integrate these employees' efforts (Colombo et al. 2016, DeSantola and Gulati 2017, Burton et al. 2019). As these employees are the main source of competitive advantage (Shane 2000, Marvel et al. 2016) yet they lack a formalized roles and routines to coordinate (Stinchcombe 1965, Aldrich and Ruef 2006), an effective organizational design can play a crucial role in the performance of start-ups—arguably even more so than in that of their mature counterparts (Burton et al. 2019). Not only does this early decision on organizational design affect the immediate performance of these nascent firms, but it also shapes their evolution by exerting a long-lasting effect on their organizational behavior, structures, and practices (Baron et al. 1999, Burton and Beckman 2007, Beckman and Burton 2008). Furthermore, strategic misfits of and subsequent changes to this initial organizational design, especially while start-ups scale up their businesses (Sutton and Rao 2014, DeSantola and Gulati 2017), can lead to major employee turnover (Baron et al. 2001). Hence, it is important to understand how start-ups should initially design their organizational structure and adjust it to meet the needs of their distinct challenges in survival and growth (Santos and Eisenhardt 2009:644, DeSantola and Gulati 2017:640–641).

Despite its importance, however, little is known on their organizational structure (Colombo and Grilli 2013:392, Burton et al. 2019:2–3). In the literature on organizational design, the mainstream scholarly view has been that start-ups have an organizational structure so simple that it is hardly worthwhile to study (Burns and Stalker 1961:121–122, Mintzberg 1979:310–311). In the literature on entrepreneurship, research on the organizational design of start-ups has lagged behind that on their formation and resource mobilization processes (for review, see Alvarez et al. 2005 and Clough et al. 2019). It has only been recently since the Stanford Project on Emerging Companies (e.g., Baron et al. 1996, 1999, Baron and Hannan 2002) that a few studies have investigate how start-ups organize their employees and how such structural configurations affect their performance (e.g., Meijaard et al. 2005, Sine et al. 2006, Colombo and Delmastro 2008, Colombo and Grilli 2013, Grimpe et al. 2019). Thus, as Burton et al. (2019:2) point out, "the empirical evidence on the antecedents and consequences of organizational design choices in entrepreneurial ventures is both limited and mixed, and there is still much to be learned."

Hence, to increase awareness and stimulate scholarly interest in this topic, this chapter reviews the existing literature on the organizational structure of start-ups. As this topic lies at the intersection of organization design literature and entrepreneurship research, I first draw attention to the relevant literature on organizational design to define the concept of organizational structure and its dimensions. Then, this chapter bridges the gap between this literature and the research in entrepreneurship by reviewing the recent studies that specifically examine these dimensions of organizational structure in the context of start-ups. Lastly, by identifying the potential gap, this chapter highlights new and fruitful avenues of research into the organizational structure of start-ups.

1.2 Organizational structure and its dimensions

An organization can be considered "the pattern of communications and relations among a group of human beings, including the processes for making and implementing decisions" (Simon 1947/1997:18–19). "Prescribing how an organization should be structured [in terms of communications and relations] in order to function effectively and efficiently" is the goal of organizational design (Burton and Obel 2018:2–3). From the information-processing view of organizations (for review, see Burton and Obel 2004), the basic problem of designing an organization is to create a management structure that matches the organization's information-processing demand with its information-processing capacity (Simon 1947/1997:293, March and Simon 1958/1993:183). Balancing the information-processing demand and capacity through organizational structure involves two complementary problems (Lawrence and Lorsch 1967/1986, Galbraith 1974:28, Mintzberg 1979:2): (1) how to decompose the overall task of the organization and allocate the smaller task components across its employees, and (2) how to coordinate these employees' efforts so that they fit together to realize the overall task or organizational goals. By addressing these problems via organizational structure, firms can achieve "organizationally rational outcomes" despite their employees' cognitive limitation (March and Simon 1958/1993:190–192, Cyert and March 1963:214–216, Fredrickson 1986:281).

The extant literature on organizational design has identified three key dimensions of organizational structure that address these two problems— formalization, centralization, and complexity (for review, see Burton and Obel 2004:73–81)—and has examined the potential trade-offs underlying each of these dimensions. First, formalization refers to the extent to which a body of rules and standard operating procedures is developed and codified to create a condition in which "everyone knows exactly what to do" (Mintzberg 1979:83). By ensuring this transparency and accountability, a high level of formalization can improve coordination; however, it can simultaneously reduce flexibility by limiting the discretion of the employees and promoting organizational inertia (Pugh et al. 1968:75–76, Hage and Aiken 1969, Galbraith 1973:10–11).

Second, centralization is defined as the extent to which the locus of decision-making authority is confined to the higher levels of the hierarchy or is delegated to lower-level employees (Simon 1947/1997:317–322, Child 1972:164, Mintzberg 1979:181). By concentrating the decision-making authority at the top of the hierarchy, a high degree of centralization can allow a firm to have tighter control and coordination. But, this tightness can also place significant cognitive demands on the top managers and restrict employees' autonomy and communication flows, thereby causing information loss and hampering the firm's flexibility (Aiken and Hage 1968, Fredrickson 1986:282, Burton and Obel 2004:80–81).

Lastly, complexity—which is "regarded as a major defining characteristic of modern organizations and also an important determinant of other structural features" (Child 1973:169)—refers to the condition of being composed of many interrelated parts (Burton and Obel 2004:73–78). This complexity arises from two main sources: horizontal and vertical differentiation (Simon 1947/1997:7–8, Hall et al. 1967, Lawrence and Lorsch 1967/1986). Horizontal differentiation (or specialization) refers to the extent to which the overall task is divided across and within subunits (Lawrence and Lorsch 1967/1986). By dividing the overall task into smaller components and allocating those task components to employees, a high level of horizontal differentiation can increase the employees' productivity by focusing their attention to and promoting learning-by-doing on a narrowly defined task component (Arrow 1962, Argote and Miron-Spektor 2011). Yet, as employees narrowly focus on their own task components, this increase in productivity can come at the expense of coordination and flexibility (Burns and Stalker 1961, Lawrence and Lorsch 1967/1986, Burton and Obel 2004:8). In turn, vertical differentiation (or hierarchy) is the number of supervisory levels between the top management and the bottom-level employees (Simon 1947/1997:7, Puranam 2018:106–126). By adding a supervisory level, a taller hierarchy can decrease the span of control of middle managers, thus promoting coordination (Graicunas 1937, Blau and Scott 1962/2003:139, Burton and Obel 2004:75–76). But, this additional layer can result in information loss and flexibility, as its middle managers may delay and prematurely filter out information processed bottom-up through the hierarchy (Sah and Stiglitz 1986, Csaszar 2012, Reitzig and Sorenson 2013, Keum and See 2017).

1.3 Contingency perspective on organizational structure

The question then would be: how should organizations configure these structural dimensions? To address this question, the classic studies on organizational design developed their arguments based on qualitative accounts of small number of firms (e.g., Burns and Stalker 1961, Chandler

1962, Lawrence and Lorsch 1967/1986, Blau 1970, Galbraith 1973, Mintzberg 1979). More recent work provide detailed insights into the mechanisms through stylized formal models (e.g., Sah and Stiglitz 1986, Radner 1992, Garicano 2000, Seshadri and Shapira 2003, Siggelkow and Levinthal 2003, Knudsen and Levinthal 2007, Csaszar 2013), lab experiments (e.g., Reitzig and Sorenson 2013, Keum and See 2017), and case analyses (e.g., Tripsas and Gavetti 2000, Joseph and Ocasio 2012, Puranam and Håkonsson 2015, Valentine 2018). These mechanisms have largely been tested empirically in the context of large mature organizations (Blau and Scott 1962/2003:224, Aldrich and Ruef 2006:7–8, Sine et al. 2006:122, Colombo et al. 2016).

These prior studies on organizational design have suggested that "there is no one best way to organize" and that "any way of organizing is not equally effective" (Galbraith 1973:2). Instead, the "optimal" structure depends on various contingencies that influence the organization's information-processing demand and capacity (Joseph and Gaba 2020). Among these contingencies, the ones that received much attention are the organization's size (e.g., Blau 1970, Meyer 1972, Miller and Conaty 1980), task (e.g., Thompson 1967, Sanchez and Mahoney 1996, Baldwin and Clark 2000, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003, Ethiraj and Levinthal 2004, Puranam et al. 2012, Csaszar 2013, Eggers and Kaul 2018), technology (e.g., Gurbaxani and Whang 1991, Brynjolfsson 1994, Brynjolfsson et al. 1994, Rajan and Wulf 2006, Bloom et al. 2014), and environment (e.g., Burns and Stalker 1961, Lawrence and Lorsch 1967/1986, Galbraith 1973, Tushman and Nadler 1978, Siggelkow and Rivkin 2005, Csaszar and Eggers 2013). Integrating these prior studies which each focus on a single contingency, Burton and Obel (2004) and Joseph and Gaba (2020) offer comprehensive reviews of previous studies on the contingency perspective of organizational design.

1.4 The common belief on the organizational structure of start-ups

Drawing upon the contingency perspective of organizational design, scholars have presumed that unlike their large mature counterparts with a "mechanistic" (or "bureaucratic") structure, start-ups have an "organic" (or "simple") structure with low formalization, high centralization, and low complexity (Burns and Stalker 1961:121–122, Mintzberg 1979:310–311, Burton and Obel 2004:388–393). This presumption is largely grounded on four main contingencies that start-ups face: the founders' experience and beliefs, the firm's size, its information and communication technologies, and its environment.

First, start-ups are assumed to have such a simple structure due to their founders' experience and belief on organizational structure. Organizational structure, as Perrow (1986) and Leavitt (2005) point out, has more than often been used as a "scapegoat" for various organizational problems: inefficiency, rigidity, immorality, and inequality. Given all these negative connotations, it is not surprising that entrepreneurs generally perceive organizational structure as a "bureaucratic threat to entrepreneurial spirit" (Davila et al. 2010, Gulati and DeSantola 2016). Saxenian (1996:59–82) find that this negative perception profoundly influenced how Silicon Valley start-ups initially designed their organizational structure in an organic form. Because employees in such start-ups are more likely than those in mature firms to start a new venture (Elfenbein et al. 2010) and because these employees tend to draw upon their prior employers in designing the organizational structure of their ventures (Baron et al. 1999), it seems logical to assume start-ups to have an organic structure.

Second, this presumption regarding the organic structure of start-ups is consistent with the premise of a "size imperative" (Burton and Obel 2004:168). Extant studies on organizational design have suggested that an increase in firm size is accompanied by an increase in coordination problems and structural differentiation (Blau 1970, Meyer 1972, Miller and Conaty 1980). As the vast majority of new ventures are "small" (Aldrich and Ruef 2006:102, Decker et al. 2014), it has been assumed that this small group of undifferentiated employees can be organically coordinated through informal communication, without formally imposing a mechanistic structure that can hinder their flexibility (Galbraith 1974, Mintzberg 1979).

Third, this literature has posited that start-ups have an organic structure due to the advancements in information and communication technologies (ICT). The introduction of more advanced ICT would decrease the costs in gathering and communicating information and thus mitigate the coordinating role of the middle managers (Leavitt and Whisler 1958, Brynjolfsson 1994, Rajan and Wulf 2006, Bloom et al. 2014). This can, in turn, reduce the firm size of start-ups and their need for a mechanistic structure (Gurbaxani and Whang 1991, Brynjolfsson et al. 1994).

Lastly, it has been argued that start-ups should, in a prescriptive sense, have such an organizational structure to adapt to their environment. Start-ups frequently operate in nascent or fast-moving industries (e.g., telecommunications, software, healthcare, biotech; D'Aveni 1994), many of which are characterized by large product, technological, and market uncertainty (Bourgeois and Eisenhardt 1988, Santos and Eisenhardt 2009). Prior studies have argued that, to flexibly adapt to such uncertain and dynamic environments, the organic structure is optimal because it allows the employees to enjoy more autonomy and embrace creativity (Burns and Stalker 1961:97, Covin and Slevin 1989, Volberda 1996, Burton and Obel 2004:198, Lee and Edmondson 2017). This is especially the case given that in such uncertain industries, omission errors can be costlier than commission errors; thus, a firm whose organic structure produces fewer omission errors will be more profitable than one whose mechanistic structure produces more omission errors (Csaszar 2012:612).

1.5 Revisiting the common belief on the organizational structure of start-ups

Based on the aforementioned contingencies regarding their founders, size, technology, and environment, it has been widely taken for granted that start-ups have an organic structure with low formalization, high centralization, and low complexity. This common belief has remained empirically untested partly because large-sample studies have remained very sparse due to the challenges in gathering detailed data on start-ups and measuring their organizational design (Keum and See 2017:667, Burton et al. 2019:2–3).

However, recent large-scale descriptive studies have identified a significant variation in the organizational structure of start-ups (e.g., Baron et al. 1996, 1999, Baron and Hannan 2002). Notably, in their Stanford Project on Emerging Companies (SPEC), Baron and Hannan (2002) find that "[t]hough some observers might think that most start-ups look pretty much the same, or that the appropriate organizational design and culture for a high-tech venture is 'obvious,' the data suggest otherwise." Since this large-scale observation from SPEC, an emerging body of research has started to employ new empirical data and methods to revisit the conventional wisdom regarding the organizational structure of start-ups (e.g., Meijaard et al. 2005, Sine et al. 2006, Beckman and Burton 2008, Colombo and Delmastro 2008, Colombo and Grilli 2013, Grimpe et al. 2019). In doing so, these studies have identified several theoretical gaps in our understandings of its antecedents and consequences.

The first gap is that much prior work has disregarded the variation in the founders' experience and beliefs. Recent studies on employee entrepreneurship (e.g., Campbell et al. 2012, Carnahan et al. 2012) have shown that if employees of established companies leave their employer, those with high earnings or performance are more likely to found a new venture than join a different established firm. To quote Baron and Hannan (2002:14), "one might expect ... that a founder who launched an entrepreneurial venture after working in older, more bureaucratic organizations would desire to escape what he or she had experienced in the past as dysfunctional bureaucratic pathologies by building a new enterprise with a radically different culture and operating style. However, for every founder in our sample whose thinking appeared to be consistent with that conjecture, another reported a desire to adopt a bureaucratic template." Similarly, Davila et al. (2010:94) observe that the founders with a larger company background tend to adopt a mechanistic structure of their prior employers "because they were used to them." Besides their experience in terms of prior employers' size, Beckman and Burton (2008) find that their functional experience can influence the type of structure their start-ups adopt. Taken together, these studies suggest that a significant number of start-ups may employ a mechanistic structure as their founders draw "organizational blueprints" from their prior employment in mature firms (Baron and Hannan 2002, Baron et al. 2001).

The second gap relates to the premise of a "size imperative." Although a few studies (e.g., Blau 1970, Meyer 1972, Miller and Conaty 1980) have established some correlations between various measures of firm size and structural characteristics, others (e.g., Hall et al. 1967, Mileti et al. 1977, Cullen et al. 1986, Meijaard et al. 2005) have found that there is, at best, only a weak relationship. What is more is that even those studies that agree on the correlations have adopted very different measures of what constitutes a small, a medium, or a large organization (Kimberly 1976, Carland et al. 1984:354, Burton and Obel 2004:171). After reviewing these previous studies with incoherent measures, Burton and Obel (2004:173) propose new criteria of firm size and conclude that "an organization with fewer than 20 people will always be categorized as small." However, although it may seem feasible for these "small" organizations with fewer than 20 employees to coordinate through informal communication (Burns and Stalker 1961:121–122, Mintzberg 1979:310–311), the micro-literature on small groups and teams have shown that such informal coordination breaks down in an even smaller group of fewer than 10 members (Steiner 1972:96, Hackman 2002:116–122). Thus, this stream of literature (for review, see Anderson and Brown 2010 and Greer et al. 2018) has paid much attention to how coordination in these even smaller groups can be improved by hierarchical differentiation—whether officially delineated with formal authority (Simon 1947/1997:7, March and Simon 1958/1993:110) or informally emerged based on status (Magee and Galinsky 2008, Anderson and Brown 2010:3). This implies that a mechanistic structure, characterized by a high level of differentiation, can be conducive to the performance of such "small" organizations as start-ups.

The third gap is associated with information and communication technologies (ICT). Although more advanced ICT can decrease communication and aggregation costs per information unit, it can simultaneously increase the total amount of information acquired, communicated, and aggregated, thereby prompting an information overload and increasing the total communication and aggregation costs (Gurbaxani and Whang 1991, Edmunds and Morris 2000). Furthermore, these technologies can reshape the underlying task and increase its complexity (Ben-Ner and Urtasun 2013) so as to require more task specialization and coordination. These increases in information-processing and coordination costs can require start-ups to increase their size and adopt a more mechanistic structure.

The last gap concerns the environment. Contrary to the predominant view that firms in uncertain environments should adopt an organic structure (Burns and Stalker 1961:121–122, Mintzberg 1979:270–272), Lawrence and Lorsch (1967/1986) find that as environmental uncertainty increased, firms increased differentiation in the organizational structure to be more efficient. Consistent with Lawrence and Lorsch's (1967/1986) qualitative findings, Colombo and Grilli (2013) provide large-sample evidence that to reduce the information overload and facilitate coordination, Italian high-tech start-ups in uncertain and hostile environments increased hierarchical differentiation by adding a layer of middle management. Using a dataset of German high-tech start-ups, Grimpe et al. (2019) further show that start-ups with more layers of middle management are more likely to introduce product innovations. In addition to these studies on hierarchical differentiation, Sine et al. (2006) find that a higher level of formalization, horizontal differentiation, and centralization among the founding team can improve the financial performance of start-ups in uncertain and hostile environments. In line with their findings, Beckman and Burton (2008) document that horizontal differentiation can be beneficial for start-ups because it allows them to go public faster and obtain venture capital funding more quickly. In sum, these results are at odds with the stylized facts of a negative association between the mechanistic structure (characterized by high levels of formalization and complexity) and the performance of start-ups in uncertain and hostile environments.

1.6 Why the findings from mature firms may not apply to start-ups

As the theoretical predictions are mixed and the empirical evidence remains sparse, more research is needed on the antecedents and consequences of the organizational structure of start-ups (Colombo et al. 2016, Burton et al. 2019). One might assume that this gap can be addressed by generalizing the findings on organizational design from mature firms to start-ups. However, from a theoretical standpoint, this generalization may not be applicable because start-ups are not simply "smaller versions of large companies" but entities with their own distinct constraints and problems (Santos and Eisenhardt 2009:644, Colombo et al. 2016:430, DeSantola and Gulati 2017:640–641). More specifically, these nascent firms face unique constraints because unlike their well-established counterparts, they are constrained not only by very limited resources (Baker and Nelson 2005) but also by the lack of legitimacy and role formalization (Stinchcombe 1965, Aldrich and Ruef 2006). In turn, start-ups face problems in human capital mobilization, venture capital funding, organizational scaling, and exit strategies of initial public offering or acquisition (Santos and Eisenhardt 2009:644, Kaplan and Vakili 2015:1436, DeSantola and Gulati 2017:640–641). Given these constraints and problems, start-ups may consider in designing their organizational structure a different set of antecedents and consequences from that of mature firms.

In addition to these theoretical reasons, there are empirical reasons for why the findings from mature firms may not generalize to start-ups. Because only a few start-ups survive to evolve into mature firms and this survival is not randomly assigned (Dunne et al. 1989, Alvarez et al. 2005:6, Decker et al. 2014:10), analyzing a sample of just the mature ones can introduce survival—or, more generally, selection—bias (Aldrich and Ruef 2006:32), which can limit the scope of inference (Heckman 1979, Angrist and Pischke 2008:12–24). Hence, although the findings from such analyses may apply to a similar set of mature firms, it is difficult to firmly conclude that those findings will generalize to start-ups (Davidsson 2016:115-154).

1.7 Potential questions for future research

Considering the theoretical and empirical reasons mentioned above, future studies may draw upon the existing theories on organizational design and empirically test these theories in the context of start-ups. In fact, although reliable data are often difficult to obtain (Keum and See 2017:667, Burton et al. 2019:2–3), start-ups could present a fruitful context to clarify the mechanisms regarding the consequences of organizational structure. This clarification could be achieved by exploiting both the large variation in organizational structure among start-ups during their early growth stage and the likely existence of performance trade-offs. First, firms are likely to vary in organizational structure to a larger extent at the early growth phase than the mature phase of their life-cycle. This is because as firms mature over time, they increase formalization and differentiation (Greiner 1972) and this formalized and differentiated structure become inertial (Hannan and Freeman 1977, 1984). Second, to survive and grow, start-ups need to balance multiple measures of performance. These performance measures include: (1) financial profitability (e.g., returns on investment, equity, assets, or sales), (2) innovation output (e.g., patent grants or licensing), (3) growth (e.g., changes in firm size or market share), (4) survival, and (5) exit (e.g., initial public offering or acquisition). While these measures are not mutually exclusive, they have important differences that could lead to a potential trade-off (Murphy et al. 1996). For example, start-ups may invest in long-term growth, sacrificing short-term financial profits (Nelson and Winter 1982). Investigating how such performance trade-offs are related to the dimensions of organizational structure could help reconcile the opposing theoretical predictions and mixed empirical findings in the prior literature on organizational design.

Going beyond examining existing theories, future work could expand upon the recent studies that revisit the conventional wisdom and further explore the antecedents and consequences unique to start-ups. First, extending the line of research on imprinting (e.g., Baron et al. 1996, 1999, Baron and Hannan 2002, Burton and Beckman 2007, Beckman and Burton 2008), an inquiry into how characteristics of the founder or the founding team (in terms of, e.g., personality, industry experience, education, age, gender, and ethnicity) can lead to a different organizational structure at inception may prove promising. Second, drawing upon the research on strategic human capital (e.g., Coff 1997, Hatch and Dyer 2004, Campbell et al. 2012, Wright et al. 2014, Campbell et al. 2017), scholars may study how start-ups adopt certain types of organizational structure as non-pecuniary incentives to compensate for their financial incentives and compete against established firms in attracting and retaining talents (Stern 2004, Gambardella et al. 2015). Third, building upon the prior work on venture capital (e.g., Hellmann and Puri 2002, Samila and Sorenson 2011, Rin et al. 2013), future studies may investigate how start-ups use their organizational structure to signal legitimacy and attract investment from venture capital firms (VC) and how VCs influence their organizational structure after the investment. Lastly, expanding on the burgeoning stream of research on organizational scaling (e.g., Sutton and Rao 2014, DeSantola and Gulati 2017), future work may probe into how organizational structure evolves as start-ups scale up their businesses and when it is optimal to adopt a more mechanistic structure (with a higher level of formalization or differentiation) during this evolutionary process. These lines of inquiry would be particularly interesting areas of examination in the context of start-ups, as there are rarely equivalent questions for large, mature firms.

1.8 Conclusion

This chapter reviewed the extant discussion on the antecedents and consequences of the organizational structure. The current state of this discussion is nicely captured by Van de Ven et al. (2013:393), who state "[m]uch has been learned, and even more needs to be learned about designing organizations." While the prior research and its findings based on mature firms are suggestive, recent empirical studies started to question whether much of it can be directly applicable to start-ups given their unique constraints and problems (Colombo et al. 2016, Burton et al. 2019). In this regard, a growing body of entrepreneurship scholars has called for more empirical research on how extant organizational theory applies to new ventures (e.g., Shane and Venkataraman 2000, Shane 2003, Aldrich and Ruef 2006, Dushnitsky and Matusik 2019).

As a step toward addressing the gap in our understanding of the organizational structure of start-ups, the following two chapters of this dissertation each present an empirical study that examines how existing theories of organizational design apply to start-ups. The second chapter examines how high-growth start-ups vary in their organizational structure of hierarchy and how this variation can translate into a difference in the performance of their first product. In turn, the third chapter investigates how organizational structure and managerial cognition play a role in adapting to disruptive innovations and how these structural and cognitive antecedents can compensate for each other. To address these questions, I examine a unique large-sample dataset of video game developers and provide qualitative support with anecdotal data and interviews. Using this dataset, these two chapters show that the organizational design of start-ups plays an important role in successfully launching their first product and adapting to disruptive innovations.

CHAPTER II

The Myth of the Flat Start-up: Reconsidering the Organizational Structure of Start-ups

2.1 Introduction

> "The dirtiest word in Silicon Valley is bureaucracy. ... [L]ayers of bureaucracy ... are seen as the enemy of speed and efficiency" (Miller 2014).

Entrepreneurs, nowadays, tend to regard the organizational structure of hierarchy as "a bureaucratic threat to their entrepreneurial souls" (Gulati and DeSantola 2016) and are thus reluctant to impose hierarchical layers of managers (Davila et al. 2010). This distaste for hierarchy is perhaps not surprising if we consider two assertions in the existing literature on organization structure (Puranam 2018:106–127). One such assertion is that start-ups are simply too small and undifferentiated to necessitate layers of managers for coordination (Blau 1970, Mintzberg 1979). The other is that they should be "flat" with minimal layers to streamline their decision-making process and flexibly adapt to their hostile environments (Burns and Stalker 1961, Lawrence and Lorsch 1967/1986). Given these assertions, existing theories on organizational structure have largely been examined in the context of large, mature organizations (Sine et al. 2006:122, Colombo and Grilli 2013:391).

However, recent qualitative studies have started to raise questions as to whether start-ups should be flat, given their distinct constraints on coordination (Sutton and Rao 2014, Puranam and Håkonsson 2015, DeSantola and Gulati 2017). These studies point out that, albeit smaller and less differentiated than their mature counterparts, start-ups face coordination problems because these nascent firms not only lack formalized routines (i.e., standard operating procedures; Stinchcombe 1965:148–150, Sine et al. 2006:121) and informal coordination devices (e.g., shared culture or norms;

Meier et al. 2019, Marchetti and Puranam 2020), but also have insufficient resources to designate integrating committees (Baker and Nelson 2005). As start-ups have no other coordination devices that can substitute for hierarchy, Sutton and Rao (2014:107) suggest that "even [these] small organizations can't function without hierarchies."

To date, this theoretical debate over whether start-ups should be flat has not been empirically addressed, partly due to the challenges in gathering a large sample dataset of start-ups and measuring their hierarchy (Keum and See 2017:667, Burton et al. 2019).

To reconcile this debate, my study distinguishes between creative success (i.e., the novelty of the product) and commercial success (i.e., its profitability) and examines how these two performance outcomes can be variously influenced by a start-up's hierarchy. Although these nascent firms strive for both outcomes (Shane and Venkataraman 2000, Kaul 2013), they more than often realize one at the expense of the other (Uzzi and Spiro 2005:468). This is because these two outcomes are shaped by distinct processes (Kaplan and Vakili 2015), thus requiring different structural configurations (Csaszar 2013, Csaszar and Eggers 2013, Keum and See 2017, Eklund 2020). Extending this line of reasoning, my study suggests that a flatter hierarchy, on the one hand, can improve ideation and creative success by stimulating cross-fertilization of disparate ideas and reducing premature filtering of ideas by managers. However, this benefit can come at the cost of execution and commercial success. This is because, without other systematic ways to coordinate, a flatter hierarchy can overwhelm managers with the burden of direction and conflict resolution, cause subordinates to drift into power struggles and aimless exploration of ideas, and result in major employee turnovers. Put differently, I submit that adding hierarchical levels can be beneficial for start-ups in achieving commercial success and ultimately in their survival, albeit at the expense of creative success.

This study provides empirical support for this performance trade-off by analyzing start-ups in the video game industry. As one of the fastest-growing venues for entrepreneurial activities (Bies 2017), this industry provides a unique context that allows me to overcome the aforementioned empirical challenges in data collection and measurement. That is, for a large number of start-ups, detailed data is available on their employees (e.g., names, job titles), critics' product review ratings, and sales figures. I use this rich dataset to compute a well-established measure of hierarchy (i.e., the number of hierarchical levels derived from text analysis of job titles) and two distinct measures of performance (i.e., creative and commercial success).

My study contributes to the literatures on entrepreneurship and organization design by offering one resolution to the debate over whether start-ups should have flat hierarchies. This study first qualifies the dominant view that start-ups should be (and are thus) flat by providing rare empirical evidence of the heterogeneity in hierarchy even among the same-sized small start-ups. This paper then shows that their hierarchy may entail a trade-off between creative and commercial success—that is, it may increase commercial success at the expense of creative success. This trade-off suggests that hierarchy is not universally good or bad for start-ups, but rather its efficacy depends on the type of performance they pursue. By sorting out the condition under which hierarchy can be conducive or detrimental to start-ups, my study offers a contingent perspective that helps reconcile the debate on the organizational structure of start-ups.

2.2 Theory and hypotheses

This section begins by drawing upon the literature on entrepreneurship to define a start-up and to explain why these nascent firms face coordination problems in achieving creative and commercial success. I then build on the literature on organization design to outline how coordination can, in principle, be achieved through hierarchy and to discuss how this vertical division of tasks may entail a trade-off between creative and commercial success in the context of start-ups. This theoretical discussion is supplemented by qualitative observations of start-ups, as the goal here is not only to consider whether a start-up's performance increases or decreases with its hierarchy, but also—and perhaps more importantly—to articulate the mechanisms specific to start-ups.

2.2.1 Start-ups and their two performance measures

In line with prior studies on entrepreneurship (e.g., Carland et al. 1984, Wasserman 2012, DeSantola and Gulati 2017, Burton et al. 2019), this study focuses on "high-growth start-ups"—that is, newly established firms (of any size) that aim to introduce innovations and achieve organizational growth.[1] To survive and grow in their hostile environments, these nascent firms need to not only

[1] This paper distinguishes these nascent, growth-oriented firms from small businesses (of any age) operating with a minimum number of employees (in colloquial terms, "mom-and-pop stores"). This is because these two represent different types of entrepreneurship: whereas the former is geared toward scaling up its business over time, the latter typically has no desire to grow its business (Carland et al. 1984:354, Wasserman 2012:6, Kim 2020:11–12). As the latter remains considerably small throughout its lifetime and thus does not necessitate hierarchical structure (Blau 1970, Mintzberg 1979, Burton and Obel 2004:168), this study focuses on the former.

flexibly generate novel ideas to differentiate their products, but also efficiently execute those ideas to make profits (Shane and Venkataraman 2000, Kaul 2013). Simply put, start-ups actively strive for both creative success (i.e., the novelty of the product) and commercial success (i.e., its profitability).[2]

However, in many cases, they only realize one at the expense of the other (Uzzi and Spiro 2005:468). This trade-off between these performance outcomes is perhaps best reflected in the following comment by an entrepreneur in the video game industry:

> "Ideally, every effort brings both artistic [i.e., creative] and commercial success. Sometimes, you only get one or the other" (Ruggiero 2017; comment in brackets added).

This trade-off occurs partly because achieving both creative and commercial success presents a daunting challenge for start-ups (Kaplan and Vakili 2015). To realize creative success, a start-up must, by definition, set its product apart from existing ones by generating a variety of novel ideas (Fleming et al. 2007). However, a purely novel product incorporating all these ideas may not be commercially successful because it is so eccentric and/or incoherent that consumers find it difficult to understand, appreciate, and adopt (Hargadon and Douglas 2001). To gain acceptance from consumers and attain commercial success, the start-up thus needs to prevent aimless exploration of novel ideas (Bangle 2001, Gulati and DeSantola 2016) and "cut features *diplomatically* when it is in the best interest" (Grossman 2003:109; emphasis added) without generating severe conflicts among employees who may be emotionally attached to their ideas. Should the start-up *tactlessly* screen out ideas, it may lose its distinctiveness as well as its employees, and ultimately fail.

2.2.2 Coordination problems in achieving the two performance measures

Therein lies a central problem for start-ups in achieving creative and commercial success: coordination (Burton and Obel 2004:84, Puranam 2018:67). That is, because start-ups struggle to mobilize new resources (Baker and Nelson 2005), they must resolve conflicts among their employees and integrate their employees' efforts to make the most out of their limited resources.

Although start-ups are not as large and horizontally differentiated as their mature counterparts, they find it particularly challenging to resolve conflicts and integrate efforts because these nascent firms are yet to develop formal coordination devices (e.g., routines, integrating committees;

[2] These two performance outcomes apply not just to creative industries, but broadly to various other contexts (see, e.g., Bangle 2001, Fleming et al. 2007, Kaplan and Vakili 2015, Eggers and Kaul 2018, Eklund 2020).

Stinchcombe 1965:148–150, Sine et al. 2006:121). Moreover, start-ups typically lack informal devices, such as a common language, shared culture and norms (Meier et al. 2019, Marchetti and Puranam 2020), because they mostly consist of inexperienced employees who newly entered the industry and, except for the co-founders, have rarely worked together before (Grossman 2003:307, Wasserman 2012:229–232). Though it may seem feasible for these relatively smaller firms to coordinate through informal communication (Burns and Stalker 1961:121–122), such informal coordination becomes cumbersome and breaks down even in a small group with less than 10 members (Steiner 1972:96, Hackman 2002:116–122). Given this lack of other systematic ways to coordinate employees, hierarchy can play an important role for start-ups.

2.2.3 Hierarchy as a coordination device

In principle, hierarchy achieves coordination by formally dividing decision-making tasks (or authorities) into smaller components and vertically delegating those components among managers at each hierarchical level (Simon 1947/1997:7, Puranam 2018:106–126).[3] This vertical division of tasks narrows each manager's span of control and restricts her subordinates' cross-relationships (Blau and Scott 1962/2003:139, Burton and Obel 2004:169–170). Here, the span of control refers to the number of subordinates that directly report to each manager through the vertical chain of command (Urwick 1956), whereas a cross-relationship refers to a lateral channel for informal communication among the subordinates within the same span of control (Graicunas 1937:192–193).

To illustrate, consider a hypothetical start-up with seven employees (see Table 2.1). If it adopts two hierarchical levels (the left figure), its manager has a span of control of six and her subordinates share 15 cross-relationships. In turn, adding a hierarchical level (the right figure) decreases the average span of control to two (i.e., each manager has two subordinates) and the average number of cross-relationships is limited to one.

More formally, assuming the unity of command (Fayol 1949/2013:24–25) and a homogeneous span of control throughout the firm, average span of control can be derived by solving for S in

[3]In line with the entrepreneurs' interpretation (i.e., hierarchical layers of managers), the term "hierarchy" in this study specifically refers to a formalized dimension of organizational structure represented by the number of hierarchical levels (Burton and Obel 2004:75–77). This study distinguishes hierarchy from "informal hierarchy" (i.e., an unofficial power/status ranking; Anderson and Brown 2010:3). This is because the former formally delineates authorities which employees officially accept when joining the firm (March and Simon 1958/1993:110). In contrast, the latter emerges over time through social interactions among employees, thus accompanying power struggle, politicking, and conflicts (Kilduff et al. 2016). To make this distinction clear, this study refers to the latter as "informal structure."

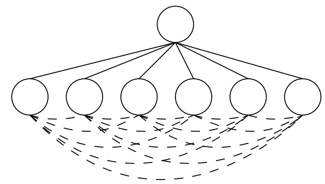
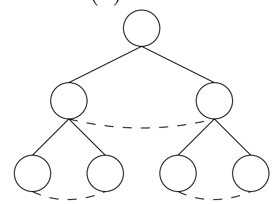
	Hierarchy	
	(a) Flatter	(b) Taller
		
Number of employees	7	7
Number of hierarchical levels	2	3
Average span of control	6	2
Average cross relationships	15	1

Table 2.1: An illustration of how adding a hierarchical level decreases each manager's span of control and her subordinates' cross-relationships. In the figures, a circle depicts an employee. A solid line between the circles represents a vertical chain of command, whereas a dashed line represents a cross-relationship.

the formula $N = \frac{S^L - 1}{S - 1}$, where N is the number of employees and L is the number of hierarchical levels.[4] In turn, average number of cross-relationships can be calculated by $\frac{S(S-1)}{2}$ (Graicunas 1937:192–193). Albeit approximations, these equations will suffice to establish that given a certain number of employees, adding a hierarchical level decreases each manager's span of control and her subordinates' cross-relationships. This decrease reduces each manager's burden of direction and conflict resolution, thus facilitating coordination (Puranam 2018:113).

In what follows, I hypothesize specific ways in which adding a hierarchical level, by restricting each manager's span of control and her subordinates' cross-relationships, may influence its creative and commercial success in the context of start-ups.

2.2.3.1 Hierarchy and creative success

A start-up's creative success may benefit from a flatter hierarchy. By specifying fewer hierarchical levels, a flatter hierarchy broadens the cross-relationships among employees and provides them more autonomy (Ghiselli and Siegel 1972). Because these employees also lack formalized routines to abide by, they can more freely exchange and self-organize around ideas (Puranam and Håkonsson 2015:3, Lee and Edmondson 2017:37). As Saxenian (1996:76) illustrates in her classic

[4] I thank Felipe Csaszar for contributing this equation. Blau and Scott (1962/2003:168–169) offer a coarser approximation $S = \sqrt[L-1]{N}$, which also indicates that adding a hierarchical level decreases the average span of control.

book on start-ups in Silicon Valley and Boston's Route 128:

> "The elimination of direct hierarchical lines of authority and the creation of autonomous groups stimulated informal communication and generated an immense reservoir of new technological ideas."

As this quotation suggests, the autonomy of self-organizing can stimulate the cross-fertilization of disparate ideas (Fleming et al. 2007), thereby promoting the start-up's ideation and creative success.

Adding a hierarchical level confines these cross-relationships (Puranam 2018:131) and requires ideas to be processed through the vertical chain of command (Fayol 1949/2013:34–36). One drawback of this vertical information processing is that as ideas are imperfectly communicated and selectively filtered by more hierarchical levels, novel ones are more likely to be distorted and fall through the cracks (Carzo and Yanouzas 1969:179, Arrow 1974:75, Csaszar 2012, Reitzig and Sorenson 2013, Lee et al. 2020). This process of premature filtering is illustrated by a game developer:

> "Ideas often get shut down *prematurely* just because some people with the power to veto an idea simply don't understand it" (Schreier 2015; emphasis added).

This premature filtering can prevent its employees from generating and sharing novel ideas, as these employees self-censor novel ideas that might be deemed too risky and share "safer" ones that seem to conform with their supervisors (Tost et al. 2013, Reitzig and Maciejovsky 2015, Keum and See 2017). Thus, by reducing the number of novel ideas generated, shared, and selected, adding a hierarchical level can impede the start-up's ideation and creative success.

In sum, the discussion above leads to the following hypothesis about the relationship between a start-up's hierarchy and its subsequent creative success:

Hypothesis 1. *The number of hierarchical levels of a start-up is negatively associated with its subsequent creative success.*

2.2.3.2 Hierarchy and commercial success

Unlike its creative success, a start-up's commercial success can be hampered by a flatter hierarchy. That is, by significantly increasing each manager's span of control, a flatter hierarchy imposes a heavy cognitive burden on the manager to be responsible for more subordinates (Graicunas 1937). As these managers are overwhelmed by the burden of direction and conflict resolution (Burton and Obel 2004:169, Puranam 2018:113), they tend to disengage from their supervisory roles (Blau and Scott 1962/2003:238), causing their subordinates to lose direction and drift into aimless exploration of ideas (Urwick 1956:43, Sine et al. 2006:123, Gulati and DeSantola 2016). This is portrayed by a former employee of Valve, a game company renowned for its flat hierarchy:

> "Without managers to keep them in line, ... many jockeyed for projects that weren't suited to their skills" (Maier 2013).

Because these subordinates lack not only their superiors' supervision but also formalized routines to follow (Stinchcombe 1965:148–150), they may alternatively gravitate towards an informal structure (i.e., unofficial rankings based on status and respect) for directions (Freeman 1972, Gruenfeld and Tiedens 2010:1262, Puranam and Håkonsson 2015:4). As one entrepreneur reflects:

> "We began to realize that by building a company with a flat org. structure, ... we had centralized all the decision-making, and we were relying on *a secret implicit structure* to make progress" (Savage 2015; emphasis added).

Because this informal structure is not clearly defined or officially agreed upon, subordinates may disagree with its directions and struggle with politicking and dysfunctional conflicts until this structure stabilizes (Kilduff et al. 2016). Even if it stabilizes, it is unlikely to be functional because the winner of such power contests tends to be one based on attractiveness or dominance, rather than competence (Tarakci et al. 2016). As the former Valve employee recalls:

> "There are popular kids that have acquired power in the company, then there are the troublemakers who actually want to make a difference. ... productivity suffered and communication broke down as well" (Maier 2013).

These power struggles and conflicts can prevent subordinates from focusing on substantive issues (Greer and van Kleef 2010) and result in the "lowest-common-denominator compromises" (Wasserman 2012:133, Kilduff et al. 2016). When these conflicts spin out of control, they can even lead to major employee turnovers (Freeman 1972). For instance, CloudFlare, a start-up once proclaimed to be flat with no hierarchical levels, lost almost one-fifth of its employees, who cited "the lack of a clear mid-level reporting structure and the non-existent HR practices" (Gulati and DeSantola 2016). Hence, by letting employees drift into aimless exploration and grapple with dysfunctional conflicts, a flatter hierarchy can result in haphazard execution and commercial failure.

Adding a hierarchical level can forestall such aimless exploration and dysfunctional conflicts by decreasing each manager's span of control (Carzo and Yanouzas 1969:189). With a smaller span of control, each manager can concentrate on providing clear guidance and can exercise her formal authority in prioritizing ideas and making legitimate decisions (Urwick 1956, Blau 1970). This clarity in guidance and decision-making authorities eliminates uncertainty in the relationships among subordinates (e.g., who should be doing what, as well as how and when they should do it) and results in more predictable behaviors (Mintzberg 1979:83, Sutton and Rao 2014:107). If those interactions become intractable and evolve into dysfunctional conflicts, the managers can leverage their authority to take control of the situation, resolve those conflicts, and keep things on track (Lawrence and Lorsch 1967/1986:146–151). As one entrepreneur succinctly puts it:

> "[Without hierarchy, start-ups] lose structure altogether and fall foul of many of the trappings of letting creativity prosper without control" (Freeman 2013).

By preventing aimless exploration and dysfunctional conflicts, adding a hierarchical level eschews chaotic execution and improves commercial success.[5]

Taken together, the above arguments suggest the following hypothesis about the relationship between a start-up's hierarchy and its subsequent commercial success:

Hypothesis 2. *The number of hierarchical levels of a start-up is positively associated with its subsequent commercial success.*

Theoretically, this hypothesis assumes that commercial success will increase with the number of hierarchical levels, but at a decreasing rate. Yet, it is empirically tested as a linear (rather than a curvilinear) relationship because boundedly rational entrepreneurs are presumably aware of this diminishing return to hierarchy and thus hardly adopt extreme hierarchical structures, for instance, where each employee occupies a hierarchical level.

[5] A taller hierarchy may not necessarily hinder execution and commercial success by slowing the decision-making process, because the greater time required for decisions to pass through more hierarchical levels can be offset by the time needed to resolve conflicts and reach a consensus in a flatter one (Carzo and Yanouzas 1969, Eisenhardt 1989).

2.3 Methods

2.3.1 Data collection

In general, examining the relationships between a start-up's hierarchy and its creative/commercial success is empirically challenging for two main reasons. First, because start-ups are, by definition, newly established and thus predominantly private, it is difficult to gather a large sample dataset of these nascent firms and their performance. Second, even when such a dataset is obtainable, their hierarchy is hard to measure because their organizational charts are not publicly available. Because of these challenges in data collection and measurement, empirical research on the organizational structure of start-ups has remained sparse (Keum and See 2017:667, Burton et al. 2019).

This study overcomes these challenges by leveraging a unique large-sample dataset of start-ups in the video game industry, which is one of the fastest-growing venues for entrepreneurial activities (Bies 2017). This dataset was collected from three major sources widely cited by industry practitioners: MobyGames, GameRankings, and VGChartz. MobyGames keeps a comprehensive database of more than 190,000 games worldwide and, for each game, specifies the game development studio (henceforth, studio) and its employees' full name and job title.[6] I used this data to identify whether a studio is newly established (i.e., no prior history in game development) and to measure its hierarchy (i.e., the number of hierarchical levels derived from text analysis of job titles). MobyGames also provides specific information on game attributes (e.g., genre, theme, business model) and financing method (e.g., whether the studio financed independently or whether it was funded by publishers), which are used to account for the task- and financing-level characteristics.

GameRankings aggregates over 240,000 critics' review ratings from both offline and online sources, including those before its launch in 1999 (e.g., GamePro's review for Nintendo's *Super Mario 64*, which was posted a few months after this game was released in 1996), and computes

[6] MobyGames database has been used as a source of data in several studies on the video game industry (e.g., Mollick 2012, Lee and Csaszar 2020, Piezunka et al. 2020). Before measuring the variables (as discussed in Section 2.3.3), I cleaned this dataset according to the following steps. First, among the 20 functional domains categorized by MobyGames (i.e., 'Administration,' 'Art/Graphics,' 'Audio,' 'Business,' 'Companies,' 'Creative Services,' 'Customer/Technical Support,' 'Design,' 'Localization,' 'Marketing,' 'Production,' 'Programming/Engineering,' 'Public Relations,' 'Quality Assurance,' 'Support,' 'Technology,' 'Thanks,' 'Video/Cinematics,' 'Writers,' and 'Others'), the category 'Thanks' was excluded because it mainly consists of friends and family, rather than employees. Next, multiple job titles of an individual for a given game were merged into one—for instance, the two job titles (i.e., 'CEO' and 'Executive Producers') of Mikael Hed for the game *Angry Birds* were combined into one (i.e., 'CEO / Executive Producers'). Lastly, the names of all 753,407 individuals were manually checked to filter out fake employees. Name disambiguation was not required because this database provides a unique identifier (i.e., "developerId"; e.g., for Mikael Hed, "444500").

their average (in terms of percentages), which is used as a measure for creative success. In turn, VGChartz documents the global sales figures for games that sold more than 10,000 units, which are used to measure commercial success. These figures from GameRankings and VGChartz were connected to the MobyGames data using a fuzzy string-matching algorithm on the game title (Python's `FuzzyWuzzy` package with a similarity threshold of 95% to account for typos and minor differences) and then by manual checking false or ambiguous matches.

Although these websites together provide a unique dataset to investigate the hierarchy of start-ups and its performance implications, they have some potential limitations. First, MobyGames specifies information not on the organizational chart but on the employees' job titles, the use of which may vary across studios (Bethke 2003:51), thus potentially leading to an imperfect measure of hierarchy. Second, GameRankings selects its sources and converts all types of ratings into percentages (according to a set of rules specified on its Help page), and this aggregation process can be subject to potential biases (Schreier 2012). Lastly, VGChartz claims that for every game in every region, it extrapolates sales figures provided by retailers and makes a weekly estimate of global sales figures, the reliability of which has been questioned (Carless 2008). I later discuss how I mitigate these concerns using various qualitative data and robustness checks.

2.3.2 Defining a start-up for empirical analyses

To be consistent with the theoretical conceptualization (in Section 2.2.1), I empirically define a start-up as a studio at the point when it releases its *first* game. These studios are, on average, less than two years old because it typically takes two years to develop a triple-A game—namely, a game with massive development and marketing budgets funded by major publishers (e.g., Infinity Ward's game *Call of Duty*, which raised $500 million from its publisher Activision; Schreier 2017:200).

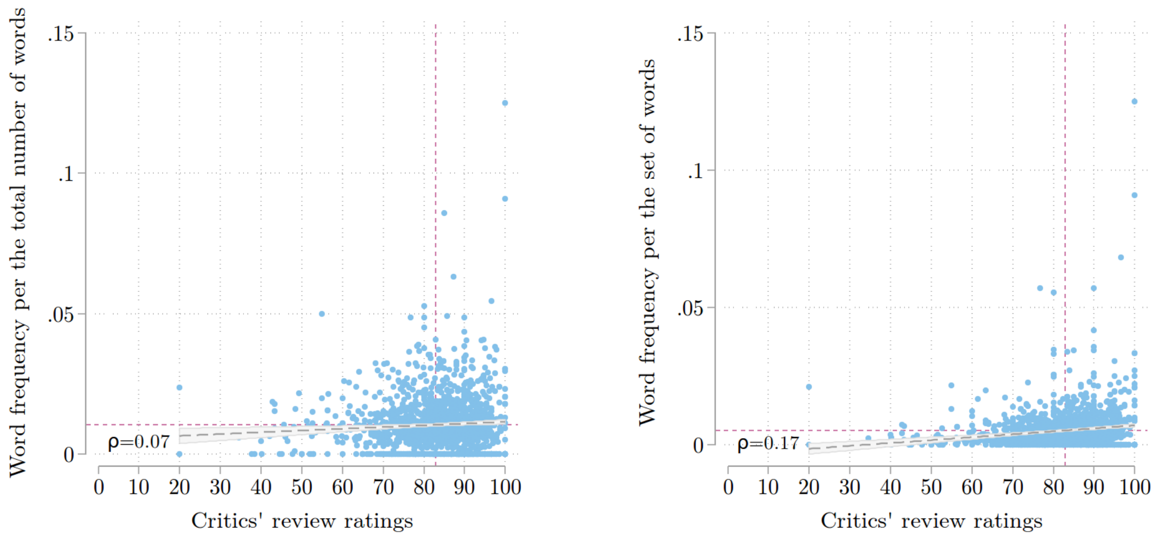
Defining start-ups as such results in a pooled cross-sectional dataset that mitigates potential selection bias, as more than 90% of studios fail after their first product. Furthermore, this dataset mitigates potential measurement error. This is because newly established studios can be accurately represented by their first game's credit (i.e., the list of employees and their job titles), as these start-ups generally focus all employees on their first game and lack the resources to simultaneously develop multiple games. However, after the first game, studios typically invest the profit from their previous game to run multiple projects and hire administrative staff (e.g., legal, accounting, intellectual property). As these concurrent projects and staff are not systematically reported at the firm-level in a given year, the credits after the first game will incompletely represent the studios, thus biasing the measurement of variables (especially their hierarchy and size).

To avoid these empirical concerns, I acquired a sample that matches the above empirical definition in the following way. First, I measured the variables as described in the following section. I then limited the observations to the first game that each company developed. Among these 6,510 observations, 276 games with more than one studio were removed to exclude potential spin-outs, joint ventures, and project teams of incumbents. This removal yielded a sample of 6,234 start-ups newly established during the period from 1971 to 2015.

2.3.3 Measurement

Dependent variables. As noted earlier, creative success is defined as the novelty of the product, whereas commercial success is defined as its profitability. Following previous work on creative industries (e.g., Uzzi and Spiro 2005), creative success was measured by the average critics' review rating (on a scale from 0 to 100). This rating, to a large extent, reflects its novelty, as indicated by the fact that (1) terms such as "novel," "creative," "unique," "groundbreaking," "new," and "original" appear disproportionately in the reviews with above-60 ratings and (2) their word frequency is positively correlated with the rating (see Figure 2.1). Thus, this rating is the industry standard used by practitioners as "an important benchmark" (Schreier 2012)—so important that publishers "stick review score bonuses into contracts, offering extra payouts to [studios] whose games hit a certain threshold on video game aggregation sites like Metacritic or GameRankings" (Schreier 2017:216).

In turn, commercial success was measured by the number of units sold globally (in millions), which is comparable to the typical measure of commercial success (i.e., attendance) in studies of the movie industry (e.g., Zuckerman and Kim 2003). These sales figures were used because profit, revenue, or return on investment are unavailable, as is generally the case in creative industries. Because these figures reflect cumulative demand rather than profitability, I account for development costs by adding various task-level characteristics (e.g., the use of 3D technology). Thus,



(a) Per the total number of words

(b) Per the set of words

Figure 2.1: The scatter plot of creative success and the word frequency of terms relevant to novelty (i.e., "novel," "creative," "unique," "groundbreaking," "new," "original," "innovative," "rare," "inventive," "innovatory," "innovational," "unconventional," and "unorthodox") in critics' reviews. The left figure shows the word frequency per the total number of words, whereas the right shows that per the set of words (to remove the duplicated words). The line represents the linear prediction with its 95% confidence interval, whereas the dashed line indicates the mean of each variable.

$$\begin{aligned} \textit{Creative} &= \text{Average critics' review rating (on a scale of 0–100)} \\ \textit{Commercial} &= \text{\# of units sold globally (in millions)} \end{aligned}$$

Independent variable. In line with both entrepreneurs' interpretation (i.e., hierarchical layers of managers) and prior studies (e.g., Burton and Obel 2004:75, Puranam 2018:106–108, Lee and Csaszar 2020), I measured hierarchy in terms of the number of hierarchical levels. This number was computed by first categorizing each employee's job title into one of 12 levels (i.e., 'Owner,' 'President,' 'VP,' 'CEO,' 'C-Suite,' 'Head,' 'Director,' 'Manager,' 'Producer,' 'Lead,' 'Supervisor,' and 'Other') and then counting the number of unique levels. Thus,

$$\textit{Hierarchy} = \text{\# of hierarchical levels}$$

These 12 levels were derived from qualitative data, verified through interviews with practitioners, and measured using text analysis through the following five steps. First, from a rich array of qualitative data (e.g., Mencher 2002, Bethke 2003, Grossman 2003, Spaulding 2009, Schreier

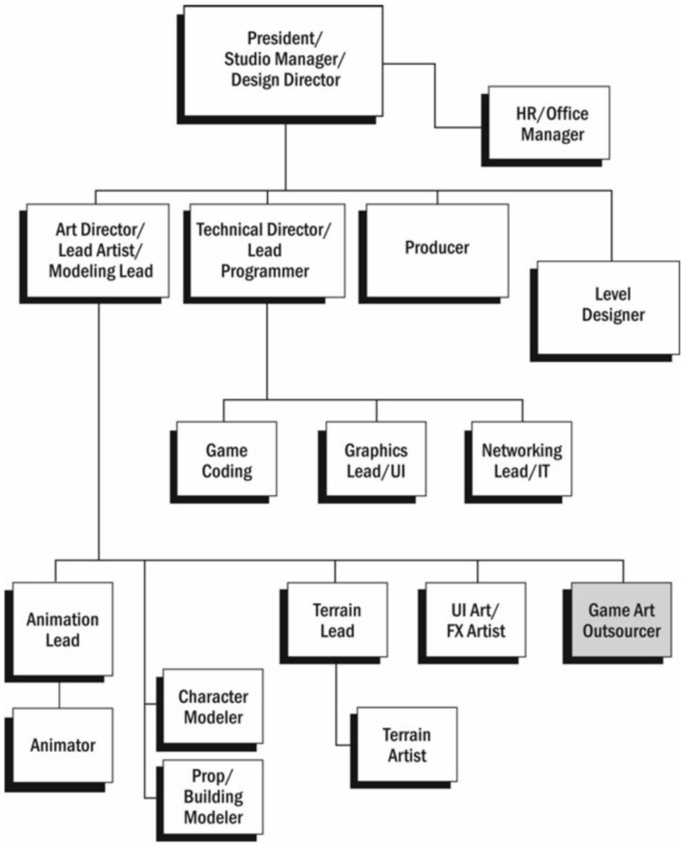


Figure 2.2: An example of a game development start-up's organization chart (Spaulding 2009:24).

2017), I extracted keywords that indicate a hierarchical level (e.g., 'President,' 'Manager,' 'Director,' 'Lead,' and 'Producer' in Figure 2.2) and categorized those terms into 12 levels. Second, from the same data, I confirmed that these levels follow a vertical chain of command. For example, one founder explains:

> "Each lead . . . will typically *report to* a director, who in turn *reports to* a studio head or president" (Spaulding 2009:2; emphasis added).

Third, through interviews with 34 practitioners located in the U.S., South Korea, and Japan, I verified that these 12 categories typically represent distinct hierarchical levels. Fourth, to measure hierarchy for the empirical analyses, I build upon Lee and Csaszar's (2020) method to categorize each employee's job title into one of the 12 levels. This is done so by applying to Rules 1 to 12 in Table 2.2 in ascending order until a match is found—that is, if a job title includes terms relevant to that level. The list of relevant terms (see the third column in Table 2.2) includes abbreviations (e.g., "snrvp" for senior vice president) and typographical errors (e.g., "cheif" is a typo of "chief")

Rule	Hierarchical level	If the job title includes any of these terms	Examples
1	Owner	*owner*, *founder*, *chairman*, *creator*, *created*, or *made*	"Created by," "Created and Developed by," "Chairman," "Made by"
2	President	*president* or *presidente* (but not *vice*)	"President," "President and CEO," "President & CEO," "President, North America"
3	VP	*vp*, *evp*, *avp*, *svp*, *snrvp*, *vice president*, or *vice presidente*	"Vice President," "Vice President of Marketing," "VP of Marketing," "Senior Vice President"
4	CEO	*ceo* or any combination of {*chief* or *cheif*} and {*executive*, *exec*, *exective*, or *executiver*}	"CEO," "Chief Executive Officer"
5	C-Suite	*cco*, *cdo*, *cfo*, *cho*, *cio*, *clo*, *cmo*, *coo*, *cpo*, *cso*, *cto*, or both *chief* and *officer*	"COO," "CFO," "Chief Creative Officer," "Chief Operating Officer"
6	Head	*head*	"Head of Production," "Studio Head," "Head of Marketing," "Head of Development"
7	Director	*director*, *directo*, *diercto*, *dir*, or *dierctor*	"Art Director," "Director," "Technical Director," "Creative Director"
8	Manager	*manager*, *mgr*, or *gm*	"Project Manager," "Product Manager," "QA Manager," "Production Manager"
9	Producer	*producer*	"Producer," "Executive Producer"
10	Lead	*lead* or *leader*	"Lead Programmer," "Lead Artist," "Lead Tester," "Lead Designer"
11	Supervisor	*supervisor*	"Supervisor," "QA Supervisor," "Music Supervisor," "Test Supervisor"
12	Other	(includes none of the above)	"Testers," "Programmers," "Artists"

Table 2.2: The rules to categorize each employee's job title into a hierarchical level.

that frequently appear in the MobyGames database. Lastly, after categorizing all the job titles into these levels, I counted the number of hierarchical levels with at least one employee.

Apart from its hierarchy, a start-up's performance may depend on the characteristics of its task, financing method, employees, and macro-environment. To account for these characteristics, I included a comprehensive set of controls and fixed-effects described in Table 2.3.

Controls. For the employees' characteristics that may influence performance, I computed their amount and breadth of experience (Shane 2000, Eggers 2012), social capital developed through prior collaboration (Meier et al. 2019), and gender diversity (Hoogendoorn et al. 2013). Here, the amount of experience is measured by the average number of prior games that employees worked on, and its breadth by the average diversity of functional domains which employees worked in (for an illustration, see Appendix 2.6.1). In turn, social capital is computed by the average pair-wise social distance among employees in the prior five-year collaboration network (for details of this measure,

Variable	Measurement
Dependent	
Creative	Average critics' review rating (on a scale of 0–100).
Commercial	The number of units sold globally (in millions).
Independent	
Hierarchy	The number of hierarchical levels.
Controls	
Experience	The average number of prior games that an employee has worked on.
Breadth	The average diversity ($1 - HHI$) of functional domains in which an employee has worked.
SocialCapital	The average inverse of pairwise shortest path length among employees.
GenderDiversity	The proportion of female employees.
Fixed-effects	
Task-level	
3D	1 if the game incorporates 3D technology; 0 otherwise.
LicensedTitle	1 if the game was adapted from a movie, TV show, book, or other work; 0 otherwise.
BusinessModel	1 if the game adopted the free-to-play business model; 0 otherwise.
Genres	59 dummies for each genre (e.g., Adventure, Role-playing, Strategy).
Themes	298 dummies for each theme (e.g., Arcade, Chess, Fighting).
Platforms	5 dummies for each platform type (i.e., PC, mobile, home console, handheld console, arcade).
Financing-level	
Indie	1 if the studio published the game by itself; 0 otherwise.
Triple-A	1 if the studio was funded by a major publisher (e.g., Activision); 0 otherwise.
Employee-level	
Size	10 quantiles of the number of employees.
Macro-level	
Year	The year of game release (1971–2015).

Table 2.3: Measurement of variables.

see Appendix 2.6.2). Lastly, gender diversity is calculated by the proportion of female employees. As the information on gender is not readily available in the MobyGames database, I used Python's `gender-guesser` package to predict each employee's gender with the full name.

Fixed-effects. To account for unobserved variation that may be driving the results, I included the following dummies. At the task-level, I added dummies for game characteristics that imply task complexity and development costs (e.g., genre, theme, and released platforms). At the financing-level, I introduced dummies for whether the studio published the game independently without the help of publishers (i.e., indie) and for whether it was funded by any of the 200 major publishers (i.e., triple-A). At the employee-level, I included 10 size-quantiles to compare among start-ups of a similar size in terms of the number of employees.[7] Lastly, I used year dummies to control for common

[7] The 10 size-quantiles were used (1) to mitigate concerns regarding multicollinearity because log(*Size*) is highly correlated ($\rho = 0.59$) with *Hierarchy* (see Section 2.4.1) and (2) to not impose any arbitrary assumptions in defining size categories given the lack of agreement in the literature on how to categorize firms by size (Carland et al. 1984:354, Burton and Obel 2004:171). Likewise, there is no industry-specific size categorization by the number of employees,

macroeconomic changes that influence all games. The inclusion of these fixed-effects, therefore, absorbs any variation attributable to invariant characteristics of the task, financing method, firm size, and macro-environment, and thus allows me to focus on the variables of interest.

2.3.4 Model specification

An ideal experimental design is to randomly assign hierarchy and examine how it affects creative/commercial success. Unfortunately, as such randomized designs were not attainable, I apply the fixed-effects model (using Stata's `reghdfe` package) to mitigate potential selection concerns with an extensive set of controls and fixed-effects. Hence, the empirical model is specified as follows:

$$Performance_i = \alpha + \beta Hierarchy_i + \Gamma CONTROL_i + FIXED_i + \varepsilon_i$$

where for start-up i, $Performance_i$ stands for one of the two performance outcomes (creative and commercial success), $Hierarchy_i$ for the number of hierarchical levels, $CONTROL_i$ for the vector of controls, and $FIXED_i$ for the vector of fixed-effects (note that because most founders establish only one studio and each studio has only one observation, both founder and studio fixed-effects are not included in $FIXED_i$ and that only one index, i, was used for simplicity). The coefficients β and Γ are the estimated parameters, and α and ε_i are the intercept and the random error term, respectively. In this model, the standard errors are clustered by genre to account for correlations among games in the same genre.

2.4 Results

2.4.1 Descriptive statistics and correlation matrix

Table 2.4 presents the descriptive statistics and the correlation matrix. First, the descriptive statistics show a substantial variation in the variables of interest. Among 6,234 start-ups, roughly a quarter (1,725 observations) were given a review rating by critics, while less than 10% (494 observations) sold more than 10,000 units. Among these start-ups with over 10,000 unit sales, commercial success is highly skewed, as observed by Andersson et al.'s (2009:310–311).[8] This

and industry practitioners typically categorize firms by revenue, rather than the number of employees (e.g., see NAICS Industry Code 511210 in the U.S. Small Business Administration's *Table of Small Business Size Standards*).

[8] The right skewness of commercial success is accounted for by applying the natural logarithm (this log transformation also applies to the amount of experience, to which one is added to avoid computing the logarithm of zero).

left-censored, right-skewed distribution of commercial success implies that most game development start-ups fail (Grossman 2003:ix–x), which is comparable to the fact that most start-ups, in general, fail. Given the left-censoring in the measures of creative and commercial success, the main results may be interpreted for start-ups that reach a certain level of success.

The descriptive statistics also show that a typical start-up consists of fewer than 30 employees (mean *Size* of 26.11) who, on average, have worked on approximately two projects before joining the start-up (mean *Experience* of 2.45) and are highly specialized in a few functional domains (mean *Breadth* of 0.09).[9] These statistics are consistent with various observations by industry practitioners (e.g., Spaulding 2009:6, Schreier 2017:64), thus implying that my data is a representative sample that closely matches the population of game development start-ups.

Next, I turn to the correlation matrix. This matrix indicates that the independent variable *Hierarchy* is highly correlated ($\rho = 0.59$) with the control log(*Size*), which is thus discretized into 10 size-quantiles and included as fixed-effects in the main analyses (as mentioned in Section 2.3.3). Another highly correlated control ($\rho = 0.47$) is log(*Experience*), which is an important source of knowledge that influences start-ups' performance (Shane 2000, Eggers 2012). To investigate whether these variables raise the concern of multicollinearity, I conducted the following three diagnostic tests. First, I computed the variance inflation factors and the condition indexes, each of which shows a maximum value (1.76 and 5.38, respectively) well below its customary threshold (10 and 30, respectively; Belsley et al. 1980:112, Kutner et al. 2004). Second, I excluded log(*Experience*) and obtained robust results (see Table 2.17 in Appendix 2.6.6). Lastly, because these two diagnostics may misleadingly dismiss multicollinearity concerns (Kalnins 2018), I ran separate regressions (1) with only *Hierarchy*, (2) with only log(*Experience*), and (3) with both variables, all of which exhibit consistent signs and relatively stable magnitudes for the two variables (see Table 2.17). Together, three diagnostics imply that my main results are not severely biased by multicollinearity.

The correlation matrix also shows that creative and commercial success are positively correlated ($\rho = 0.30$). This correlation is not surprising given that creative success partially explains commercial success: novel ideas tend to be more commercially successful. However, what is surprising is the significant amount of divergence between these two measures. This divergence is illustrated

[9]To understand why the mean *Breadth* of 0.09 corresponds to a high level of functional specialization, consider an individual with 20 units of experience. If 19 of these units fall in the same functional domain, she would have *Breadth* $= 0.095$ $(= 1 - (19^2 + 1^2)/20^2)$, which is larger than the mean value.

	Descriptive statistics					Correlation matrix											
	Obs.	Mean	Std. Dev.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent																	
(1) Creative (review rating)	1,725	66.24	14.96	10	100	1.00											
(2) Commercial (million units)§	494	0.97	2.53	0.01	30.26	0.30***	1.00										
Independent																	
(3) Hierarchy	6,234	2.28	2.03	1	12	−0.03	0.08†	1.00									
Controls																	
(4) Experience§	6,234	2.45	4.07	0	64	0.05*	−0.04	0.47***	1.00								
(5) Breadth	6,234	0.09	0.12	0	0.84	0.03	−0.09*	0.25***	0.69***	1.00							
(6) SocialCapital	6,234	0.12	0.21	0	1	0.04	0.03	0.27***	0.61***	0.54***	1.00						
(7) GenderDiversity	6,234	0.12	0.15	0	1	−0.02	−0.10*	0.29***	0.11***	0.03*	0.09***	1.00					
Fixed-effects																	
(8) 3D	6,234	0.09		0	1	−0.04†	−0.11*	0.22***	0.13***	0.10***	0.06***	0.04***	1.00				
(9) LicensedTitle	6,234	0.10		0	1	−0.12***	0.14**	0.21***	0.16***	0.10***	0.13***	0.05***	0.03*	1.00			
(10) BusinessModel	6,234	0.14		0	1	0.08***	0.04	−0.07***	−0.05***	−0.04**	−0.08***	−0.03*	−0.06***	−0.07***	1.00		
(11) Indie	6,234	0.31		0	1	0.07**	0.01	−0.31***	−0.31***	−0.22***	−0.26***	−0.13***	−0.12***	−0.18***	0.21***	1.00	
(12) Triple-A	6,234	0.32		0	1	−0.05*	0.04	0.49***	0.40***	0.24***	0.29***	0.18***	0.13***	0.18***	−0.15***	−0.44***	1.00
(13) Size§	6,234	26.11		1	2450	0.13***	0.23***	0.59***	0.27***	0.12***	0.15***	0.17***	0.16***	0.11***	−0.04**	−0.16***	0.28***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$

§ In the correlation matrix, the natural logarithm was applied to commercial success, experience, and size to account for their right skewness.

Table 2.4: Descriptive statistics and correlation matrix.

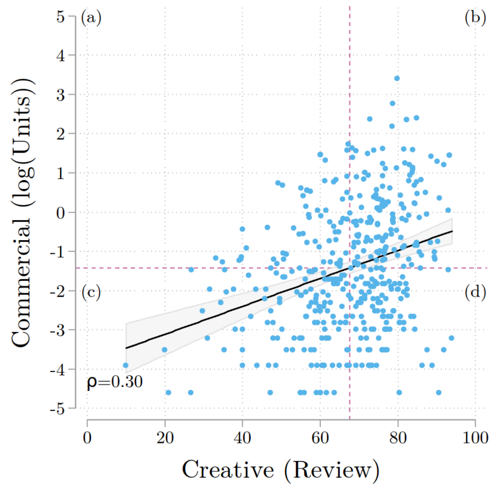
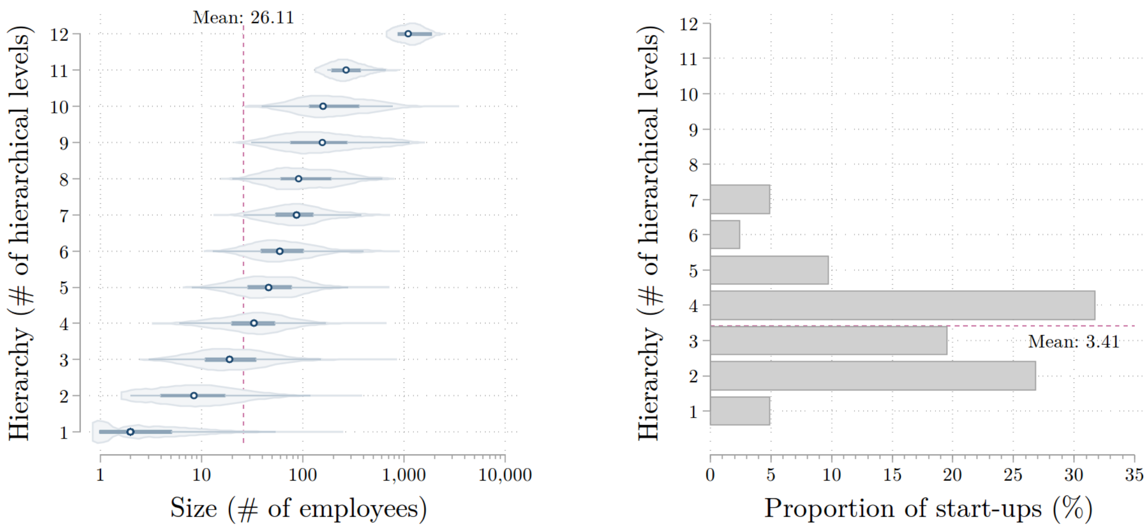


Figure 2.3: The scatter plot of creative and commercial success. The line represents the linear prediction with its 95% confidence interval, whereas the dashed line indicates the mean of each performance metric.

in Figure 2.3, which plots creative success (x-axis) against commercial success (y-axis). This figure shows that a large proportion of start-ups (more than 40%) achieved one or the other: that is, received an above-average review rating but sold below-average global sales units, or vise versa (and are thus in quadrants (a) and (d)).

An example of a game that achieved above-average creative success but commercially failed is Troika Games' *Vampire: The Masquerade–Bloodlines*. This game received an average review rating of 80 (i.e., roughly one standard deviation above the mean), winning both IGN's and Computer Gaming World's *2004 Best PC Role-Playing Game* awards. Unfortunately, this critically acclaimed game "was such a costly [commercial] failure that it doomed its developers to closure, leaving it without further official patches or any hope of legitimate follow up" (Hartup 2015). In contrast, a game that was lambasted by critics but was commercially successful is Office Create's *Cooking Mama*. This game earned a below-average review rating of 68, being heavily criticized that it "lacks direction and depth" (Navarro 2006). Despite such criticisms, this game was a blockbuster selling over 4 million copies just in the U.S., later becoming a game franchise with several spin-offs (e.g., *Gardening Mama*, *Babysitting Mama*, and *Crafting Mama*) selling more than 12 million copies worldwide (Caoili 2011).



(a) All observations

(b) Mean-sized start-ups with 26 employees

Figure 2.4: The variation in start-ups' hierarchy. The left figure includes all 6,234 observations (i.e., start-ups of any size), whereas the right is for 43 mean-sized start-ups with 26 employees.

2.4.2 Exploratory data analysis of the variation in hierarchy

To explain this divergence between creative and commercial success, hierarchy should substantively vary across start-ups. According to the descriptive statistics in Table 2.4, a typical start-up has roughly two hierarchical levels (mean *Hierarchy* of 2.28), which aligns with the common belief that start-ups look alike with flat hierarchies. But, this averaging across start-ups of any size can be misrepresentative because whether start-ups are flat will depend on their size. If we thus plot the number of hierarchical levels by the number of employees (see Figure 2.4a), the two variables show a strong positive relationship, which is consistent with the prior studies on "size imperative" (Blau 1970, Burton and Obel 2004:168).[10]

Here, if we just focus on the same-sized start-ups (i.e., observations vertically above a given point on the x-axis in Figure 2.4a), we can see that they vary substantively in terms of their hierarchy. For instance, among the mean-sized firms with 26 employees (see Figure 2.4b), the number of hierarchical levels ranges from one to seven. This variation is congruent with Baron and Hannan's

[10]The observations with a large number of employees and hierarchical levels (in the upper right-hand corner of Figure 2.4a) represent the game development start-ups whose first product was a triple-A game (e.g., Infinity Ward and its first game *Call of Duty* mentioned in Section 2.3.2). To mitigate the concern that such extreme observations are driving the main findings, I ran a robustness test excluding those with more than 250 employees, and found consistent results (see Table 2.13 in Appendix 2.6.6).

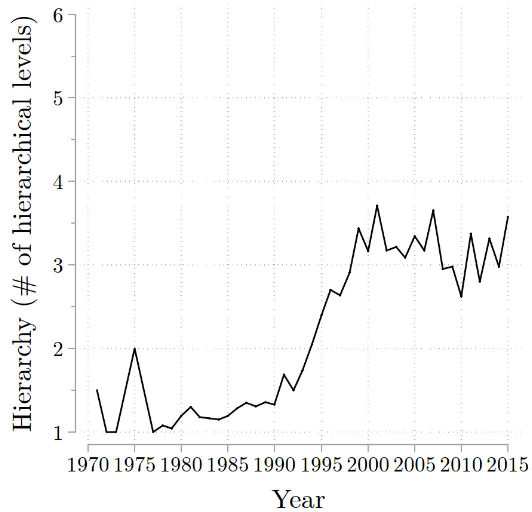


Figure 2.5: The trend towards a taller hierarchy. The line represents the average number of hierarchical levels in start-ups that released their first game in a certain year.

(2002:9) observation that "Though some observers might think that most start-ups look pretty much the same, or that the appropriate organizational design ... for a high-tech venture is 'obvious,' the data suggest otherwise." Adding to their observation, this finding qualifies the conventional wisdom that start-ups are homogeneously flat.

In fact, start-ups at entry (i.e., when they developed their first game) have become taller over the past four decades (see Figure 2.5). That is, the average number of hierarchical levels in start-ups that released their first game in a given year has steadily increased from 1.3 in the 1980s to 3.2 in the 2000s. This "tallening" of start-ups occurred largely during the 1990s, the period in which major advancements in information technology (e.g., CD/DVDs, the Internet, and multi-core CPUs) were widely introduced and commercialized. This tallening of start-ups is surprising because it counters both the widespread distaste for hierarchy among practitioners and the conventional wisdom in the literature on organization design. As mentioned earlier, this literature has posited that firms will flatten to streamline the decision-making process and flexibly adapt to today's rapid technological and economic changes (Burns and Stalker 1961, Lawrence and Lorsch 1967/1986). It has further asserted that firms will "flatten" (or "delayer") because more advanced information technology decreases the role of the middle managers in coordinating information (Brynjolfsson 1994, Brynjolfsson et al. 1994, Burton and Obel 2004:76–77, Rajan and Wulf 2006, Zhou 2013:351).

Based on the rapid spike during the 1990s, one plausible explanation for this tallening is the advancements in information technology (Grossman 2003:x, Edwards 2005, Spaulding 2009:4–7). These advancements (e.g., CD/DVDs, the Internet, and multi-core CPUs) have enabled studios to create more media-rich, complex games (e.g., Massively Multiplayer Online Role-Playing Games), which require a decomposition into smaller task components (e.g., programming, graphics, network) and a team of specialized individuals dedicated to a particular component. To integrate the efforts of these specialists, start-ups have introduced more hierarchical layers. As one practitioner highlights:

> "Now, . . . [studios] employ programming teams divided into sub-teams of coders dedicated to four or five specialties . . . requiring more individuals to take leadership positions on a given team" (Spaulding 2009:6–7).

Thus, in contrast to the conventional wisdom about flattening, this observation suggests that by increasing task complexity, more advanced information technology can, in fact, "tallen" start-ups.[11]

Given this large-scale evidence of variation and trend in the hierarchy of start-ups, I discuss below the regression results of how this variation translates into a difference in their performances in terms of creative and commercial success (for the results, see Table 2.5).

2.4.3 Regression results

Part A of Table 2.5 reports the main regression results using the fixed-effects model with standard errors clustered by genre. For ease of reading, only the baseline model (excluding all fixed-effects) and the full model (including all fixed-effects) are presented. The results of these models are consistent when the fixed-effects are sequentially added (see Tables 2.11 and 2.12 in Appendix 2.6.6). Note that, as the measures of creative and commercial success are left-censored (as discussed in Section 2.4.1), these results may be interpreted for start-ups that reach a certain level of success.

I begin by examining the relationship between a start-up's hierarchy and its creative success. In Hypothesis 1, I proposed that a start-up's hierarchy is negatively associated with its subsequent

[11] I offer further empirical support for this conjecture regarding tallening by using Massively Multiplayer Online Role-Playing Games as a moderator (see Appendix 2.6.5). Though task complexity may seem context-specific, it is broadly considered an important contingency for hierarchy in the literatures on organization design (e.g., Van De Ven et al. 1976, Zhou 2013), groups and teams (e.g., Halevy et al. 2011, Bunderson et al. 2016), and organizational economics (e.g., Garicano and Wu 2012). As this phenomenon of tallening and its alternative explanations require a more thorough investigation that goes beyond the scope of this paper, I leave this inquiry for future research.

	Part A Main analyses				Part B Testing the mechanism		Part C Assessing the scope condition	
	(1) Creative (Review)		**(2) Commercial** (log(Units))		**(2) Commercial** (log(Units))		**(1) Creative** (Review)	**(2) Commercial** (log(Units))
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Independent								
Hierarchy	-0.45^{**}	-0.99^{***}	0.09^{*}	0.10^{*}	0.21^{**}	0.18^{**}		
	(0.13)	(0.27)	(0.04)	(0.04)	(0.07)	(0.06)		
Moderator								
Hierarchy×Breadth					-0.60^{*}			
					(0.26)			
Hierarchy×SocialCapital						-0.26^{*}		
						(0.13)		
Hierarchy×Size								
Micro (1–9 employees)							−2.13	0.32
							(1.35)	(0.37)
Small (10–49)							-1.07^{***}	0.16^{*}
							(0.28)	(0.06)
Medium-Sized (50–249)							-0.84^{*}	$0.10^{\dagger}$
							(0.31)	(0.05)
Large ($\geq$ 250)							$0.78^{\dagger}$	−0.10
							(0.39)	(0.09)
Controls								
log(Experience)	$2.23^{\dagger}$	1.27	−0.21	−0.03	0.01	−0.01	1.21	0.01
	(1.27)	(1.80)	(0.15)	(0.16)	(0.17)	(0.16)	(1.85)	(0.15)
Breadth	−6.43	−1.41	-3.22^{**}	1.17	3.78	1.33	−0.47	1.75
	(6.13)	(7.60)	(0.99)	(2.43)	(2.41)	(2.48)	(8.47)	(1.95)
SocialCapital	0.61	4.96	1.56^{**}	0.05	0.10	1.21	4.11	−0.18
	(2.42)	(3.72)	(0.44)	(0.84)	(0.93)	(1.11)	(3.31)	(0.70)
GenderDiversity	−1.29	−4.22	-1.86^{*}	-1.57^{*}	$-1.49^{\dagger}$	-1.64^{*}	−3.84	$-1.49^{\dagger}$
	(2.20)	(3.10)	(0.71)	(0.71)	(0.73)	(0.71)	(2.79)	(0.74)
Fixed-effects								
Task-level								
3D		$-2.10^{\dagger}$		-0.50^{*}	-0.54^{*}	-0.56^{*}	$-2.08^{\dagger}$	-0.43^{*}
		(1.13)		(0.19)	(0.20)	(0.20)	(1.18)	(0.19)
LicensedTitle		-4.44^{**}		0.50^{*}	0.51^{*}	0.47^{*}	-4.34^{**}	$0.42^{\dagger}$
		(1.32)		(0.22)	(0.22)	(0.21)	(1.22)	(0.22)
BusinessModel		2.04		−0.28	−0.22	−0.25	2.19	0.06
		(1.84)		(0.60)	(0.63)	(0.58)	(1.81)	(0.41)
Genres		Y		Y	Y	Y	Y	Y
Themes		Y		Y	Y	Y	Y	Y
Platforms		Y		Y	Y	Y	Y	Y
Financing-level								
Indie		0.50		0.34	0.32	0.27	0.73	0.82
		(1.02)		(0.69)	(0.77)	(0.76)	(1.03)	(0.84)
Triple-A		−1.09		−0.28	−0.37	−0.29	−0.87	0.01
		(1.15)		(0.35)	(0.36)	(0.35)	(1.18)	(0.36)
Employee-level								
Size		10Q		10Q	10Q	10Q	NSF/EC	NSF/EC
Macro-level								
Year		Y		Y	Y	Y	Y	Y
No. observations	1,725	1,477	494	375	375	375	1,477	375
R-squared	0.01	0.23	0.05	0.58	0.59	0.58	0.23	0.59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses. The number of observations decreased since singleton observations were dropped. For size fixed-effects, "10Q" stands for 10 size-quantiles, whereas "NSF/EC" for NSF and EC's size categorization.

Table 2.5: Regression results. Part A reports the main analyses on the relationships between hierarchy and creative/commercial success. Parts B and C display the supplementary analyses using moderators to test the theorized mechanism and the scope condition of firm size.

creative success, because adding a hierarchical level can hamper cross-fertilization and prematurely filter out novel ideas. Supportive evidence for this hypothesis is provided in Models 1 and 2, where the former is the baseline model and the latter is the full model. Model 1 shows that when including just the controls, the coefficient of hierarchy is negative ($p < 0.01$). This remains consistent in Model 2 ($p < 0.001$) even when accounting for the vast list of fixed-effects. In Model 2, the coefficient size of hierarchy indicates that one additional hierarchical level is correlated with a one-point decrease in the average review rating, which is a minor change representing less than 0.07 standard deviations (or 1.6% of the mean of 60). Overall, Models 1 and 2 show that creative success is negatively associated with hierarchy, thus offering empirical support for Hypothesis 1.

I move on to establish the relationship between hierarchy and commercial success. Hypothesis 2 states that a start-up's hierarchy is positively correlated with its subsequent commercial success, because adding a hierarchical level can prevent aimless exploration and dysfunctional conflicts among employees. Supporting evidence for this hypothesis is displayed in Models 3 and 4. Model 3 (the baseline model) shows that commercial success is positively associated with hierarchy ($p < 0.05$). In Model 4, the positive coefficient of hierarchy remains stable in terms of size and significance ($p < 0.05$), despite adding the long list of fixed-effects. The coefficient size in Model 4 implies that one additional hierarchical level is correlated with a 10% increase in the number of units sold globally. In sum, Models 3 and 4 show that commercial success is positively associated with hierarchy, thereby lending supportive evidence for Hypothesis 2.

Together, Models 1 to 4 allude to an interesting observation that, for start-ups, adding a hierarchical level may entail a trade-off between creative and commercial success. What is surprising—especially considering the empirical context of the video game industry—is that one additional level is correlated with only a small decrease in creative success: that is, 0.07 standard-deviation decrease in average review rating. In contrast, it is associated with a large increase in commercial success: that is, 10% increase in global sales units. For an average start-up in my sample, this 10% increase translates to approximately 10,000 units, or \$0.6 million in revenue (assuming an average price of \$60; Yan and Gilbert 2018). This observation hints that, even in creative industries, adding a hierarchical level could be substantially beneficial for start-ups in achieving commercial success at the very marginal expense of creative success.

Below, I use a set of moderators to evaluate the theorized mechanism and the scope condition of firm size (see Parts B and C of Table 2.5).

2.4.4 Testing the theorized mechanism

Part B of Table 2.5 presents the results using moderators to test the theorized mechanism underlying the relationship between a start-up's hierarchy and its commercial success. For Hypothesis 2, I theorized that adding a hierarchical level may lead to better commercial success by preempting aimless exploration and dysfunctional conflicts among employees. Because this mechanism is difficult to observe across a large sample, I test it using two moderators—namely, the employees' breadth of experience (henceforth, breadth) and social capital. The intuition (for details, see Appendix 2.6.3) is that the more breadth the employees have, the more cognitively flexible they are, and the less likely to engage in misunderstandings and dysfunctional conflicts (Greer et al. 2018:594). In turn, the more social capital that employees have developed through prior collaborations, the more mutual understanding and trust they share, and thus the less likely to engage in dysfunctional conflicts (Meier et al. 2019). Because these moderators would decrease the extent to which dysfunctional conflicts arise, I expect that hierarchy will have the largest positive relationship with commercial success when employees lack breadth or social capital (i.e., when dysfunctional conflicts are the most severe), and that this positive relationship will decrease as these moderators increase.

As expected, in both Models 5 and 6, the coefficients of *Hierarchy* are positive (with $p < 0.01$), whereas those for the interactions ($Hierarchy \times Breadth$ and $Hierarchy \times SocialCapital$) are negative (with $p < 0.05$). Because breadth and social capital each have a value between 0 and 1 and the coefficients of *Hierarchy* can be interpreted as the relationship between hierarchy and commercial success given $Breadth = 0$ and $SocialCapital = 0$, these results show that the positive relationship between hierarchy and commercial success is the largest when employees lack breadth or social capital (i.e., when employees are most likely to engage in severe dysfunctional conflicts) and that this positive relationship decreases as these moderators increase. Thus, Models 6 and 7 provide empirical support for my theorized mechanism.

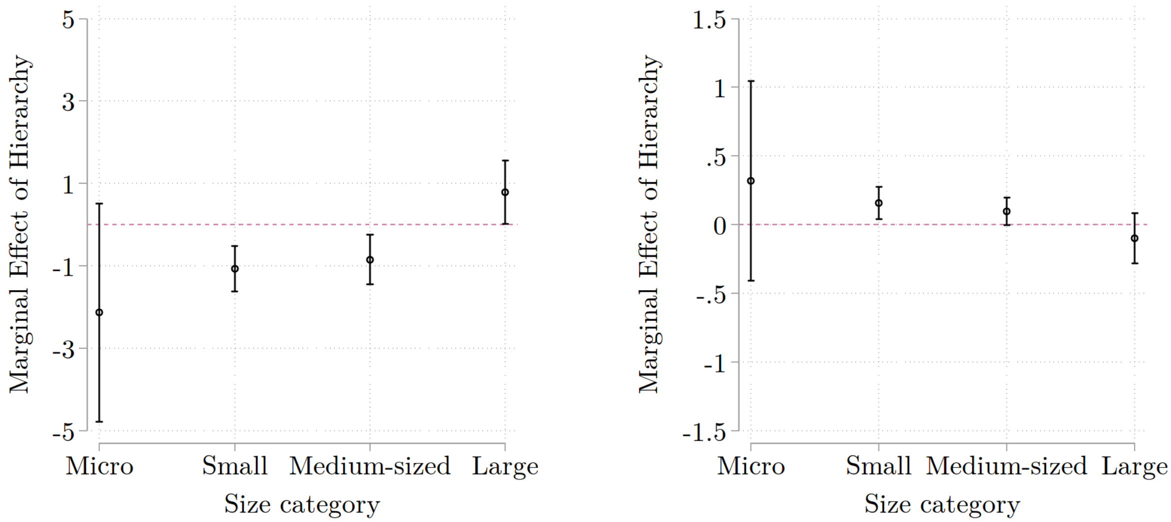
2.4.5 Assessing the scope condition of firm size

As I defined start-ups as nascent firms of any size (theoretically in Section 2.2.1 and empirically in Section 2.3.2), a potential question would be whether the observed relationships between hierarchy and creative/commercial success vary across different sizes—if not, are purely driven by the extremely small and large start-ups. To investigate whether this is the case, I extend my analyses by interacting hierarchy with size. Because the 10 size-quantiles used in the main analyses are specific to my data and are thus difficult to generalize and because there is no industry standard for categorizing studios by the number of employees, I instead adopt a size categorization defined by the National Science Foundation (NSF) and the European Commission (EC). This categorization labels a firm as a "micro-business" if it has fewer than 10 employees, a "small enterprise" if between 10 and 49 employees, a "medium-sized enterprise" if between 50 and 249 employees, and a "large enterprise" if at least 250 employees.[12]

Part C of Table 2.5 displays the results for the marginal effects of hierarchy on creative/commercial success by size categories. These results show that its marginal effects are statistically significant for small and medium-sized start-ups, but not for micro-businesses and large enterprises. Along with the robustness checks excluding these two size categories (see Table 2.13 in Appendix 2.6.6), these results suggest that extremely small and large firms are not driving my main findings. Moreover, these results imply that hierarchy may become consequential when start-ups grow beyond micro-businesses to small/medium-sized enterprises, thereby providing empirical support to the burgeoning stream of research on "scaling" (Sutton and Rao 2014, DeSantola and Gulati 2017).

If these results are plotted with the 95% confidence intervals, two interesting observations become more apparent (see Figure 2.6). First, as firm size increases, the marginal effect of hierarchy on creative success seems to increase, whereas its marginal effect on commercial success seems to decrease. Second, the trade-off between creative and commercial success seems to flip for large start-ups—that is, adding a hierarchical level may be conducive to creative success but be detrimental to commercial success. These observations seemingly contradict the conventional wisdom that, as firms

[12]The results are consistent when using this categorization, instead of 10 size-quantiles (see Table 2.16 in Appendix 2.6.6). For details on this categorization, see NSF's *Business R&D and Innovation Survey–Microbusiness* and EC's *Recommendation of 6 May 2003 Concerning the Definition of Micro, Small and Medium-Sized Enterprises*.



(a) Creative success

(b) Commercial success

Figure 2.6: The marginal effects of hierarchy on creative/commercial success by size categories. The vertical line for each size category indicates the 95% confidence interval.

grow, they impose more hierarchical levels to gain efficiency in execution, at the cost of flexibility in ideation (Blau 1970, Burton and Obel 2004:168–171). As these observations are partially supported and cannot be further tested with the present data, more research is needed to determine whether (if so, why) large start-ups may face the opposite trade-off between creative and commercial success.

2.4.6 Robustness checks

Though the video game websites offer a rare dataset to observe start-ups' hierarchy and performance outcomes, they carry some limitations in measuring the variables of interest (as discussed in Section 2.3.1). Also, despite delving into the empirical context, it was hard to find exogenous variation in hierarchy (as mentioned in Section 2.3.4). As these data limitations raise potential empirical concerns that deserve careful considerations, I ran an extensive array of stress tests explained below (for a summary, see Table 2.6). These test results (reported in Tables 2.11 to 2.20 in Appendix 2.6.6) are consistent in terms of both sign and significance, thereby granting more credence to my findings.

Sequentially adding controls and fixed-effects. To check whether a certain control or fixed-effect drastically changes the main results, I added those variables sequentially. These analyses all show

Empirical concern: The main results may be sensitive to or driven by …	**Robustness check:** To mitigate this empirical concern, I run a series of stress tests that …	**Results:** See Table(s) …
… certain controls or fixed-effects	… sequentially add controls and fixed-effects	2.11 and 2.12
	… subsample start-ups with	2.13
… extremely small and large start-ups	– 10–249 employees (i.e., $10 \leq Size < 250$)	
… large start-ups that could be spin-outs	– less than 250 employees (i.e., $Size < 250$)	
… one-person businesses	– more than one employee (i.e., $Size \geq 2$)	
… single-level start-ups	– more than one level (i.e., $Hierarchy \geq 2$)	
… common shock across genres	… use alternative clustered standard errors (i.e., two-way cluster by genre and year)	2.14
	… use alternative model specification of	2.14
… the data's left-censoring	– Tobit	
… the data's high-dimensionality	– post-double-selection LASSO	
… the measurement of	… use alternative measurement of	
– creative success based on GameRankings' review ratings	– the critics' review ratings from Metacritic	2.15
– commercial success based on VGChartz's data	– the number of Google Search results	2.15
– hierarchy using the ascending order of the rules	– hierarchy measured by randomizing the order of the rules	2.15
– hierarchy potentially overestimated by distinguishing all of the middle management levels	– hierarchy measured by combining middle managers into one hierarchical level	2.15
– using size-quantiles	– the log number of employees	2.15
– size potentially overestimated by including external contractors	– 10 size-quantiles by dropping employees in potentially outsourced functions (e.g., 'Audio', 'Quality Assurance')	2.15
– the number of size-quantiles	– 5 size-quantiles, each size, and various size categorizations	2.16
… the high correlation between *Hierarchy* and *log(Experience)*	… mitigate multicollinearity concerns by – dropping *log(Experience)* – showing separate regressions with only one, then the other, and then both collinear variables	2.17
… the exclusion of creative success in estimating the relationship between hierarchy and commercial success	… include creative success, despite the potential "bad control" bias	2.17
… average span of control	… estimate and control for average span of control	2.18
… the potential omitted variable regarding	… additionally include	
– the start-ups' founding locations	– state/country-level fixed-effects	2.19
– the founder's prior employment	– a control variable for the size/hierarchy of the founder's prior employer	2.19
– the employees' ethnic backgrounds	– a fixed-effect for the dominant ethnicity and a control variable for the ethnic diversity	2.19
– the star developers	– 50 dummies for the top 50 star developers and a control variable for the maximum amount of experience	2.20
– the horizontal division of tasks	– a control variable for the number of job titles per employee	2.20
– the platforms	– 158 dummies for each platform (e.g., Microsoft Xbox 360, Nintendo 3DS)	2.20
– the publishers	– 200 dummies for each major publisher (e.g., Electronic Arts, Activision Blizzard)	2.20
– the industry maturation	– a control variable for industry age, instead of year fixed-effects	2.20

Table 2.6: List of potential empirical concerns and robustness checks (for Tables 2.11 to 2.20, see Appendix 2.6.6).

stable coefficients for hierarchy (see Tables 2.11 and 2.12).

Subsampling. To verify that my findings are not driven by extremely small and large start-ups (as discussed in Section 2.4.5), I dropped both the micro-businesses (i.e., $Size < 10$) and the large enterprises (i.e., $Size \geq 250$). Furthermore, I ran additional analyses excluding (1) just the large enterprises, some of which could be spin-outs with legacy job titles, (2) one-person businesses, which cannot have more than one hierarchical level, and (3) start-ups with only one level, some of which specified the game title as the job title in the MobyGames database (e.g., for the game *#IDARB*, all employees have the job title '#IDARB'). These analyses show robust results (see Table 2.13).

Using alternative clustered standard errors. In the main analyses, the standard errors were clustered by genre to account for correlations among games within the same genre. To also account for potential common shocks that result in correlations across genres, I used two-way clustering by genre and year and obtained compatible results (see Table 2.14).

Using alternative model specifications. To assess whether the results are sensitive to the model specification, I used two different models. First, I applied the Tobit model to account for the left-censoring in creative and commercial success. Second, to reduce the number of controls and fixed-effects and avoid potential over-fitting that biases the estimates, I employed the post-double-selection LASSO model (using Stata's `pdslasso` package; Belloni et al. 2013). Both models demonstrate consistent results (see Table 2.14).

Using alternative measurements. To investigate whether my findings are sensitive to the measurements, I conducted several tests. First, to ensure that the results for creative success are not driven by GameRankings' process of aggregating critics' review ratings, I instead used the ratings from Metacritic (the second most comprehensive website). Second, to check whether the results for commercial success are potentially biased by the VGChartz data, I collected the number of Google Search results (assuming that more search results will appear for more commercially successful games) and ran supplementary analyses additionally controlling for the number of characters in the game's title and the average frequency of the words in its title (i.e., *TitleLength* and *WordFrequency* in Table 2.15). Third, to see whether my findings are affected by the ascending order in which the rules are applied to measure hierarchy, I applied those rules in a random order for every job title.

Fourth, as hierarchy might be overestimated by distinguishing middle managers who are, in fact, at the same hierarchical level, I combined all middle management levels (i.e., 'Head,' 'Director,' 'Manager,' 'Producer,' 'Lead,' and 'Supervisor') into one. Fifth, as 10 size-quantiles may potentially throw away too much variation in the data, I used the log number of employees (putting aside the multicollinearity concern discussed in Section 2.4.1). Sixth, because the number of employees can be overestimated by including outsourced contractors (Mollick 2012:1008–1009), I recalculated 10 size-quantiles after dropping the individuals in the functional domains most likely to be outsourced (i.e., 'Audio,' 'Customer/Technical Support,' 'Localization,' 'Quality Assurance,' 'Support,' and 'Other'). Lastly, to confirm that the results are not sensitive to 10 size-quantiles, I used five-quantiles, dummies for each size, and size categorizations by NSF and EC (discussed in Section 2.4.5), by Burton and Obel (2004:172–174), and by Elfenbein et al. (2010). All of these tests show robust results—the only exception being the one in which dummies for each size dropped almost half of the observations in estimating the relationship between hierarchy and commercial success (see Tables 2.15 and 2.16).

Addressing multicollinearity concerns. To examine whether the high level of correlation ($\rho = 0.47$) between *Hierarchy* and log(*Experience*) biases my results, I ran two tests. First, I excluded the control log(*Experience*) from the models (i.e., Models 2 and 4 in Table 2.5). Second, I ran separate regressions (1) with only *Hierarchy*, (2) with only log(*Experience*), and (3) with both variables. These tests show stable coefficients for hierarchy (see Table 2.17), implying that the results are not severely affected by multicollinearity (Kalnins 2018).

Controlling for creative success when regressing commercial success on hierarchy. In the regression for commercial success, creative success was not controlled for because it is an intermediate outcome of hierarchy and thus a "bad control" that can bias the estimates (Angrist and Pischke 2008:64–68). However, creative success can be consequential to commercial success and thus, when controlled for, may drastically change the estimate of hierarchy on commercial success. To see whether this is the case, I included creative success and found consistent results (see Table 2.17).

Controlling for span of control. As span of control is negatively correlated with both hierarchy and commercial success, omitting this variable can lead to an upward bias in the coefficient estimate of hierarchy for commercial success. To mitigate this concern, I first computed average span of control using the two estimations discussed in Section 2.2.3: (1) by solving for S in the formula $N = \frac{S^L - 1}{S - 1}$, where N is the number of employees and L is the number of hierarchical levels and (2) by applying Blau and Scott's (1962/2003:168–169) formula of $S = \sqrt[L-1]{N}$. I then ran additional analyses with (a) only hierarchy, (b) only span of control, and (c) both variables (see Table 2.18). The results of these tests imply that my findings are due to hierarchy, rather than span of control. First, irrespective of which estimation of span of control I use, these test results show that the explanatory power (in terms of R-squared) decreases in (b) with only span of control, compared with (a) with only hierarchy. Second, regardless of its estimation, span of control has a statistically insignificant coefficient in (b) when regressing commercial success on only span of control. Lastly, whichever estimation of span of control I add as a control, the tests (c) with both hierarchy and span of control show that my main results are robust.

Addressing potential selection based on omitted variables. Despite the comprehensive list of controls and fixed-effects, the observed relationships could be driven by some omitted variables that are not readily available in the current dataset. Among the most plausible ones are the start-ups' founding locations (Saxenian 1996), their founder's prior employment (Baron et al. 1999), their employees' ethnic backgrounds (Gruenfeld and Tiedens 2010:1263), their star developers (Baron et al. 1996), their horizontal division of tasks (Sine et al. 2006), their game's platforms (Rietveld and Eggers 2018), and their publishers (Hellmann and Puri 2002).

In particular, omitting publishers in the regression analyses may lead to an upward bias in the coefficients of hierarchy for commercial success. This is because bigger publishers have different product preferences (e.g., toward franchises and sequels; Schreier 2017:121), offer idiosyncratic contracts (e.g., bonus deals based on critics' review ratings; Schreier 2017:216), and provide distinct resources (e.g., special game engine licenses; Schreier 2017:143). These publisher-specific characteristics can influence not only a start-up's product success (Piezunka et al. 2020) but also its hierarchy. For instance, start-ups may designate a managerial position ("Producer") to signal legitimacy and sign a contract with these bigger publishers (Hellmann and Puri 2002, Mollick 2012).

As the industry practitioners I interviewed suggested that publishers tend to be consistent in their investment behaviors, I mitigate this concern by including fixed-effects for the top 200

	Specification	R_{full}	Oster's test		
			(1) $R_{max} = R_{full}$	(2) $R_{max} = 1.3R_{full}$	(3) $R_{max} = 1$
Creative	Model 2	0.23	250.61	10.53	1.88
Commercial	Model 4	0.58	−363.63	−8.45	−5.35

Table 2.7: Results of Oster's (2019) test. For these results, I use the R-squared of Models 2 and 4 in Table 2.5 (with the largest R-squared) and three values of R_{max} (i.e., R_{full}, $1.3R_{full}$, and 1).

publishers (ranked by the number of games they have published). Even when accounting for their invariant effects, the coefficients for hierarchy remain statistically significant, stable in terms of magnitude, and consistent in their directions (that is, negative for creative success, whereas positive for commercial success). These results suggest that my findings are robust when assuming publishers are consistent in their investment behaviors.

Similarly, the results accounting for the other potentially omitted variables (for the rationale behind each variable, see Appendix 2.6.4) are robust, except for only when 158 platform dummies diminished the analytic power by dropping over 40% of the observations (see Tables 2.19 and 2.20).

2.4.7 Supplementary tests for selection based on potential omitted variables

Though the above analyses validate my findings, the possibility of selection bias from unobserved omitted variables may yet remain. The typical approach to mitigate this concern is to use a randomized experimental design. Because such an approach was difficult to obtain,[13] I follow prior empirical studies (e.g., Mian and Sufi 2014, Starr et al. 2019) and conduct a series of diagnostic tests using a formal approach proposed by Altonji et al. (2005) and developed by Oster (2019).

Oster's test computes a parameter δ which reflects the amount of variation that the unobservables should explain (relative to the observables) to reduce the coefficient of hierarchy to zero and thus nullify my results. Specifically, $|\delta| = 1$ implies that the unobservables would need an explanatory power as strong as all the observables to invalidate the results, whereas $|\delta| > 1$ suggests

[13] Among the many candidates for a valid instrument that were hinted during my interviews, the most plausible one was the sudden leak in 2012 of Valve's *Handbook for New Employees*, which discusses why this company adopted a flat hierarchy. Another was the first article released in 2007 on "Holacracy," which lays out Ternary Software's principles of a flat hierarchy. Because both these documents would have influenced how start-ups perceive, shape, and legitimize a flat hierarchy—as they have done so for companies such as Zappos and Medium—but would be uncorrelated with their creative/commercial success, I tested as an instrument the dummies for post-2012 and post-2007. Unfortunately, both dummies and their variations incorporating information on founding locations turned out to be a "weak" instrument.

that unobservables would need a stronger power than do all the observables. Here, the absolute value ($|\cdot|$) is applied to capture only the amount of the relative variation, because the sign of delta shows its direction. That is, a positive sign implies that if the observables are positively correlated with the treatment, the unobservables have to be positively correlated. In contrast, a negative sign implies that if the observables are positively correlated with the treatment, the unobservables have to be negatively correlated.

To estimate δ, this test requires (1) the set of advanced controls that are unrelated to the set of proportionally related unobservables and (2) the value of R_{max} which represents the R-squared from a hypothetical regression that includes both observed and unobserved variables. For the advanced controls, I used all of the fixed-effects. For R_{max}, I employed the following three values. Following Oster's (2019) experimental evidence and recommendation, I applied R_{full} and $1.3R_{full}$, where R_{full} represents the R-squared of the most saturated model (i.e., Models 2 and 4 in Table 2.5). To be the most stringent, I also used the maximum possible value of R-squared (i.e., one).

The results of these diagnostic tests (using Stata's `psacalc` package) are reported in Table 2.7. The results for creative success (the first row) imply that, to reduce the coefficient of hierarchy to zero, the amount of variation explained by an unobservable needs to be 1.88 to 250.61 times as large as the amount of variation explained by the observables included. In turn, for commercial success (the second row), this amount is between 5.35 and 363.63. Because these values are considerably larger than one—even when assuming the maximum possible value of R-squared—and because the full models include an extensive array of controls and fixed-effects, these results suggest that the selection bias from the unobservables is unlikely to overturn the main findings.

2.5 Discussion

Investigating how start-ups should configure their hierarchy is a key area of inquiry for organization scholars. To address this question, my work provides a large sample study using a novel dataset of game development start-ups, and supplements these empirical analyses with qualitative observations. I discuss the theoretical and managerial implications of my findings below.

2.5.1 Theoretical implications

My study contributes to the literatures on entrepreneurship and organization design on three fronts. First, this study offers large-scale evidence of the heterogeneity in hierarchy of start-ups, albeit within a single industry. Thus far, it has been widely taken for granted that these nascent firms should be and are thus flat (DeSantola and Gulati 2017:657). This conventional wisdom has remained untested partly because empirical research on the organizational structure of start-ups has been stymied by data limitations (Keum and See 2017:667, Burton et al. 2019). Adding to recent qualitative observations (e.g., Baron and Hannan 2002), my study qualifies this common belief by showing that same-sized small start-ups can significantly vary in their number of hierarchical levels.

Second, this paper highlights the underappreciated importance of organizational structure for start-ups. Much of the research on start-ups, to date, has overlooked their organizational structure (Wasserman 2012:3, DeSantola and Gulati 2017, Burton et al. 2019), mostly focusing instead on their resource mobilization and composition (Clough et al. 2019). On the other hand, extant theories on organizational structure have primarily been examined in the context of large, mature organizations (Sine et al. 2006:122, Colombo and Grilli 2013:391). This tendency to neglect the organizational structure of start-ups is largely due to the presumption that they are simply too small and undifferentiated to necessitate any form of organizational structure (Blau 1970, Mintzberg 1979, Burton and Obel 2004:168). Advancing the recent work that calls this presumption into question (e.g., Sine et al. 2006, Sutton and Rao 2014, Puranam and Håkonsson 2015, DeSantola and Gulati 2017, Burton et al. 2019), this study finds that, given its lack of alternative coordination devices, a start-up's hierarchy has significant relationships with its creative and commercial success. My results also demonstrate that these relationships may become considerable when start-ups grow beyond micro-businesses (1–9 employees) to small/mid-sized (10–249 employees) enterprises and thus face difficulty in coordinating via informal communication. These findings—contrary to the conventional wisdom about the stifling effects of hierarchy in hostile environments (Burns and Stalker 1961, Lawrence and Lorsch 1967/1986)—imply that even for start-ups in such an environment as the video game industry, hierarchy is a consequential factor that warrants further investigation.

Lastly, my work speaks more broadly to the longstanding debate over whether hierarchy is conducive to firm performance. Although the pervasiveness of hierarchy—even in start-ups, as shown in this study—would seem to indicate the answer is yes, prior studies have offered opposing arguments (for reviews, see Anderson and Brown 2010, Lee and Edmondson 2017, Puranam 2018). To reconcile this debate, this study distinguished between two measures of a firm's performance (i.e., creative and commercial success) and showed that these two measures can be variously associated with its hierarchy. These results suggest that hierarchy is not universally good or bad, but rather its efficacy depends on the type of performance firms pursue. Put differently, firms should organize differently depending on their goal—that is, "flatten" their hierarchy for creative success, whereas "tallen" for commercial success. Extending the burgeoning stream of research that revisits hierarchy and its behavioral mechanisms (e.g., Csaszar 2013, Reitzig and Maciejovsky 2015, Keum and See 2017, Kocak et al. 2019, Lee and Csaszar 2020, Ghosh et al. 2020, Lee et al. 2020), my study thus provides large-sample evidence that helps resolve the contrasting assessments of hierarchy.

2.5.2 Managerial implications

> "[Start-ups'] managers tend to worry about avoiding bureaucracy but are blind to the danger of chaos" (Davila et al. 2010).

My study offers managerial implications for how start-ups should organize to capture entrepreneurial opportunities. For decades, academics, management gurus, and popular media outlets have argued that "authoritarian," tall hierarchies are outmoded and will be supplanted by "egalitarian," flat structures (Urwick 1956:42, Leavitt 2005, Sutton and Rao 2014:107). In recent years, this argument has been largely substantiated by a few "successful" flat start-ups, such as Valve, Zappos, Github, Medium, and Buffer (Puranam and Håkonsson 2015, Lee and Edmondson 2017:38, Puranam 2018:137). As these firms constantly garner much attention for their egalitarian ideal—which itself is a signal of their rarity—the myth of the flat start-up (often referred to as 'holacracy,' 'boss-less firm,' or 'flat organization') has become widespread among entrepreneurs (Davila et al. 2010, Gulati and DeSantola 2016). As one founder succinctly put it: "Flat [is] startup-y and awesome. Structure [is] BigCorp-y and boring" (Savage 2015).

However, most of these experiments have failed (Leavitt 2005:29, Puranam 2018:137), as these start-ups drifted into aimless exploration and dysfunctional conflicts, eventually abandoning their flat hierarchies (Maier 2013, Miller 2014, Ferro 2016, Mittelman 2016). As the very entrepreneur who once thought "Flat [is] start-upy and awesome" explains: "We had hoped that being flat would let us move faster and be more creative, but ... we ended up with an unspoken hierarchy that actually slowed down our ability to execute" (Savage 2015). In line with this anecdote, my study cautions against the myth of the flat start-up, suggesting that adding a few hierarchical levels of managers can significantly help start-ups achieve commercial success and survival in their hostile environments, albeit at a potentially marginal cost of creative success.

2.5.3 Limitations and future work

Although my study makes progress in understanding the organizational structure of start-ups, it has some limitations which could be addressed by future work. First, the empirical analyses were carried out within a single industry. One plausible scope condition of my results is that the task is creative and complex. If the task does not call for creativity, hierarchy may not entail a trade-off, but may still be positively correlated with commercial success. In turn, if the task is so simple as to require only a few employees and/or as to not necessitate any coordination among employees, hierarchy need not be imposed. Future research could test the generalizability in different industries. Second, despite the comprehensive list of controls and the extensive array of robustness checks, there might be some form of unobserved heterogeneity. While my qualitative observations give confidence to my theoretical predictions, future work could revisit these predictions using an experimental design that randomly assigns hierarchy. Third, as critics review the published game, their review ratings could reflect the game's overall quality in terms of both its novelty and its execution (Rietveld and Eggers 2018:312). Future studies could revisit my findings using a more direct measure of creative success, for instance, by asking the critics to review only the game's description in terms of its novelty but not allowing them to play the game and observe its execution.

Fourth, this study concentrated on one dimension of organizational structure, namely hierarchy (vertical division of tasks). Future studies could expand my work by exploring other dimensions—for instance, horizontal division of tasks, for which I surprisingly find in the robustness checks negative associations with both creative and commercial success. Fifth, each start-up's hierarchy was cross-sectionally measured when it released its first product (on average, less than two years from its founding). Future work could examine how its hierarchy evolves from its founding and changes after its first product. Fifth, this paper probed into the consequences of start-ups' hierarchy. Drawing upon my descriptive findings regarding its variation and trend, future research could investigate the antecedents of hierarchy and its tallening.

Lastly, given the motivation, this study focused on start-ups. Although the empirical findings could hold for mature firms, there are potential reasons why the mechanisms will attenuate or be absent. In particular, unlike start-ups, mature firms typically have (1) adequate resources to organize integrating committees (Lawrence and Lorsch 1967/1986:12–13), (2) formalized routines (Stinchcombe 1965:148), and (3) well-established informal structure or culture that can substitute for hierarchy (Meier et al. 2019, Marchetti and Puranam 2020). Future studies could extend this study by examining the performance implications of hierarchy in the context of mature firms.

2.5.4 Conclusion

This paper began by describing the myth of the flat start-up and then sought to revisit this untested myth. This was done by unveiling intriguing patterns in hierarchy of start-ups and by investigating how it may entail a non-trivial trade-off between creative and commercial success. By identifying its relationship with this fundamental dilemma, my work calls for more attention to the organizational structure of start-ups and makes headway in understanding their survival and growth.

2.6 Appendix

2.6.1 Measuring experience and breadth

Employee	Functional domain			*IndExperience*	*IndBreadth*
	Business	Design	Programming		
A	3	2	0	$5 = 3 + 2 + 0$	$0.48 = 1 - \frac{3^2+2^2+0^2}{(3+2+0)^2}$
B	1	1	1	3	0.67
C	0	0	1	1	0
D	0	0	0	0	0

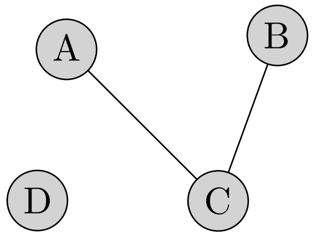
Experience: $2.25 = \frac{5+3+1+0}{4}$ *Breadth*: $0.29 = \frac{0.48+0.67+0+0}{4}$

Table 2.8: An illustration of measuring the employees' experience and breadth.

Table 2.8 illustrates how experience and breadth are measured using a hypothetical start-up with four employees (A, B, C, and D). As described in this table, they each have a set of experience in the following functional domains: 'Business,' 'Design,' and 'Programming.' At the individual level, the amount of experience (i.e., *IndExperience*) was measured by the sum of experience, and the breadth of experience (i.e., *IndBreadth*) by the diversity across all functional domains in terms of $1 - HHI$, where *HHI* stands for Herfindahl–Hirschman Index. By averaging, these individual-level characteristics were aggregated to the firm-level (i.e., *Experience* and *Breadth*, respectively).

2.6.2 Measuring social capital

Table 2.9 shows an example of measuring social capital. To calculate this variable, I first constructed the collaboration network in a given year (panel (a)), where two individuals have a tie if they collaborated within the previous five years (results hold for different time frames; e.g., 3, 7). Then, for each start-up founded in that year, I identified its employees and measured their pairwise shortest path lengths (panel (b)). Because the shortest path length to an isolate (e.g., employee D) is infinite, the average shortest path length is infinite for any start-up with at least one "isolate" employee. Since the vast majority of start-ups have one isolate who newly entered the industry (Grossman 2003:307, Wasserman 2012:229–232), I instead calculated the inverse of pairwise shortest path lengths (panel (c)) and averaged those values (panel (d)). This average represents how closely the employees are connected through collaboration, and is considered a measure of social capital.



(a) Prior collaboration network, where employees A, B, C, and D found a start-up.

	A	B	C	D
A		2	1	∞
B	2		1	∞
C	1	1		∞
D	∞	∞	∞	

(b) Pairwise shortest path length among the employees.

	A	B	C	D
A		0.5	1	0
B	0.5		1	0
C	1	1		0
D	0	0	0	

(c) Inverse of the path lengths.

$$\mathit{SocialCapital}\colon\ 0.42 = \tfrac{0.5+1+1+0+0+0}{6}$$

(d) Average the inverse of the path lengths.

Table 2.9: An illustration of measuring the employees' social capital.

2.6.3 Rationales behind the moderators

Breadth of experience. When employees lack breadth by specializing in a functional domain, they tend to narrowly focus on the parts of the information relevant to their domain and neglect the other parts that may be essential to the overall task (Dougherty 1992:182). This selective processing of information can result in non-overlapping, narrow interpretations which are difficult to integrate into one coherent decision. As employees continue to share these disjoint interpretations but only encounter more disagreements and misunderstandings (Garicano and Wu 2012:6), frustration grows, prompting dysfunctional conflicts (Greer et al. 2018:594). As one entrepreneur illustrates:

> "With specialization [i.e., less breadth] often comes tunnel-vision. ... People become biased towards their own expertise. It makes decision-making a lot more complicated. More often than not, it's the loudest voice who wins ... even if it doesn't make much sense" (Beaudoin 2016; comment added).

On the contrary, employees with more breadth can stimulate overlapping, broader interpretations and flexibly coordinate using various function-specific languages. This cognitive flexibility enables employees to bridge their differences and avoid dysfunctional conflicts.

Social capital. Dysfunctional conflicts can decrease when employees have strong social relationships developed through prior collaboration. This is because former collaborators develop and share social capital, such as a common language and tacit routines (Puranam 2018:128–144) and a mutual understanding and trust (Stinchcombe 1965:149). As one founder explains:

> "[Former collaborators] have history and shared communication. Communication is easy and you know what other people are thinking. You've already agreed on your values. . . . [Because of] the trust that you have built up with people, a lot does not have to be said and, in theory, you are comfortable enough to say important things" (Yee 2015).

Therefore, the more closely connected through collaboration the employees are, the more social capital they share, and thus the less likely that they face dysfunctional conflicts (Meier et al. 2019).

2.6.4 Rationales behind the omitted variables

Founding locations. The founding location of a start-up can affect how it perceives and shapes hierarchy. For instance, Saxenian (1996:59–82) found that compared with their Silicon Valley counterparts, Boston's Route 128 start-ups had more layers of hierarchy because "[w]hile Silicon Valley's entrepreneurs rejected the corporate practices of the large, established East Coast producers, the [entrepreneurs] along Route 128 saw the same corporations as their models." As different locations can also provide access to different resources and knowledge spillover and thus influence performance, their omission can lead to biased estimates for hierarchy. To examine whether this is the case, I collected from other public sources (e.g., Wikipedia, LinkedIn, Twitter) the information on founding locations in terms of the state, if U.S./Canada, and the country, otherwise (i.e., *State/country* in Table 2.19). The results including these location fixed-effects are robust.

Founder's prior employment. Entrepreneurs tend to draw upon their prior employers in designing the organizational structure of their start-ups (Baron et al. 1999). As Davila et al. (2010:94) observe: "Senior managers at start-up companies with a larger company background often adopted systems and processes because they were used to them." Because their prior employment can also affect the type of performance they pursue, entrepreneurs who worked for a larger/taller company may select a taller hierarchy and aim for commercial success, whereas those from a smaller/flatter one may choose a flatter hierarchy and target creative success. This potential selection can lead to overestimating the coefficients of hierarchy. To address this concern, I measured two characteristics of the founder's prior employer: the number of employees and the number of hierarchical levels (i.e., *PriorEmpSize* and *PriorEmpHierarchy* in Table 2.19). If there is more than one founder, these two measures were averaged across those founders. As these two measures are highly correlated ($\rho = 0.86$), I included them separately, and found consistent results.

Employees' ethnic backgrounds. Employees of different ethnic backgrounds can vary in how they perceive hierarchy: for instance, Asians view hierarchy more positively than do Americans (Gruenfeld and Tiedens 2010:1263). To mitigate potential selection based on ethnic backgrounds, I gathered additional information on ethnicity. Because this information is not readily available, I employed Python's `ethnicolr` package to predict with each employee's full name her ethnicity in terms of four categories: Non-Hispanic Whites, Non-Hispanic Blacks, Asians, or Hispanics. These predicted values were used to measure (1) a categorical variable for the dominant ethnicity and (2) a continuous variable (using $1 - HHI$) for the ethnic diversity (i.e., *EthnicDiversity* in Table 2.19). The results accounting for these variables are robust.

Star developers. Because star developers are extremely valuable in the video game industry (Andersson et al. 2009:312), founders are "frequently faced with the dilemma of having one of their most valued production personnel requesting a lead role" (Spaulding 2009:10–11). As these developers can request for and select into a specific hierarchical structure (Baron et al. 1996) and also affect product success, their omission can result in an upward bias in the coefficients of hierarchy. To mitigate this concern, I added (1) dummies for the top 50 game developers based on the amount of experience and (2) a control variable for the log value of the maximum amount of experience in each start-up (i.e., $\log(MaxExperience)$ in Table 2.20). The results with these variables are consistent (note that $\log(Experience)$ was excluded as it is highly correlated ($\rho = 0.89$) with $\log(MaxExperience)$).

Horizontal division of tasks. Horizontal division of tasks assigns each employee to a narrow task component (e.g., programming, marketing), thereby requiring a taller hierarchy to coordinate these employees (Burton and Obel 2004:74–75). Because this horizontal structure can also positively influence performance (Sine et al. 2006:124), its omission could lead to overestimating the coefficient of hierarchy. Thus, I controlled for the number of job titles per employee (i.e., *Horizontal* in Table 2.20), and found robust results.

Platforms. Each platform typically has its own game development kit (i.e., specialized hardware and software used to develop games) and encrypted distribution medium (e.g., cartridge, online server). Whereas some platforms (e.g., Microsoft Xbox 360) require a non-disclosure agreement to gain access to their game development kits and mediums, others (e.g., Nintendo 3DS) provide them for free. This difference can make start-ups select different hierarchies (e.g., designate a level to negotiate the non-disclosure agreement with a platform maker). At the same time, it can affect product success (Rietveld and Eggers 2018). Hence, I ran additional analyses with 158 dummies for each platform, and the results were consistent.

2.6.5 Testing the conjecture regarding tallening

For tallening of start-ups (in Section 2.4.2), I conjectured that advancements in information technology have enabled game developers to make more complex games, requiring more functional specialization among employees and thus more hierarchical levels. To empirically test this conjecture, I use as a moderator the genre of Massively Multiplayer Online Role-Playing Games (MMORPG), arguably the most complex genre that emerged with the recent advancements in information technology. Games in this genre (e.g., *World of Warcraft*, *League of Legends*, and *Dota 2*) need to accommodate thousands (if not, millions) of online players worldwide, who select a game character and simultaneously interact with other player's characters in the virtual world. This virtual world, which continues to exist and evolve regardless of whether the players are offline, has its own economy where players can use the virtual currency they have earned through battles to trade items. Creating, hosting, and maintaining this virtual space which closely resembles the real world makes MMORPG the most complex genre to develop (Waguespack et al. 2018:428–429).

The results using this genre as a moderator are reported in Table 2.10. This table shows that both *Hierarchy* and *Hierarchy* $\times$ *MMORPG* have a positive coefficient (with $p < 0.05$ and $p < 0.01$, respectively). These coefficients indicate that the positive relationship between hierarchy and commercial success significantly increases when the game is an MMORPG, thus offering additional support for my conjecture regarding tallening.

	(2) Commercial (log(Units))
Independent	
Hierarchy	0.09*
	(0.04)
Moderator	
Hierarchy×MMORPG	1.33**
	(0.46)
Controls	
log(Experience)	−0.02
	(0.16)
Breadth	1.25
	(2.46)
SocialCapital	0.01
	(0.85)
GenderDiversity	−1.66*
	(0.73)
MMORPG	−9.13*
	(3.62)
Fixed-effects	
Task-level	
3D	Y
LicensedTitle	Y
BusinessModel	Y
Genres	Y
Themes	Y
Platforms	Y
Financing-level	
Indie	Y
Triple-A	Y
Employee-level	
Size (10 quantiles)	Y
Macro-level	
Year	Y
No. observations	375
R-squared	0.59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$
Note. Standard errors clustered by genre in parentheses.

Table 2.10: Testing the conjecture regarding tallening.

2.6.6 Results of the robustness checks

	Sequentially adding controls and fixed-effects											
	(1) Creative (Review)											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Independent												
Hierarchy	−0.17	−0.45**	−0.43**	−1.27***	−1.23***	−1.21***	−1.18***	−1.09***	−1.12***	−1.11***	−1.01***	−0.99***
	(0.12)	(0.13)	(0.12)	(0.20)	(0.21)	(0.21)	(0.22)	(0.27)	(0.28)	(0.28)	(0.28)	(0.27)
Controls												
log(Experience)		2.23†	1.71	1.26	1.41	1.43	1.30	1.13	1.10	1.10	1.28	1.27
		(1.27)	(1.27)	(1.05)	(1.03)	(1.02)	(1.07)	(1.78)	(1.77)	(1.73)	(1.78)	(1.80)
Breadth		−6.43	−4.52	−1.90	−2.30	−2.21	−1.15	−1.61	−1.57	−1.54	−1.75	−1.41
		(6.13)	(6.13)	(4.24)	(4.24)	(4.26)	(4.08)	(7.69)	(7.73)	(7.49)	(7.39)	(7.60)
SocialCapital		0.61	3.01	4.38†	4.71†	4.74†	5.72†	6.10†	5.71	5.59	5.18	4.96
		(2.42)	(2.43)	(2.56)	(2.58)	(2.55)	(3.21)	(3.43)	(3.66)	(3.65)	(3.75)	(3.72)
GenderDiversity		−1.29	−2.51	−3.97	−3.72	−3.67	−2.51	−4.95	−3.22	−3.51	−3.85	−4.22
		(2.20)	(2.68)	(3.31)	(3.45)	(3.43)	(3.84)	(3.25)	(3.19)	(3.13)	(3.12)	(3.10)
Fixed-effects												
Task-level												
3D												Y
LicensedTitle											Y	Y
BusinessModel										Y	Y	Y
Genres									Y	Y	Y	Y
Themes								Y	Y	Y	Y	Y
Platforms							Y	Y	Y	Y	Y	Y
Financing-level												
Indie						Y	Y	Y	Y	Y	Y	Y
Triple-A					Y	Y	Y	Y	Y	Y	Y	Y
Employee-level												
Size (10 quantiles)				Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro-level												
Year			Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	1,725	1,725	1,725	1,725	1,725	1,725	1,725	1,491	1,477	1,477	1,477	1,477
R-squared	0.00	0.01	0.05	0.08	0.08	0.08	0.10	0.19	0.21	0.22	0.23	0.23

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses. The number of observations decreased since singleton observations were dropped.

Table 2.11: Robustness Check – Sequentially adding controls and fixed-effects.

	Sequentially adding controls and fixed-effects											
	(2) Commercial (log(Units))											
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Independent												
Hierarchy	$0.05^{\dagger}$	0.09^{*}	0.19^{***}	0.10^{**}	0.10^{***}	0.10^{***}	0.09^{**}	0.11^{*}	0.11^{*}	0.11^{*}	0.09^{*}	0.10^{*}
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Controls												
log(Experience)		−0.21	0.20	0.11	0.10	0.11	0.14	0.03	0.01	0.01	−0.04	−0.03
		(0.15)	(0.17)	(0.17)	(0.16)	(0.16)	(0.13)	(0.19)	(0.17)	(0.16)	(0.17)	(0.16)
Breadth		-3.22^{**}	−0.51	0.23	0.27	0.30	0.40	0.20	1.29	1.23	1.32	1.17
		(0.99)	(1.08)	(1.26)	(1.20)	(1.16)	(1.23)	(2.22)	(2.30)	(2.35)	(2.42)	(2.43)
SocialCapital		1.56^{**}	0.67	0.85	0.84	0.81	0.52	0.10	−0.03	0.00	0.10	0.05
		(0.44)	(0.45)	(0.51)	(0.50)	(0.48)	(0.44)	(0.82)	(0.81)	(0.84)	(0.87)	(0.84)
GenderDiversity		-1.86^{*}	−0.23	−1.05	−1.08	−1.07	-1.19^{*}	−0.78	$-1.64^{\dagger}$	$-1.64^{\dagger}$	$-1.50^{\dagger}$	-1.57^{*}
		(0.71)	(0.73)	(0.75)	(0.78)	(0.78)	(0.58)	(0.80)	(0.89)	(0.88)	(0.80)	(0.71)
Fixed-effects												
Task-level												
3D												Y
LicensedTitle											Y	Y
BusinessModel										Y	Y	Y
Genres									Y	Y	Y	Y
Themes								Y	Y	Y	Y	Y
Platforms							Y	Y	Y	Y	Y	Y
Financing-level												
Indie						Y	Y	Y	Y	Y	Y	Y
Triple-A					Y	Y	Y	Y	Y	Y	Y	Y
Employee-level												
Size (10 quantiles)				Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro-level												
Year			Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	494	494	490	490	490	490	490	381	375	375	375	375
R-squared	0.01	0.05	0.28	0.33	0.33	0.33	0.38	0.51	0.57	0.57	0.58	0.58

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses. The number of observations decreased since singleton observations were dropped.

Table 2.12: Robustness Check – Sequentially adding controls and fixed-effects (cont'd).

	Subsampling start-ups with …							
	… 10–249 employees (i.e., $10 \leq Size < 250$)		… less than 250 employees (i.e., $Size < 250$)		… more than one employee (i.e., $Size \geq 2$)		… more than one level (i.e., $Hierarchy \geq 2$)	
	(1) Creative (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))
Independent								
Hierarchy	-1.12^{***}	0.10^{*}	-1.22^{***}	0.12^{*}	-1.01^{***}	0.09^{*}	$-0.54^{\dagger}$	0.11^{*}
	(0.29)	(0.04)	(0.22)	(0.05)	(0.24)	(0.04)	(0.31)	(0.04)
Controls								
log(Experience)	1.69	−0.09	1.12	−0.11	1.94	−0.02	0.78	0.06
	(2.28)	(0.22)	(1.79)	(0.22)	(1.70)	(0.18)	(2.00)	(0.17)
Breadth	0.20	2.60	0.08	2.27	−7.11	1.20	−7.65	0.52
	(10.82)	(2.59)	(7.78)	(2.03)	(9.73)	(2.67)	(10.55)	(2.81)
SocialCapital	3.26	0.17	4.89	0.18	$5.47^{\dagger}$	0.07	10.91^{*}	0.39
	(5.06)	(0.96)	(3.57)	(0.84)	(3.16)	(0.87)	(4.91)	(0.90)
GenderDiversity	−4.39	-2.19^{*}	−4.26	-2.11^{*}	−4.23	-1.66^{*}	−6.89	-1.76^{*}
	(4.00)	(1.03)	(3.14)	(0.88)	(3.16)	(0.73)	(4.23)	(0.75)
Fixed-effects								
Task-level								
3D	Y	Y	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y	Y	Y
Financing-level								
Indie	Y	Y	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y	Y	Y
Employee-level								
Size (10 quantiles)	Y	Y	Y	Y	Y	Y	Y	Y
Macro-level								
Year	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	1,009	296	1,404	330	1,374	368	1,057	350
R-squared	0.28	0.57	0.24	0.61	0.23	0.57	0.26	0.57

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$
Note. Standard errors clustered by genre in parentheses.

Table 2.13: Robustness Check – Subsampling.

	Using alternative standard errors …		Using alternative model specification of …			
	… by genre and year		… Tobit		… post-double-selection LASSO	
	(1) Creative (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))
Independent						
Hierarchy	-0.99^{***}	0.10^{**}	-0.19^{**}	0.49^{***}	-0.89^{***}	0.09^{**}
	(0.21)	(0.03)	(0.07)	(0.00)	(0.13)	(0.03)
Controls						
log(Experience)	1.27	-0.03	4.03^{***}	0.60^{***}	Y	Y
	(1.78)	(0.21)	(0.20)	(0.01)	Y	Y
Breadth	-1.41	1.17	13.54^{***}	1.23^{***}	Y	Y
	(8.28)	(2.39)	(1.37)	(0.08)	Y	Y
SocialCapital	4.96	0.05	-4.37^{***}	0.01	Y	Y
	(4.02)	(0.83)	(1.11)	(0.04)	Y	Y
GenderDiversity	-4.22^{*}	-1.57^{*}	-21.68^{***}	-2.74^{***}	Y	Y
	(1.58)	(0.66)	(0.79)	(0.05)	Y	Y
Fixed-effects						
Task-level						
3D	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y
Financing-level						
Indie	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y
Employee-level						
Size (10 quantiles)	Y	Y	Y	Y	Y	Y
Macro-level						
Year	Y	Y	Y	Y	Y	Y
Standard errors clustered by	Genre and Year	Genre and Year	Genre	Genre	Genre	Genre
No. observations	1,477	375	6,234	6,234	1,725	494
(Pseudo) R-squared	0.23	0.58	0.14	0.43		

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$
Note. Clustered standard errors in parentheses.

Table 2.14: Robustness Check – Alternative clustered standard errors and model specifications.

	Using alternative measurement for …									
	… creative success	… commercial success	… hierarchy				… size			
	Use Metacritic	Use Google Search	Randomize rule order		Combine middle management		Use log(Size)		Drop potential contractors	
	(1) Creative (Metacritic's ratings)	**(2) Commercial** (log(# of search results))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))
Independent										
Hierarchy	-0.85^{*}	0.07^{*}	-0.99^{***}	0.09^{*}	-1.26^{**}	$0.11^{\dagger}$	-0.77^{***}	0.10^{*}	-0.90^{**}	0.12^{**}
	(0.41)	(0.03)	(0.26)	(0.04)	(0.41)	(0.06)	(0.17)	(0.04)	(0.29)	(0.04)
Controls										
log(Experience)	1.76	0.16^{**}	1.28	−0.03	0.93	0.01	1.38	0.08	1.63	0.14
	(1.94)	(0.05)	(1.81)	(0.15)	(1.70)	(0.15)	(1.98)	(0.14)	(2.02)	(0.18)
Breadth	2.77	0.13	−1.39	1.15	−0.39	0.95	−0.75	1.48	−2.12	0.79
	(9.49)	(0.36)	(7.60)	(2.43)	(7.28)	(2.36)	(9.32)	(2.19)	(9.01)	(2.37)
SocialCapital	0.49	0.05	4.96	0.07	4.75	0.09	3.23	−0.33	4.87	−0.13
	(6.95)	(0.16)	(3.72)	(0.84)	(3.81)	(0.84)	(3.15)	(0.69)	(3.45)	(0.67)
GenderDiversity	$-10.74^{\dagger}$	−0.45	−4.19	-1.56^{*}	−4.66	-1.64^{*}	−3.79	−0.95	−4.79	$-1.36^{\dagger}$
	(5.24)	(0.30)	(3.09)	(0.72)	(3.15)	(0.74)	(2.78)	(0.78)	(2.83)	(0.75)
WordFrequency		0.65^{***}								
		(0.04)								
log(Size)							0.02^{***}	0.00^{***}		
							(0.01)	(0.00)		
Fixed-effects										
Newly added										
TitleLength		Y								
Task-level										
3D	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Financing-level										
Indie	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Employee-level										
Size (10 quantiles)	Y	Y	Y	Y	Y	Y	N	N	Y	Y
Macro-level										
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	639	5,775	1,477	375	1,477	375	1,477	375	1,477	375
R-squared	0.34	0.52	0.23	0.58	0.22	0.58	0.23	0.60	0.22	0.57

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses.

Table 2.15: Robustness Check – Alternative measurements.

	Using alternative measurement for 10 size-quantiles									
	5 size-quantiles		Each size		NSF and EC		Burton and Obel (2004:172–174)		Elfenbein et al. (2010)	
	(1) Creative (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))
Independent										
Hierarchy	-0.62^{*}	0.16^{***}	-1.49^{***}	0.12	-0.90^{***}	0.10^{*}	-1.17^{***}	0.08^{*}	-0.65^{*}	0.18^{***}
	(0.29)	(0.04)	(0.22)	(0.08)	(0.21)	(0.04)	(0.18)	(0.04)	(0.26)	(0.04)
Controls										
log(Experience)	1.35	0.04	0.95	−0.09	1.29	0.00	1.39	−0.06	1.25	0.07
	(1.81)	(0.17)	(1.66)	(0.30)	(1.80)	(0.15)	(1.91)	(0.16)	(1.90)	(0.18)
Breadth	−1.74	0.78	1.83	1.84	−0.64	1.72	−0.27	1.45	−1.44	1.02
	(8.30)	(2.64)	(6.97)	(1.90)	(8.32)	(1.93)	(8.13)	(1.69)	(8.68)	(2.66)
SocialCapital	4.45	−0.03	4.45	−0.48	4.05	−0.16	3.58	0.09	4.04	−0.12
	(3.62)	(0.71)	(4.18)	(1.48)	(3.23)	(0.69)	(3.19)	(0.65)	(3.31)	(0.76)
GenderDiversity	−3.34	−1.08	−1.87	0.00	−4.37	$-1.34^{\dagger}$	-5.71^{*}	−1.28	−4.64	−1.19
	(3.15)	(0.72)	(3.29)	(1.06)	(2.83)	(0.71)	(2.72)	(0.91)	(2.95)	(0.75)
Fixed-effects										
Task-level										
3D	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Financing-level										
Indie	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Employee-level										
Size	5Q	5Q	Each size	Each size	NSF/EC	NSF/EC	BO	BO	EHZ	EHZ
Macro-level										
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	1,477	375	1,371	261	1,477	375	1,456	371	1,477	375
R-squared	0.22	0.55	0.24	0.60	0.22	0.58	0.24	0.63	0.21	0.54

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses. For size fixed-effects, "5Q" stands for 5 size-quantiles, "NSF/EC" for NSF and EC's categorization, "BO" for Burton and Obel's (2004:172–174) categorization, and "EHZ" for Elfenbein et al.'s (2010) categorization.

Table 2.16: Robustness Check – Alternative measurements (cont'd).

	Addressing multicollinearity								Controlling for creative success
	Exclude *log(Experience)*		Separate regressions for collinear variables						
	(1) Creative (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)			**(2) Commercial** (log(Units))			**(2) Commercial** (log(Units))
			Only *Hierarchy*	Only *log(Experience)*	Both	Only *Hierarchy*	Only *log(Experience)*	Both	
Independent									
Hierarchy	-0.94^{***}	0.10^{*}	-0.17		-0.44^{**}	$0.05^{\dagger}$		$0.08^{\dagger}$	0.11^{**}
	(0.21)	(0.04)	(0.12)		(0.15)	(0.03)		(0.04)	(0.04)
Controls									
log(Experience)				$0.96^{\dagger}$	1.68^{**}		-0.09	-0.22^{*}	0.02
				(0.51)	(0.59)		(0.07)	(0.10)	(0.16)
Breadth	2.67	1.09							0.84
	(3.48)	(2.49)							(2.48)
SocialCapital	6.65^{**}	0.02							0.37
	(2.19)	(0.82)							(0.89)
GenderDiversity	-4.50	-1.56^{*}							-1.45
	(3.10)	(0.71)							(0.88)
Creative (Review)									0.04^{***}
									(0.01)
Fixed-effects									
Task-level									
3D	Y	Y							Y
LicensedTitle	Y	Y							Y
BusinessModel	Y	Y							Y
Genres	Y	Y							Y
Themes	Y	Y							Y
Platforms	Y	Y							Y
Financing-level									
Indie	Y	Y							Y
Triple-A	Y	Y							Y
Employee-level									
Size (10 quantiles)	Y	Y							Y
Macro-level									
Year	Y	Y							Y
No. observations	1,477	375	1,725	1,725	1,725	494	494	494	332
R-squared	0.23	0.58	0.00	0.00	0.01	0.01	0.00	0.01	0.64

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$
Note. Clustered standard errors by genre in parentheses.

Table 2.17: Robustness Check – Mutlicollinearity and controlling for creative success.

	Controlling for span of control					
	(2) Commercial (log(Units))					
	First estimation			Second estimation		
	(a) Only Hierarchy	(b) Only Span of Control	(c) Both	(a) Only Hierarchy	(b) Only Span of Control	(c) Both
Independent						
Hierarchy	0.10^{*}		0.15^{**}	0.10^{*}		0.12^{**}
	(0.04)		(0.04)	(0.04)		(0.04)
Span of Control		0.01	0.01^{**}		0.00	$0.01^{\dagger}$
		(0.00)	(0.00)		(0.00)	(0.00)
Controls						
log(Experience)	−0.03	−0.01	−0.02	−0.03	−0.02	−0.03
	(0.16)	(0.15)	(0.16)	(0.16)	(0.15)	(0.16)
Breadth	1.17	0.98	1.14	1.17	1.02	1.18
	(2.43)	(2.35)	(2.26)	(2.43)	(2.39)	(2.38)
SocialCapital	0.05	0.10	−0.03	0.05	0.12	0.03
	(0.84)	(0.82)	(0.79)	(0.84)	(0.83)	(0.83)
GenderDiversity	-1.57^{*}	-1.55^{*}	-1.57^{*}	-1.57^{*}	-1.56^{*}	-1.59^{*}
	(0.71)	(0.74)	(0.71)	(0.71)	(0.74)	(0.71)
Fixed-effects						
Task-level						
3D	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y
Financing-level						
Indie	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y
Employee-level						
Size (10 quantiles)	Y	Y	Y	Y	Y	Y
Macro-level						
Year	Y	Y	Y	Y	Y	Y
No. observations	375	375	375	375	375	375
R-squared	0.58	0.58	0.59	0.58	0.57	0.58

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses.

Table 2.18: Robustness Check – Controlling for span of control.

	Addressing concerns on selection based on omitted variables of …							
	… geographical locations		… the prior employer's size		… the prior employer's hierarchy		… ethnic backgrounds	
	(1) Creative (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))
Independent								
Hierarchy	-1.12^{***}	0.15^{*}	-0.99^{**}	0.09^{*}	-0.89^{*}	0.09^{*}	-0.95^{**}	0.10^{*}
	(0.25)	(0.05)	(0.27)	(0.04)	(0.34)	(0.04)	(0.27)	(0.04)
Controls								
log(Experience)	0.62	−0.03	0.96	−0.13	1.80	−0.06	1.19	−0.04
	(1.69)	(0.42)	(1.51)	(0.16)	(1.33)	(0.15)	(1.82)	(0.16)
Breadth	−0.74	$3.46^{\dagger}$	−1.77	0.91	−0.30	1.09	0.24	1.15
	(7.85)	(1.77)	(7.99)	(2.40)	(8.62)	(2.36)	(8.04)	(2.31)
SocialCapital	5.92	−0.88	4.89	−0.10	6.36	−0.06	4.25	0.01
	(3.89)	(1.10)	(3.76)	(0.80)	(5.13)	(0.92)	(3.68)	(0.74)
GenderDiversity	−1.22	−0.88	−4.10	$-1.35^{\dagger}$	−4.35	$-1.50^{\dagger}$	$-5.85^{\dagger}$	-1.99^{*}
	(4.10)	(1.17)	(3.14)	(0.73)	(3.09)	(0.78)	(3.20)	(0.75)
log(PriorEmpSize)			0.35	0.23^{*}				
			(0.52)	(0.10)				
PriorEmpHierarchy					−0.56	0.04		
					(0.55)	(0.08)		
EthnicDiversity							1.66	1.74^{*}
							(2.62)	(0.66)
Fixed-effects								
Newly added								
State/country	Y	Y						
Dominant ethnicity							Y	Y
Task-level								
3D	Y	Y	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y	Y	Y
Financing-level								
Indie	Y	Y	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y	Y	Y
Employee-level								
Size (10 quantiles)	Y	Y	Y	Y	Y	Y	Y	Y
Macro-level								
Year	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	1,143	238	1,477	375	1,477	375	1,476	374
R-squared	0.30	0.74	0.23	0.58	0.23	0.58	0.23	0.59

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Note. Standard errors clustered by genre in parentheses.

Table 2.19: Robustness Check – Addressing concerns on selection based on omitted variables.

	Addressing concerns on selection based on omitted variables of …							
	… star developers		… horizontal division of tasks		… platforms		… publishers	
	(1) Creative (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))	**(1) Creative** (Review)	**(2) Commercial** (log(Units))
Independent								
Hierarchy	-1.21^{***}	0.11^{**}	-0.71^{*}	0.18^{***}	-0.82^{*}	0.07^{*}	-1.28^{***}	$0.11^{\dagger}$
	(0.23)	(0.03)	(0.27)	(0.04)	(0.33)	(0.03)	(0.31)	(0.05)
Controls								
log(Experience)			1.35	0.01	0.38	0.08	1.20	−0.34
			(1.82)	(0.15)	(1.76)	(0.21)	(1.72)	(0.25)
log(MaxExperience)	0.94	0.09						
	(0.84)	(0.10)						
Breadth	−1.70	1.81	−1.07	1.61	−2.24	1.39	−0.94	0.53
	(5.04)	(2.08)	(7.42)	(1.98)	(7.17)	(1.68)	(5.48)	(2.53)
SocialCapital	5.63^{**}	−0.35	4.75	−0.18	8.44^{*}	−0.10	4.47	0.19
	(1.89)	(0.87)	(3.73)	(0.84)	(4.02)	(0.93)	(5.40)	(1.21)
GenderDiversity	−3.88	−1.16	−3.75	−1.15	−4.05	−0.24	−5.03	−0.60
	(3.29)	(1.36)	(3.01)	(0.83)	(4.04)	(0.84)	(3.64)	(1.30)
Horizontal			-6.91^{***}	-2.65^{***}				
			(1.31)	(0.63)				
Fixed-effects								
Newly added								
Top 50 developers	Y	Y						
158 platforms					Y	Y		
Top 200 publishers							Y	Y
Task-level								
3D	Y	Y	Y	Y	Y	Y	Y	Y
LicensedTitle	Y	Y	Y	Y	Y	Y	Y	Y
BusinessModel	Y	Y	Y	Y	Y	Y	Y	Y
Genres	Y	Y	Y	Y	Y	Y	Y	Y
Themes	Y	Y	Y	Y	Y	Y	Y	Y
Platforms	Y	Y	Y	Y	Y	Y	Y	Y
Financing-level								
Indie	Y	Y	Y	Y	Y	Y	Y	Y
Triple-A	Y	Y	Y	Y	Y	Y	Y	Y
Employee-level								
Size (10 quantiles)	Y	Y	Y	Y	Y	Y	Y	Y
Macro-level								
Year	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	1,477	371	1,477	375	1,448	374	1,434	305
R-squared	0.27	0.68	0.23	0.61	0.31	0.71	0.34	0.76

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$
Note. Standard errors clustered by genre in parentheses.

Table 2.20: Robustness Check – Addressing concerns on selection based on omitted variables (cont'd).

CHAPTER III

Cognitive and Structural Antecedents of Innovation: A Large-Sample Empirical Study

3.1 Introduction

Adaptation to disruptive innovations is one of the most significant challenges in a firm's survival (Christensen 1997)—one that has become more threatening due to accelerating technological change. Much work has examined how firms can better adapt to disruptive innovations. This work has highlighted the role of two intra-firm antecedents: the managers' cognition (see, e.g., Tripsas and Gavetti 2000, Eggers and Kaplan 2009) and the organization's structure (see, e.g., Tushman and O'Reilly 1996, Gavetti 2005). For example, in their analysis of the videocassette recording industry, Christensen and Rosenbloom (1995:236) point out that RCA and Ampex failed to adapt to disruptive changes due to "strongly held *beliefs* and inappropriate *organizational structures*" (emphasis added).

Research has characterized adaptation to disruptive innovations in terms of two major phases: *adoption* (the phase in which the firm decides whether to adopt the disruptive innovation or to pursue the existing technology) and *implementation* (the phase in which the firm implements the chosen technology). This, in turn, implies that there are two strategies for adapting to disruptive innovations (Adner and Snow 2010): (i) adopting and successfully implementing the disruptive innovation or (ii) not adopting the disruptive innovation but rather implementing the existing technology exceptionally well. Should the firm fail in either strategy, it may be driven out of business. The possible outcomes can be understood in terms of a two-by-two (see Figure 3.1) and illustrated with cases on how the firms in the photography industry reacted to the arrival of digital photography

		Implementation	
		Poor	Successful
Adoption	Yes	(a) Kodak	(b) FujiFilm
	No	(c) Polaroid	(d) Harman

Figure 3.1: The four possible scenarios of adaptation to a disruptive innovation. We illustrate each scenario with an incumbent's reaction to the introduction of digital photography.

in the late 1990s (for details, see Adner and Snow 2010, Gans 2016:107–108): Kodak and FujiFilm both adopted digital imaging but only FujiFilm implemented it successfully (respectively, quadrants (a) and (b) in Figure 3.1). Neither Polaroid nor Harman Technology adopted digital imaging, but only the latter succeeded—by focusing on specialty paper and other niche products (quadrants (c) and (d), respectively).

In line with the aforementioned research on adaptation antecedents, the responses by these firms have been largely attributed to cognitive and structural antecedents, such as managers' beliefs regarding the source of profits (e.g., that profits stem from selling film rather than cameras; Tripsas and Gavetti 2000) and organizational structures that prevented change (e.g., tall hierarchies stymying innovation; Gavetti 2005).

For four reasons, however, it remains unclear exactly how these antecedents affect each of the two phases of adaptation. First, previous research is based on cases and small samples (Gans 2016:116), making it difficult to rule out alternative explanations. Second, prior studies have mostly paid attention to the adoption phase (Lanzolla and Suarez 2012:837), implicitly assuming that adopting the disruptive innovation is the only way to adapt and thus overlooking the successful "bold retreat" strategy depicted in quadrant (d) (Adner and Snow 2010). Third, most empirical studies have focused on just one of these antecedents, hence, neglecting the potential interplay between cognitive and structural antecedents suggested by previous research (Tripsas and Gavetti 2000, Gavetti 2005, Csaszar 2014). Lastly, cognition and structure are multidimensional constructs (Walsh 1995:286–291, Burton and Obel 2004:73–83), different aspects of which could have different effects. For instance, organizational structure has vertical and horizontal dimensions (also known as *hierarchy* and *differentiation*) while individual cognition is commonly described in terms of *volume of expertise* and *breadth of expertise*. But research on how these dimensions of cognition and structure may affect decision making has produced conflicting predictions and, in any case, has not been specific to the context of adaptation to disruptive innovations. In sum, not much is known about the question of how the two phases of adaptation to disruptive innovations—adoption and implementation—are affected by cognitive and structural antecedents.

This article presents the first large-sample study addressing that question. We examine it in the context of the video game industry, which is a rare and ideal setting for a large-sample analysis for two reasons. First, this industry recently underwent a disruptive change with the introduction of the free-to-play (F2P) business model, which consists of providing the game for free and making revenues from in-game purchases (e.g., the game *Pokémon Go* sells "Premium Raid Passes" to users) and advertising (e.g., the same game sells "PokéStops" to local businesses). F2P exemplifies Christensen's (2018:1043–1047) notion of a disruptive innovation, as the introduction of this business model redefined the product architecture and the revenue model, enlarged the customer base, and eroded the incumbents' profitability, eventually forcing most of them to switch to the new technological regime (see Moore 2015 for an account of these changes).[1] Second, the video game industry is a "fruit fly" setting for studying the cognitive and structural antecedents of adoption and implementation because there is detailed data on the dependent variables (whether or not firms adopted F2P and how well each performed under the chosen business model) and on the independent variables (the managers' cognitive characteristics and the organizations' structures) for a large number of firms that faced this disruption (461 project teams, collectively with 83,157 employees). This rich dataset allows us to observe the two phases of adaptation and identify how each depends on well-established measures of cognitive and structural antecedents.

Our study makes several contributions. First, we show that cognitive and structural antecedents affect adoption, implementation under the new technological regime, and implementation under the existing regime in different ways; that is, not all antecedents matter in all cases (e.g., volume of expertise only matters when implementing under the existing regime) and not always in the same direction (e.g., breadth hampers implementation under the new regime, but benefits

[1]Although incumbents initially considered F2P to be an inferior business model, by 2016 92% of mobile games available on Google Play were F2P (Appfigures 2017). A well-known trade magazine captures this disruptive effect of F2P on the video game industry by noting that this new business model affected "most aspects and actors of the game industry: marketing, publishing, hardware manufacturers, and of course, designers and developers" (Luban 2011).

implementation under the existing regime).

Second, our findings suggest that a firm should organize markedly differently depending on its goal: to succeed under the existing technological regime, the firm should employ inexperienced generalists; whereas to succeed under the new one, the firm should employ specialists and place them in an undifferentiated structure. We also find that firms using taller hierarchies are more likely to adopt and successfully implement the disruptive innovation. Although running against the common wisdom, these results are consistent with information processing arguments regarding the ability of different organizational configurations to cope with the greater uncertainty and complexity accompanying the new technological regime.

Third, we describe the conditions under which structure may and may not compensate for cognition (e.g., structure can be used to compensate for inappropriate cognitive factors under the new technological regime, but not under the existing one). Fourth, our analyses suggest that firm performance under the new technological regime may depend more on cognitive and structural antecedents than on traditional considerations such as complementary assets. Fifth, our paper also makes a methodological contribution: we present a method that allows deriving detailed measures of organizational structure and individual cognition starting from job title data. Lastly, and from a practical standpoint, our study suggests how different types of managers and structures fit with different adaptation strategies.

3.2 Theoretical motivation

After reviewing how research has conceptualized adaptation, we provide an overview of the research that has studied the effect of managers' cognition and organizational structure on decision making, showing that it remains unclear how adaptation depends on these antecedents.

3.2.1 Adaptation to disruptive innovations and its two main phases

Holland (1992:xiii) defines *adaptation* as "any process whereby a structure is progressively modified to give better performance in its environment." The concept of adaptation is central to the strategy and organizations literatures. Different authors have distinguished a number of constituent phases, though not always using the same terms to describe them (see Table 3.1 for a synopsis of

Theory	Adoption	→ Implementation
Innovation		
Thompson (1965)	Initiation → Adoption	→ Implementation
Utterback (1971)	Idea generation → Problem solving	→ Implementation and diffusion
Zaltman et al. (1973)	Initiation	→ Implementation
Rogers (1983)	Knowledge → Persuasion → Decision	→ Implementation → Confirmation
Lanzolla and Suarez (2012)	Technology adoption	→ Technology use
Strategy process		
Hrebiniak and Joyce (1984)	Formulation	→ Implementation/Execution
Strategic decision making		
Schwenk (1984)	Problem identif. → Alt. generation → Selection	→ Implementation
Dynamic capabilities		
Teece (2007)	Sensing → Seizing	→ Reconfiguring
Organizational design		
Glueck (1972)	Appraisal → Choice	→ Implementation → Evaluation

Table 3.1: Taxonomies describing the phases of adaptation.

these terms). For instance, in the research on innovation, Zaltman et al. (1973) refer to the phases as *initiation* and *implementation* while in the research on strategy process, Hrebiniak and Joyce (1984) refer to *formulation* and *implementation*. Other research streams have further divided the phases; for example, in the research on dynamic capabilities, Teece (2007) splits adaptation into the *sensing*, *seizing*, and *reconfiguration* phases.

Nevertheless, these taxonomies agree that there is a distinction between two major phases: choosing a solution and implementing it. We call these two major phases *adoption* and *implementation* (Table 3.1 aligns the different taxonomies according to these two major phases). Adoption refers to the phase of choosing whether to pursue the existing or the new technological regime, while implementation refers to the phase of improving performance in the chosen technological regime, be it the existing or the new one.[2]

In what follows, we show that it remains unclear how these two phases depend on the managers' cognition and the organization's structure. Part of the problem is that research on cognition and organizational structure has discussed their effects on decision quality in a variety of contexts (rather than, specifically, in the context of adoption and implementation) and, in any case, has provided predictions in both directions. Table 3.2 summarizes the mechanisms predicting the positive and negative effects of cognitive and structural antecedents on decision quality. These

[2]Since successful implementation under either technological regime can require both exploration and exploitation, the choice of a technological regime should not be interpreted as a choice between exploration and exploitation.

		Mechanisms predicting ...	
		... positive effects	**... negative effects**
Cognitive antecedents	Volume	(1a) Expertise in decision making (Ericsson and Lehmann 1996)	(1b) Cognitive fixedness (Duncker and Lees 1945)
	Breadth	(2a) Cognitive diversity (Schilling et al. 2003)	(2b) Conflicting interpretations (Jacoby 1984)
Structural antecedents	Hierarchy	(3a) Information aggregation (Seshadri and Shapira 2003)	(3b) Premature filtering (Csaszar 2012)
	Differentiation	(4a) Economies of learning (Burton and Obel 2004:74)	(4b) Cognitive silos (Dougherty 1992)

Table 3.2: Summary of the mechanisms predicting the positive and negative effects of cognitive and structural antecedents on decision quality. For each mechanism, we include one illustrative cite and mention others in the text.

mechanisms will play a role again when interpreting the results of our analyses. The rest of this section follows this table in a row-wise manner.

3.2.2 Prior arguments for the effects of cognitive antecedents

A manager makes a decision based on her cognitive representation—an incomplete and imperfect mental model of the task environment (Craik 1943:61; see also Csaszar 2018 and references therein). A common way of understanding and measuring cognitive representations is in terms of the volume and breadth of the individual's experience, where *volume* is the number of mental objects in the cognitive representation (Chase and Simon 1973) and *breadth* is the diversity of these mental objects (Bantel and Jackson 1989:111).[3] In colloquial terms, volume distinguishes between a novice and an expert, whereas breadth distinguishes between a functional specialist and a generalist. For instance, in Figure 3.2, panel (a) illustrates an experience profile of a novice with only one unit of experience, whereas panels (b) and (c) illustrate experience profiles of experts with three units of experience. The difference between panels (b) and (c) is that the former represents a specialist (with experience in only one functional domain), whereas the latter represents a generalist with experience across all functional domains.

[3]Mental objects can take multiple forms, such as rules (Johnson-Laird 1980), stories (Schank 1995), and images (Shepard 1978).

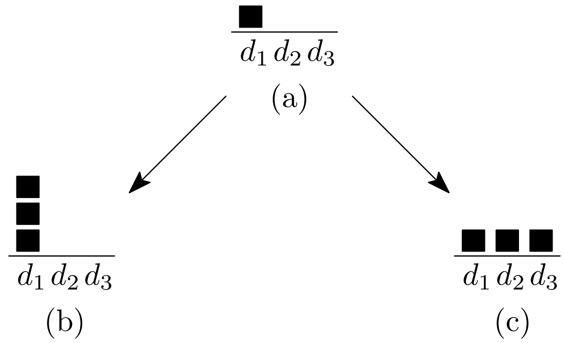


Figure 3.2: Illustration of volume and breadth of expertise. Panels (a), (b), and (c) characterize three different experience profiles. Each box represents a unit of experience (e.g., having worked in a given functional domain for the extension of a project). The functional domains are denoted d_1, d_2, and d_3.

3.2.2.1 Volume

More volume can have a positive effect on decision quality through its effect on expertise (Ericsson and Lehmann 1996; mechanism 1a in Table 3.2).[4] That is, a manager with more experience has more abundant and more fine-grained mental objects (Chase and Simon 1973). Recombining these objects allows the manager to simulate a broader set of plausible alternatives, make inferences, and derive solutions that go beyond her direct experience. As mental objects accumulate, they tend to become better organized (Newell and Simon 1972:781), allowing the manager to make faster and better decisions. In support of this argument, King and Tucci (2002) find that in the disk drive industry, managers with more volume are more likely to identify, enter, and create more value in a new niche market.

A different line of research has pointed out that more volume can have a negative effect on decision quality. The mechanism underlying this effect is cognitive fixedness (Duncker and Lees 1945; mechanism 1b). As a manager's cognitive representation develops into a more elaborate structure, it becomes more stable and resistant to modification (Crocker et al. 1984). The manager may therefore simply neglect new information that contradicts her current representation, rather than modifying it to incorporate the contradictory information (Dane 2010). Thus, the manager can become blind to new superior alternatives. For instance, Henderson (1998) finds that engineers steeped in a particular technology were unable to see what was different about a superior competing

[4] Here, expertise is defined as the "possession of an organized body of conceptual and procedural knowledge that can be readily accessed and used with superior monitoring and self-regulation skills" (Chi et al. 1988:xxi).

technology.

3.2.2.2 Breadth

More breadth can improve decision quality because it can foster cognitive diversity (Schilling et al. 2003; mechanism 2a). That is, a manager exposed to a broader range of problems belonging to different functional domains has more differentiated mental objects (Hitt and Tyler 1991:334), making her more sensitive to changes in various functional domains. Such multiplicity of objects may also stimulate new cross-functional perspectives and lend new perspectives in looking at a problem (Gavetti et al. 2005:697). In line with this argument, Bunderson and Sutcliffe (2002) found that teams with high-breadth managers were more likely to achieve performance targets than teams with low-breadth ones.

However, there are also arguments on the negative effects of breadth. More breadth can lower decision quality because it can generate conflicting interpretations (Jacoby 1984; mechanism 2b). That is, as the manager becomes more sensitive to various functional domains, she may face an overload of function-specific interpretations that interact in complex ways and contradict each other (Dougherty 1992:180). This can make it difficult to identify relevant interpretations and can delay reaching a decision. Even if a decision is reached, it may be of a low quality (Streufert 1973). In line with this argument, in a study of innovation at 3M, Boh et al. (2014) note that high-breadth innovators are prone to finding low impact innovations.

3.2.3 Prior arguments regarding the effects of structural antecedents

To process information efficiently, firms develop an organizational structure that divides and delegates tasks (Simon 1947/1997:7) and is commonly conceptualized and measured in terms of hierarchy and differentiation (Burton and Obel 2004:73–77). Hierarchy refers to *vertical* division of labor: how a firm divides the decision-making process into smaller duties and vertically delegates them among managers at different levels of supervision (Simon 1947/1997:70). In turn, differentiation refers to *horizontal* division of labor: how a firm decomposes the task into smaller components and horizontally allocates them within each level of supervision (Simon 1947/1997:112).[5]

[5] We prefer the term "differentiation" to "specialization," as the latter is more commonly used to describe an individual-level characteristic (such as a specialist CEO versus a generalist CEO).

3.2.3.1 Hierarchy

A taller hierarchy can enhance decision quality because it can make information aggregation more effective (Seshadri and Shapira 2003; mechanism 3a). At each level of supervision, managers can integrate complementary ideas from subunits and filter out what is unimportant or erroneous (Cyert and March 1963:85, Keum and See 2017). This sequential process of information aggregation at each level of supervision can generate a more "lean and mean" idea that enables upper-level managers to focus on core issues, increasing their chances of making better decisions (Nonaka 1994:30). Seshadri and Shapira (2003:1101) illustrate this process with the case of Sony, where a taller hierarchy helped integrate the knowledge of engineers across different divisions to create the Walkman, one of the most popular entertainment devices in history.

Yet, a taller hierarchy can also undermine decision quality through premature filtering (Csaszar 2012; mechanism 3b). This can happen because, in a taller hierarchy, potentially beneficial information is more likely to overlooked during the sequential aggregation process, as information is imperfectly communicated (Sah and Stiglitz 1986:717) or imperfectly processed (Gavetti 2005:612–613) while flowing up the hierarchy. Thus, under this logic, the more levels of supervision, the more information filtering and thus the higher the probability of omitting potentially beneficial information. This premature filtering of information is exemplified by the cases of Xerox PARC and AT&T Bell Labs, which failed to commercialize several valuable innovations due to the many layers of management separating their R&D divisions from its top management (see, e.g., Chesbrough and Rosenbloom 2002:542).[6]

3.2.3.2 Differentiation

More differentiation across job specifications can increase decision quality through economies of learning (Burton and Obel 2004:74; mechanism 4a). As a firm decomposes a task into smaller components, managers can better focus on their assigned components and reap the rewards of the learning curve effect (Argote and Miron-Spektor 2011). This can, in turn, create a pool of experts with more fine-grained, component-specific knowledge, which the firm can draw on to make

[6] Hierarchy can also affect the speed of decision making. As with the other variables, prior studies have conflicting predictions regarding the sign of this relationship (compare, e.g., the predictions of Burns and Stalker 1961 and Siggelkow and Rivkin 2005 vis-à-vis Carzo and Yanouzas 1969 and Eisenhardt 1989). We do not investigate effects on decision-making speed, as our setting does not allow for measuring it.

better decisions. Leonard-Barton (1995:67) illustrates this benefit of differentiation with the case of Hitachi, which created its high-capacity disk drive by leveraging component-specific knowledge from its nuclear and chemical engineers.

Yet, more differentiation can also decrease decision quality if it creates cognitive silos (Dougherty 1992; mechanism 4b). As managers narrowly focus on their components, they may neglect available information that is irrelevant to their components but is essential to the task as a whole (Levinthal and March 1993:97). Such partial interpretations can impede the dialogue among the managers and make it difficult for them to react in a coordinated manner (Burton and Obel 2004:8). Consistent with this argument, Dougherty (1992:182) finds in her multiple-case study of large high-tech companies, that more differentiation can lead to ignoring information that may be essential to the total task.

Given such opposing arguments and the paucity of large-sample empirical research in the context of adaptation to disruptive innovations, it remains unclear which of these effects will be at work in adoption and implementation.[7] This lack of clarity motivates our research question: how do cognition and organizational structure affect adoption and implementation of disruptive innovations?

3.3 Methods

Before delving into our methods, it is important to understand the empirical challenges of our research question and how they can be overcome using the video game setting. We then explain how we collected the data, measured the variables, and specified our model.

3.3.1 Empirical challenges

Large-sample research on the cognitive and structural antecedents of adoption and implementation is difficult due to two empirical challenges: data availability and reverse causality.

Data availability. In order to examine how adoption and implementation depend on cognition and organizational structure, all of the following ingredients must be measurable for a large sample

[7]Because there is no a priori reason to assume the results will go in one direction or another, our research method is consistent with an inductive-quantitative approach (Vogt et al. 2014:370). Given the abundance of competing mechanisms (i.e., all cells in Table 3.2 are occupied), we believe it is more natural not to write down hypotheses in this section.

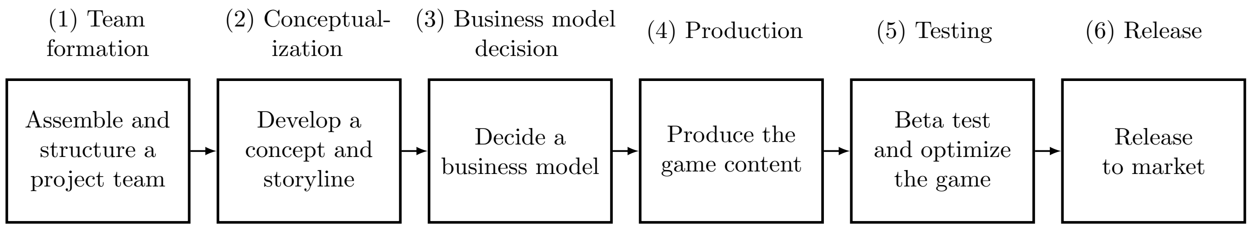


Figure 3.3: Process of video game development.

of firms: (a) whether a firm adopted a disruptive innovation, (b) the firm's performance (i.e., the quality of implementing the chosen technology), (c) the firm's organizational structure, and (d) the cognitive characteristics of the firm's members. These four ingredients are rarely available across a large sample of firms. They have, however, been carefully recorded for most video games because a number of databases provide historical data on each game's business model, performance, and credits (which includes the list of project members along with their job titles and the functional domain corresponding to each job title). This rich data allows us to measure adoption and implementation and to estimate well-established measures of cognition and organizational structure.

Reverse causality. In settings like ours, reverse causality can arise if (a) adoption affected organizational structure (i.e., a firm chose its structure in order to adopt the disruptive innovation) or (b) performance affected adoption (i.e., a firm's unsatisfactory performance caused it to search for new alternatives and thus adopt the innovation). Although these two types of reverse causality cannot be entirely ruled out, they are mitigated to a large extent by the unique, project-based nature of the game industry. In particular, in this industry (i) a project decides its business model after its structure and (ii) a project cannot change its business model once the game is released. The rationale behind this sequence of events becomes clearer when considering the process by which a game is developed (illustrated in Figure 3.3). This development process is well documented in existing descriptions of the industry (see, e.g., Bethke 2003, Liming and Vilorio 2011) and was confirmed in interviews we conducted with 14 video game developers in the US, South Korea, and Japan.

For a more concrete understanding of how this sequence of events mitigates reverse causality, we illustrate the game development process with the case of *Candy Crush Soda Saga* (adapted from Sundman 2015 and Judge 2015). To develop a new game in 2013, the game studio, King Digital

Entertainment, assembled a project team of 16 game designers, programmers, and artists, who organized themselves as a flat structure (Stage 1 in Figure 3.3). Initially, the team did not have a concrete idea for the new game: "[t]he only directive was to build the next big thing" (Sundman 2015). After experimenting for several months, the team pieced together the game concept, storyline, and features for *Candy Crush Soda Saga* (Stage 2) and, based on these, chose an F2P business model in which gamers can purchase, for instance, "boosters" to pass difficult levels (Stage 3). The team then produced the game's alpha version (Stage 4), which went through multiple stages of beta testing on Facebook to fix errors and eliminate unnecessary features (Stage 5). The game was then released on all major mobile platforms, generating more than $500 million in revenue in the first 12 months (Stage 6).

As this example illustrates, the first type of reverse causality (adoption affecting structure) is mitigated because project teams in our setting are generally not structured around a preconceived business model (i.e., Stage 3 happens after Stage 1). As one of our interviewees put it, "We don't make a game for the sake of a business model. We come up with the game idea and then see how we can make money out of it." Similarly, the director of Lionhead Studios highlights that "[n]obody came to Lionhead Studios and said, 'We want you to make a Free-to-Play game'" (Makuch 2015). In turn, the second type of reverse causality (performance affecting adoption) is also largely mitigated, as the team observes its performance after adopting and implementing a business model and, once the game is released, cannot change its business model, given the short life-cycle of video games, the large cost of modifying and testing the game design, and the risk of losing existing users (i.e., Stage 6 happens after Stage 3). After a project is finished, the team dissolves and its members may join other projects.

3.3.2 Data collection

We gathered detailed data on 461 mobile games released between 2012 and 2015 (the years in which the bulk of the transition to F2P took place) by merging data from three sources: ThinkGaming, MobyGames, and VGChartz.

ThinkGaming is the industry-standard source for information on the prices and revenues of mobile games (this information is available from 2012 onward).[8] We used this information to

[8]ThinkGaming estimates revenues using a proprietary model that combines games' prices, number of downloads,

construct the dependent variables of adoption and implementation. Adoption was measured using the games' prices (i.e., Price = 0 implies that the game adopted F2P); performance was measured using the games' revenues.

MobyGames keeps a comprehensive database of the project members of video games produced since 1987. For each member, this database includes full name, job title, and functional domain (which categorizes the job title according to functions such as administration, design, and production). We used this data to measure the independent variables relating to cognition and organizational structure. To measure cognition, we coded a member's experience upon joining a project in terms of volume (the number of previous projects on which she had worked) and breadth (the diversity of the functional domains in which she had worked). To measure organizational structure, we coded project members' job titles in terms of hierarchy (the number of levels of supervision in a project team, derived from a text analysis of the job titles) and differentiation (the number of different job titles in the team). MobyGames also provides detailed information on game characteristics, which we used to construct control variables. We provide detailed definitions of all our measures later in this section.

VGChartz tracks the sales figures for all paid games (not just mobile games) that sell more than 10,000 units. We used these figures to create a measure of brand recognition. VGChartz also identifies which companies produce video game consoles, the most significant alternative to mobile platforms as a distribution channel. We use the information on brand recognition and console manufacturing as controls reflecting complementary assets.

We connected these three datasets by the game titles using a fuzzy string-matching algorithm (Python's *FuzzyWuzzy* package with a similarity threshold of 90% to account for typos and minor differences). We eliminated false or ambiguous matches by checking that the release date and the set of participating game studios matched (note that we matched using the *set* of game studios producing a game, since many games are produced by partnerships of studios). These checks eliminated 68% of the fuzzy string-matching results, yielding a sample of 461 mobile games released during the period of disruption (2012–2015). The (per dataset) descriptive statistics of the selected and eliminated games were similar, revealing no selection bias. Other research that has used video game data, albeit using different datasets and pursuing different research questions, include Mollick

and sales data shared by F2P games.

(2012) and Rietveld (2018).

3.3.3 Measurement

3.3.3.1 Dependent variables

To capture adoption, we create a binary dummy variable which equals 1 if project p adopted F2P and 0 otherwise. A project's business model is F2P if its game can be downloaded for free (i.e., it does not require upfront payment to be played); otherwise it is non-F2P. In our sampling period, every game was released under just one of these business models. Before our sampling period, some games (e.g., Angry Birds) were released under both business models, but this practice faded out after Apple introduced the in-app purchasing functionality in October 2009. The adoption variable focuses on whether or not a project adopted F2P; how well the chosen business model is implemented, is captured by our next dependent variable.

To measure performance, we use the natural logarithm of the revenues (in US dollars) generated in the first 12 months after the game was released. Because profit data is unavailable, we measure performance as revenues instead and include multiple controls that account for development costs (e.g., the characteristics of the game, such as the number of platforms and the use of 3D graphics; see Table 3.3 for details).[9] Thus, formally:

$$Adoption_p = \begin{cases} 1 & \text{if project } p \text{ adopted F2P} \\ 0 & \text{otherwise} \end{cases}$$

$$Performance_p = \log\left(\text{project } p\text{'s revenue for the first 12 months after the release}\right)$$

3.3.3.2 Independent variables

To examine the effects of cognitive and structural antecedents, we measure cognition in terms of volume and breadth and organizational structure in terms of hierarchy and differentiation. Below, we define these measures formally.

[9] We limit the time span to the first 12 months after release because mobile apps, on average, achieve half their lifetime usage in the first six months and have a life-cycle of less than a year (Fried 2015, Sinclair 2016). The regression results in the next section are robust to different time spans. We preferred 12 months rather than longer time spans to avoid decreasing the sample size unnecessarily.

Measures of cognition. We measure volume as the number of prior projects that an individual has worked on and breadth as the diversity of functional domains in which she has worked. These measures are computed using the experience profile of each individual (for details on how experience profiles are derived from job title data, see Appendix 3.6.1). More formally, if e_{idp} represents the number of projects in which individual i worked in functional domain d before working on project p, then her volume when joining project p is simply the sum of e_{idp} across all D functional domains (MobyGames categorizes job titles into $D = 20$ functional domains[10]). In turn, her breadth when joining project p is a measure of the diversity across functional domains of her prior projects. Mathematically:

$$IndVolume_{ip} = \sum_{d=1}^{D} e_{idp}$$
$$IndBreadth_{ip} = \begin{cases} 1 - HHI_{ip} = 1 - \left(\sum_{d=1}^{D} e_{idp}^2\right) / \left(\sum_{d=1}^{D} e_{idp}\right)^2 & \text{if } IndVolume_{ip} > 0 \\ 0 & \text{otherwise,} \end{cases}$$

where HHI_{ip} is the Herfindahl–Hirschman Index (HHI). The measure $1 - HHI$, often referred to as Blau's index (1977), is a common measure of diversity (Hambrick et al. 1996; for a survey, see Bunderson and Sutcliffe 2002:876–877).

To turn these individual-level measures into team-level measures, we average them across the N members of project p. That is:

$$Volume_p = \frac{1}{N} \sum_{i=1}^{N} IndVolume_{ip}$$
$$Breadth_p = \frac{1}{N} \sum_{i=1}^{N} IndBreadth_{ip}$$

Measures of organizational structure. In line with previous studies (see Burton and Obel 2004:73–77 and references therein), we measure hierarchy and differentiation using the project members' job titles. To measure hierarchy, we categorize each member's job title into one of 11 levels

[10] These functional domains are Administration, Art/Graphics, Audio, Business, Companies, Creative Services, Customer/Technical Support, Design, Localization, Marketing, Production, Programming/Engineering, Public Relations, Quality Assurance, Support, Technology, Thanks (results are robust to removing this category), Video/Cinematics, Writers, and Others.

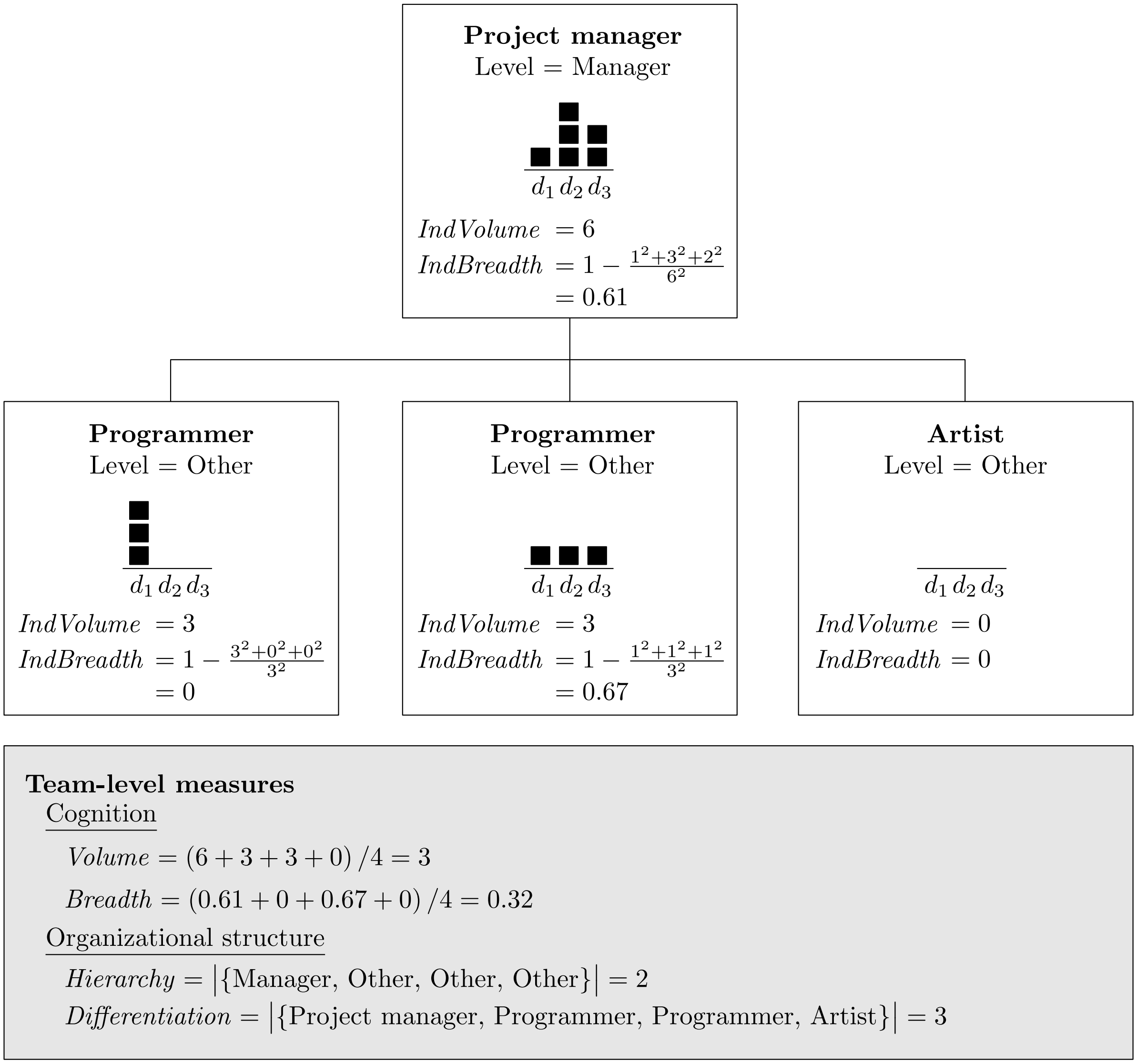


Figure 3.4: Computing the cognitive and structural measures for a hypothetical four-person project team.

of supervision and count the number of unique levels in a project (for details, see Appendix 3.6.2). To measure differentiation, we count the number of unique job titles. More formally:

$$\textit{Hierarchy}_p = \left|\{\text{unique levels of supervision in project } p\}\right|$$

$$\textit{Differentiation}_p = \left|\{\text{unique job titles in project } p\}\right|$$

To illustrate our measures, consider the hypothetical four-person project team shown in Figure 3.4, which includes a project manager, two programmers, and an artist. Each team member has an experience profile, where each black box represents a unit of experience in functional domains d_1 to d_3. To compute individual-level measures of cognition, we summarize each individual's experience profile in terms of its volume (*IndVolume* is the count of "boxes" within each profile) and breadth (*IndBreadth* is the diversity in the composition of boxes across functional domains; $1 - HHI$). To compute the team-level measures (shown in the lower part of Figure 3.4), we average the individual-level measures of cognition and count the unique levels of supervision and unique job titles. In this example there are two unique levels of supervision ("Manager" and "Other") and three unique job titles ("Project manager", "Programmer," and "Artist"), hence this structure has *Hierarchy* $= 2$ and *Differentiation* $= 3$.

3.3.3.3 Controls

Apart from cognition and structure, adoption and implementation could also depend on task-, team-, and studio-level characteristics. To control for these, we include the control variables described in Table 3.3. At the task level, we control for game characteristics that relate to task complexity and development costs (*nThemes*, *nPerspectives*, *nPlatforms*, *Add-on*, *3D*, and *LicensedTitle*).[11] We also include genre dummies (*Genre*) to control for any idiosyncratic effects of different genres and year dummies (*Year*) to control for macroeconomic changes affecting all games. At the team level, we control for team size (*nEmployees*). To take into account the overall breadth of experience of the team (not just the average of the individuals' breadths captured by *Breadth*), we compute team-level breadth (*TeamBreadth*), which is equivalent to computing the breadth of a "virtual individual" that combines all the experience of the project members. At the studio level, we account for characteristics of the game studios that formed the project team, including the number of participating studios (*nStudios*), their complementary assets (*Brand* and *Console*), and their experience in the industry and in F2P (*ExpStudios* and *PriorF2PStudios*, respectively).

[11] These variables affect a game's task complexity and development costs because (a) more themes and perspectives require more programming, visuals, and sounds; (b) supporting multiple platforms increases programming complexity; (c) add-ons are usually simple to develop because they build on a game's storyline and features; (d) 3D games require more complex modeling and motion-capture technologies; and (e) licensed titles require coordinating with the franchisor (e.g., the developers of *The Lion King* game must coordinate with Disney).

Level	Variable	Measurement
Task	*nThemes*	Number of themes in the game (e.g., fantasy, puzzle-solving, shooter).
	nPerspectives	Number of perspectives in the game (e.g., first-person, third-person, isometric, side-scrolling).
	nPlatforms	Number of platforms for which the game was released (e.g., Android, iPhone, Nintendo DS).
	Add-on	1 if the game is an extension of an existing game; 0 otherwise.
	3D	1 if the game incorporates 3D technology; 0 otherwise.
	LicensedTitle	1 if the gameplay, storyline, or setting was inspired by a movie, TV show, book, or other work; 0 otherwise.
	Genre	Dummy variables for 23 genres categorized by MobyGames (e.g., action, role-playing, strategy).
	Year	Dummy variables for the year of game release.
Team	*nEmployees*	Number of individuals who participated in the game development.
	TeamBreadth	$1 - HHI$ of all members' prior projects combined.
Studio	*Brand*	Natural logarithm of the total revenues from paid games that the participating game studios produced before the current game.
	Console	Number of console makers (e.g., Nintendo, Sony, Microsoft) among the participating game studios.
	nStudios	Number of game studios that participated in the game development.
	ExpStudios	Average number of video games that the participating game studios developed before the current game.
	PriorF2PStudios	Average number of F2P games that the participating game studios developed before the current game.

Table 3.3: Description of the control variables.

3.3.4 Descriptive statistics and correlation matrix

Table 3.4 presents the descriptive statistics for the variables discussed above. There is considerable variation. For instance, the maximum value of performance (i.e., 21.73) is equivalent to \$2.7 billion ($= e^{21.73}$), which the F2P game *Clash of Clans* earned in its first 12 months (Goodman 2016). Also, the mean of adoption (i.e., 0.50) indicates that 50% of our sample adopted F2P. As this percentage grew consistently from 42% in 2012 to 67% in 2015, our sampling period captures the transition from the old to the new technological regime and the establishment of F2P as the dominant technological regime.

In our sample, the average project team has approximately 180 members (mean *nEmployees*).

	Obs	Mean	Std. Dev.	Min	Max
Dependent					
Performance	461	11.90	3.57	0	21.73
Adoption	461	0.50	0.50	0	1
Independent					
Cognition					
Volume	461	5.63	4.70	0	45.50
Breadth	461	0.16	0.10	0	0.57
Organizational structure					
Hierarchy	461	3.91	2.81	1	11
Differentiation	461	52.48	78.87	1	848
Controls					
Task-level					
nThemes	461	1.60	0.86	1	7
nPerspectives	461	1.35	0.62	1	5
nPlatforms	461	4.41	2.06	1	17
Add-on	461	0.02	0.15	0	1
3D	461	0.06	0.23	0	1
LicensedTitle	461	0.21	0.41	0	1
Team-level					
nEmployees	461	180.38	391.90	1	4432
TeamBreadth	461	0.78	0.17	0	1
Studio-level					
Brand	461	1.30	2.37	0	10.17
Console	461	0.02	0.15	0	2
nStudios	461	1.92	0.79	1	5
ExpStudios	461	89.65	154.56	0	757.50
PriorF2PStudios	461	2.30	3.07	0	26

Table 3.4: Descriptive statistics.

On average, project members have worked on 5.63 prior projects (mean *Volume*) and are highly specialized (mean *Breadth* of 0.16).[12] Also, the average team has roughly four levels of supervision (mean *Hierarchy*) and 52 different job titles (mean *Differentiation*).

As the variables *Volume*, *Differentiation*, *nEmployees*, and *ExpStudios* are highly skewed, we use the natural logarithm (for variables with a minimum value of 0, we add 1 before logging to avoid computing the logarithm of 0).

Table 3.5 displays the correlation matrix, which shows a high level of correlation (larger than

[12]To get a sense of the high level of specialization corresponding to a mean *Breadth* of 0.16, consider an individual with 10 units of experience. If 9 of these units fall in the same functional domain, she would have *Breadth* $= 0.18$ $(= 1 - (9^2 + 1^2)/10^2)$; and if 8 units fell in the same domain, she would have *Breadth* $= 0.34$ $(= 1 - (8^2 + 1^2 + 1^2)/10^2)$.

0.7) between number of employees, hierarchy, and differentiation. Such correlations are natural, as more employees allow for (and perhaps demand) more levels of supervision and more detailed job specifications (Burton and Obel 2004:168–171). To investigate whether this level of correlation raises the concern of multicollinearity, we checked that the variance inflation factors and the condition numbers were below their customary thresholds. The highest values were 5.31 and 25.74, below their respective customary thresholds of 10 and 30, which suggests that the regression estimates are not biased by multicollinearity (Belsley et al. 1980:112, Kutner et al. 2004). To further allay multicollinearity concerns, we conducted four additional analyses (results available from the authors). First, we used alternative measures standardized by size (for hierarchy, the number of hierarchical levels divided by the log number of employees; and for differentiation, the number of job titles per employee). Second, instead of using the number of employees as a direct control, we created size quantile dummies (we used 5, 10, 20, and 40 quantiles). Third, we ran four separate regressions, each with only one independent variable (e.g., only including *Volume* and excluding the other three). Lastly, we ran regressions excluding one independent variable at a time (e.g., including all independent variables but *Volume*). All these additional analyses exhibited consistent signs and relatively stable magnitudes for the independent variables, thus implying that multicollinearity is unlikely to bias the main results.

3.3.5 Model specification

Because the video game development process is sequential (as shown in Figure 3.3), we can specify our empirical model using two equations—one to estimate the probability of adoption and the other to estimate performance. Thus, our empirical model is specified as follows:

$$\mathbb{P}[\mathit{Adoption} = 1] = L(\alpha_0 + \alpha_1 \mathit{Volume} + \alpha_2 \mathit{Breadth} + \alpha_3 \mathit{Hierarchy} + \alpha_4 \mathit{Differentiation} + \mathit{Controls}) \tag{3.1}$$

$$\begin{aligned} \mathbb{E}[\mathit{Performance}] = \beta_0 + {} & \mathit{Adoption} \times (\beta_1 \mathit{Volume} + \beta_2 \mathit{Breadth} + \beta_3 \mathit{Hierarchy} + \beta_4 \mathit{Differentiation}) \\ & + (1 - \mathit{Adoption}) \times (\beta_5 \mathit{Volume} + \beta_6 \mathit{Breadth} + \beta_7 \mathit{Hierarchy} + \beta_8 \mathit{Differentiation}) \\ & + \beta_9 \mathit{Adoption} + \mathit{Controls} \end{aligned} \tag{3.2}$$

where $L(\cdot)$ is the logistic function and *Controls* stands for the control variables (described in Table 3.3) in both equations. Equation 3.1, which specifies the probability of adoption as a function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent																		
(1) Performance	1.00																	
(2) Adoption	0.02	1.00																
Independent																		
(3) Volume (log)	0.03	0.04	1.00															
(4) Breadth	-0.11^{*}	-0.12^{*}	0.63^{***}	1.00														
(5) Hierarchy	0.28^{***}	0.18^{***}	0.47^{***}	0.15^{**}	1.00													
(6) Differentiation (log)	0.28^{***}	0.09^{+}	0.49^{***}	0.08^{+}	0.85^{***}	1.00												
Controls																		
(7) nThemes	-0.09^{*}	-0.06	0.01	0.05	-0.04	-0.01	1.00											
(8) nPerspectives	0.12^{**}	-0.12^{*}	0.03	0.01	0.08^{+}	0.08^{+}	-0.09^{*}	1.00										
(9) nPlatforms	0.10^{*}	-0.26^{***}	-0.04	-0.02	0.01	0.06	-0.07	0.08^{+}	1.00									
(10) Add-on	0.07	-0.06	0.11^{*}	0.07	0.20^{***}	0.16^{***}	0.05	-0.06	-0.02	1.00								
(11) 3D	-0.02	-0.11^{*}	0.01	0.00	0.06	0.07	0.04	0.01	0.00	0.03	1.00							
(12) LicensedTitle	0.22^{***}	0.12^{**}	0.20^{***}	-0.01	0.40^{***}	0.38^{***}	-0.05	-0.01	-0.01	0.07	0.03	1.00						
(13) nEmployees (log)	0.32^{***}	0.13^{**}	0.40^{***}	0.01	0.72^{***}	0.88^{***}	-0.00	0.08^{+}	0.06	0.14^{**}	0.06	0.38^{***}	1.00					
(14) TeamBreadth	0.00	0.04	0.15^{***}	0.24^{***}	0.38^{***}	0.42^{***}	0.08^{+}	0.04	0.00	0.05	0.03	0.15^{**}	0.47^{***}	1.00				
(15) Brand (log)	0.23^{***}	0.09^{*}	0.38^{***}	0.15^{***}	0.46^{***}	0.44^{***}	-0.07	0.17^{***}	-0.03	0.09^{+}	-0.05	0.28^{***}	0.41^{***}	0.20^{***}	1.00			
(16) Console	0.01	0.00	0.11^{*}	0.08	0.05	0.05	-0.01	0.10^{*}	0.02	-0.02	0.04	0.01	0.01	0.01	0.18^{***}	1.00		
(17) nStudios	0.09^{+}	0.05	0.19^{***}	-0.01	0.39^{***}	0.35^{***}	-0.00	0.11^{*}	0.07	0.15^{**}	0.11^{*}	0.20^{***}	0.34^{***}	0.13^{**}	0.39^{***}	0.11^{*}	1.00	
(18) ExpStudios (log)	0.10^{*}	0.12^{*}	0.55^{***}	0.22^{***}	0.49^{***}	0.55^{***}	0.03	-0.03	-0.04	0.10^{*}	0.03	0.16^{***}	0.51^{***}	0.18^{***}	0.52^{***}	0.06	0.34^{***}	1.00
(19) PriorF2PStudios	-0.06	0.19^{***}	0.21^{***}	0.01	0.07	0.13^{**}	0.01	-0.14^{**}	-0.14^{**}	-0.05	-0.02	-0.01	0.10^{*}	-0.06	0.13^{**}	0.01	-0.06	0.57^{***}

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Table 3.5: Correlation matrix.

of cognition and organizational structure, is estimated using logistic regression. In turn, Equation 3.2, which specifies performance as a function of the interactions between adoption and the cognitive and structural antecedents, is estimated using ordinary least squares (OLS). In both equations, we cluster the standard errors according to the set of participating game studios in order to account for the potential correlation among projects initiated by the same set of studios.

The specification of Equation 3.2 allows us to distinguish the effect of the antecedents on implementation contingent on whether the firm adopts F2P. That is, the value of adoption switches which coefficients are estimated (i.e., if $Adoption = 1$, we estimate β_1 to β_4; if $Adoption = 0$, we estimate β_5 to β_8). The main effect of adoption is captured by coefficient β_9.

3.4 Results

Table 3.6 provides the results of the regression analyses. Models 1 and 2 show the logistic estimates for adoption (Model 1 is a baseline that only includes controls and Model 2 replicates Equation 3.1). In turn, Models 3 and 4 present the OLS estimates for implementation (Model 3 is a baseline and Model 4 replicates Equation 3.2). For ease of view, we split Model 4 into two columns: the left and right columns including the coefficients when $Adoption = 1$ (i.e., β_1 to β_4) and $Adoption = 0$ (i.e., β_5 to β_8), respectively.

Comparing Models 2 and 4 yields the interesting observation that what matters to adoption is different from what matters to implementation. That is, which coefficients are significant varies across Models 2 and 4, as do some of those coefficients' directions. For instance, differentiation is statistically significant for adoption, but not for implementation. This suggests that it is paramount to distinguish between adoption and implementation, as these phases call for different sets of cognitive and structural antecedents.

Comparing the left and right columns of Model 4 points to another interesting observation: that what antecedents matter to performance—and in what directions—depends on the technological regime chosen. For example, breadth decreases performance under the new technological regime, but increases performance under the existing one.

Taken together, these observations imply that the effects of cognitive and structural antecedents on adaptation are contingent on both the phase of adaptation (adoption or implementation)

	Adoption		Performance		
	Model 1	Model 2	Model 3	Model 4	
				Adoption=1	*Adoption*=0
Independent					
Volume (log)		0.39		0.22	-1.12^{*}
		(0.30)		(0.60)	(0.46)
Breadth		-4.69^{**}		-11.87^{**}	7.52^{*}
		(1.81)		(4.01)	(3.11)
Hierarchy		0.38^{***}		0.52^{**}	0.10
		(0.09)		(0.17)	(0.16)
Differentiation (log)		-0.88^{***}		−0.90	0.14
		(0.24)		(0.55)	(0.50)
Adoption			−0.35	1.98	
			(0.39)	(1.38)	
Controls					
nThemes	0.03	0.10	−0.09	−0.03	
	(0.14)	(0.16)	(0.22)	(0.22)	
nPerspectives	-0.47^{*}	-0.52^{*}	0.42	0.37	
	(0.20)	(0.20)	(0.27)	(0.28)	
nPlatforms	-0.24^{***}	-0.23^{***}	0.13	0.11	
	(0.06)	(0.06)	(0.08)	(0.08)	
Add-on	-1.54^{*}	-1.97^{*}	0.68	0.53	
	(0.76)	(0.97)	(1.12)	(1.10)	
3D	-1.13^{+}	-1.18^{+}	−0.51	−0.39	
	(0.59)	(0.62)	(0.57)	(0.54)	
LicensedTitle	0.45	0.14	0.61	0.30	
	(0.38)	(0.36)	(0.43)	(0.43)	
nEmployees (log)	0.17	0.34^{*}	0.77^{***}	0.83^{**}	
	(0.11)	(0.16)	(0.19)	(0.31)	
TeamBreadth	−0.63	−0.11	-4.17^{**}	-3.62^{*}	
	(0.73)	(0.76)	(1.39)	(1.47)	
Brand	−0.01	−0.02	0.15	0.15^{+}	
	(0.07)	(0.07)	(0.09)	(0.09)	
Console	0.27	0.53	−0.13	0.44	
	(0.67)	(0.64)	(0.44)	(0.42)	
nStudios	0.19	0.04	−0.41	-0.65^{*}	
	(0.21)	(0.20)	(0.28)	(0.29)	
ExpStudios	−0.10	−0.09	−0.04	0.04	
	(0.16)	(0.16)	(0.19)	(0.19)	
PriorF2PStudios	0.18^{+}	0.19^{*}	−0.06	−0.08	
	(0.10)	(0.09)	(0.08)	(0.07)	
Dummies					
Genre	Y	Y	Y	Y	
Year	Y	Y	Y	Y	
No. observations	435	435	461	461	
No. clusters	347	347	361	361	
(Pseudo) R-squared	0.17	0.22	0.25	0.32	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$
Note. Standard errors clustered by the set of studios in parentheses. All models include an intercept and dummy variables for genre and year, which are suppressed for ease of view. There are fewer observations in Models 1 and 2 than in Models 3 and 4 because some observations were dropped during the estimation, as their genre dummies were perfect predictors of adoption.

Table 3.6: The effects of cognition and organizational structure on adoption and implementation.

and the technological regime that a firm chooses (the existing or the new). To discuss these and other results in detail, we organize the presentation below around what determines the probability of adoption (Model 2), the performance in the new regime (left column of Model 4), and the performance in the existing regime (right column of Model 4).

3.4.1 What determines the probability of adoption?

Recall that, as summarized in Table 3.2, there are competing predictions regarding the effects of cognition and organizational structure on decision quality. Model 2 sheds light on which of these predictions apply in the adoption phase.

Model 2 shows that hierarchy increases the probability of adoption, which is consistent with the argument that hierarchy can improve the effectiveness of information aggregation (mechanism 3a) espoused by the emerging line of research looking at hierarchies in a more positive light (e.g., Seshadri and Shapira 2003, Keum and See 2017). Interestingly, this finding runs counter to the common wisdom (e.g., Hamel 2011) and research (e.g., Burns and Stalker 1961, Csaszar 2013) indicating that hierarchy gets in the way of innovation. We conjecture that this result stems from the fact that F2P redefined the product architecture and the revenue model and, hence, adopting this new business model required a significant amount of information processing across all functional domains (e.g., employees needed to collectively make sense of the situation and figure out how to change the product and the organization; Zott et al. 2011). And, as theorized by Seshadri and Shapira (2003), this increased requirement for information processing is more likely to be effectively achieved through a taller hierarchy. We conjecture that adding hierarchical levels is particularly valuable for organizations that do not yet have well-developed structures to deal with complex problems, such as young project-based organizations and start-ups.

Model 2 also shows that cognitive breadth and structural differentiation both decrease the probability of adoption, which conforms with the arguments that breadth and differentiation can result in conflicting interpretations and cognitive silos (mechanisms 2b and 4b, respectively). These negative effects of breadth and differentiation seemingly imply a contradiction, as breadth and differentiation capture the concept of “specialization” at different levels of analysis: cognitive and structural. That is, the negative coefficient for breadth means that it is better to have high cognitive specialization (i.e., managers who are specialists in a few functional domains), whereas the negative coefficient for differentiation calls for a low level of structural specialization (i.e., broad job specifications). Such decoupling between cognitive and structural specialization, however, is not contradictory, since it points to something practicable: to adopt a disruptive innovation, firms need specialists (who can provide a more fine-grained understanding of the disruptive innovation) as well as broad job specifications (which can deter cognitive silos). In other words, specialists organized in an undifferentiated structure favor adoption.

3.4.2 What determines performance under the new technological regime?

We move on to examine how performance under the new technological regime depends on cognitive and structural antecedents (see the left column of Model 4; i.e., $Adoption = 1$). The statistically significant coefficients and their directions in the left column of Model 4 almost match those in Model 2 (the only disparity is in the statistical significance of differentiation). More specifically, the probability of adoption and performance under the new technological regime both decrease with breadth, increase with hierarchy, and decrease with differentiation. This suggests that adoption and implementation under new technological regimes call for similar configurations of cognition and organizational structure.

The fact that hierarchy has positive effects on performance under the new technological regime supports the argument that hierarchy can make information aggregation more effective (mechanism 3a). In line with our conjecture on why hierarchy benefited adoption, we speculate that implementing under the new technological regime imposed high information processing demands, which could be better served by using a taller hierarchy (Seshadri and Shapira 2003).

In turn, breadth has negative effects on both the probability of adoption and the performance under the new technological regime, supporting the argument that breadth can generate conflicting interpretations (mechanism 2b). In line with the conjecture above on hierarchy, we speculate that because resolving task uncertainty and complexity requires processing a significant amount of information (Galbraith 1973:26), generalists (i.e., individuals with greater breadth) can be overloaded with conflicting interpretations and thus make low-quality decisions (Streufert 1973, Jacoby 1984).

3.4.3 What determines performance under the existing technological regime?

We now discuss what determines performance under the existing technological regime (see the right column of Model 4; i.e., $Adoption = 0$). We observe that there is much variation regarding significant coefficients and their directions across the two columns of Model 4, which suggests that implementing under the current technological regime requires a different configuration of cognitive and structural antecedents than implementing under a new technological regime. More specifically, we have seen that both adoption and implementation under the new technological regime decrease with breadth and increase with hierarchy. In contrast, implementation under the existing technological regime *increases* with breadth and decreases with volume (a variable that was not significant before). Below, we discuss each of these results.

First, a positive effect of breadth on performance under the existing technological regime is consistent with the argument that breadth can enhance cognitive diversity (mechanism 2a). This positive effect contrasts starkly with the negative effects of breadth on adoption and on implementation under the new technological regime. We conjecture that the positive effect is due to the lower task uncertainty and complexity of implementing the existing, non-F2P business model. That is, faced with a simpler task environment, generalists (i.e., individuals with greater breadth) are better able than specialists to come up with performance improvements.

Volume has a negative effect on performance under the existing technological regime, which is consistent with the argument that volume can result in cognitive fixedness (mechanism 1b). This negative effect is interesting, as it diverges from the predominant view that experience fosters adaptation (e.g., Ericsson and Lehmann 1996, Argote and Miron-Spektor 2011) and instead supports the idea of competency traps (Levitt and March 1988) and related arguments that warn about the limitations of experience (e.g., Dane 2010, Csaszar and Levinthal 2016:2045). We speculate that in our setting volume was detrimental for the firms that did not switch to F2P, as making successful non-F2P games required being attuned to novel technologies and changing market trends, something that is better done by those coming to the industry with "fresh eyes."

A striking overall observation from the right column of Model 4 is that the only significant antecedents of successfully implementing existing technologies are cognitive, not structural. A plausible explanation for this is that because the existing technological regime of F2P involves low

	Adoption	Implementation under ...	
		... the new technological regime	... the existing regime
Cognitive			
1. Volume (log)			-0.80^{*}
2. Breadth	-0.09^{**}	-1.18^{**}	0.75^{*}
Structural			
3. Hierarchy	0.19^{***}	1.46^{**}	
4. Differentiation (log)	-0.23^{***}		

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 3.7: Marginal effects of cognitive and structural antecedents. For clarity, statistically insignificant coefficients (i.e., p-value ≥ 0.05) are shown as empty cells.

task uncertainty and complexity, there is not much need for structural coordination (Galbraith 1973:26); instead, what matters is cognitive flexibility, which stems from having low volume (which avoids cognitive fixedness) and high breadth (which fosters cognitive diversity). In sum, organizational structure appears to be more important under the new technological regime than under the existing regime.

3.4.4 Comparison of effect sizes

To compare the effect sizes of cognitive and structural antecedents, we standardized the variables (zero mean and unit variance) and computed their marginal effects, as summarized in Table 3.7. These marginal effects can be interpreted as how a one-standard-deviation increase in each antecedent from its average value affects the dependent variables, all else being equal. Comparing these marginal effects yields two interesting observations.

One observation from Table 3.7 is that the main drivers in each column are qualitatively different. The first column of the table shows that adoption is mostly driven by structural antecedents (both hierarchy and differentiation are statistically significant, whereas at the cognitive level, only breadth is significant and it has a considerably smaller effect). The second column shows that implementation under the new technological regime is driven equally by cognitive and structural antecedents. And in contrast to the first column, the third column shows that implementation under the existing technological regime is driven by cognitive antecedents alone (both volume and breadth are significant, but structural antecedents are insignificant).

Another observation relates to how cognitive and structural antecedents can compensate for each other in different situations. In the first column, breadth has roughly half the magnitude of hierarchy and differentiation. This implies that to compensate for the adverse effect of breadth on adoption, firms can increase hierarchy (or decrease differentiation) by a small amount. In the second column, breadth and hierarchy have roughly the same magnitude. This suggests that to compensate for the adverse effect of breadth on performance under the new technological regime, firms can increase hierarchy by an equivalent amount (and vice versa). In the last column, since none of the structural antecedents are significant, we find no evidence to suggest that cognitive and structural antecedents can compensate for each other when implementing under the existing technological regime. Overall, these results highlight that compensation between cognition and organizational structure may only be possible sometimes: for adoption and for implementation under new technological regimes, but not for implementation of existing technologies. In that last case, it is crucial to have managers with the appropriate cognitive representations.

3.4.5 Interesting non-results regarding adoption and complementary assets

An interesting observation from Table 3.6 is that the coefficients associated with adoption (*Adoption*) and complementary assets (*Brand* and *Console*) are all statistically insignificant. These non-results contrast with previous research on the role of adoption and complementary assets.

The non-result for adoption is surprising, given the well-known emphasis on adopting disruptive innovations (e.g., Foster 1986, Christensen 1997). We are reminded by this finding that adoption is not the only way to adapt: firms can also succeed by staying under the current technological regime (in terms of Figure 3.1, the strategies in quadrants (b) and (d) are both valid). This observation lends support to the stream of research that has studied retrenching and "bold retreats" as viable strategies in the face of disruptive technological change (Utterback 1994:195–200, Adner and Snow 2010).

In turn, our non-results for complementary assets contrast with the studies highlighting the role of such assets (e.g., Teece 1986). We conjecture that complementary assets are insignificant in this setting, as brand recognition and console distribution may have lost much of their value with the introduction of F2P. Among F2P games, which are sold via app stores, brands are not very visible and few F2P games target consoles. And among non-F2P games, the increased competition from F2P lowered sales (by 2016, 92% of new mobile games were F2P; Appfigures 2017), making the effect of brand recognition and console distribution less relevant in absolute terms. These conjectures are consistent with research showing that complementary assets can lose their value under competence-destroying change (Tripsas 1997). Our results suggest the intriguing possibility that cognition and structure may be more reliable tools than traditional complementary assets when adapting to disruptive innovations. More research is necessary to determine when this may be the case.

3.4.6 Robustness checks

To validate the robustness of our results, we ran a series of stress tests explained below. The results of these tests (reported in detail in Appendix 3.6.3) are consistent with the findings presented so far, thereby increasing confidence in the validity of our findings.

First, to check whether potential common shocks across studios cause spurious correlations, we used two-way clustering by year and set of studios, obtaining robust results. Second, to ensure that firms with only one employee (which cannot have more than one supervisory level and one job title) do not bias the results, we dropped those observations from the sample and found that the results are consistent. Third, since adoption is an intermediate outcome that may bias the results for performance (this is sometimes referred as "bad control" bias; Angrist and Pischke 2008:64–68), we ran an additional analysis for performance by excluding adoption, attaining robust results. Fourth, to account for the variation in experience profiles across team members, we added as controls the standard deviations of both individual-level volume and individual-level breadth (*IndVolume* and *IndBreadth*, respectively), and found consistent results. Lastly, to check whether our results drastically change when adding a given control, we conducted a set of regression analyses that sequentially add these variables. These regressions show stable and consistent coefficients for the cognitive and structural antecedents, thus providing further evidence for the robustness of our findings.

3.5 Discussion

To date, the roles of cognition and organizational structure in the context of adaptation have remained unclear, given the conflicting theoretical predictions and the paucity of large-sample

	(1) Adoption	(2) Implementation under the new technological regime	(3) Implementation under the existing regime
Cognitive			
1. Volume			–
2. Breadth	–	–	+
Structural			
3. Hierarchy	+	+	
4. Differentiation	–		

Table 3.8: Summary of the effects of cognitive and structural antecedents on adoption and implementation. The symbols "+" and "–" each indicate the direction of the effect. Empty cells denote nonsignificant effects (i.e., $p > 0.05$).

empirical research. To address this problem, we took a process-based view and dissected adaptation into its constituent phases—adoption and implementation—providing the first large-sample study on how these two phases depend on cognitive and structural antecedents. We used the video game industry setting, which offers a rare opportunity to tease out the effects of these antecedents.

3.5.1 Managerial implications

For a firm facing a disruptive innovation, the dilemma is whether to embark on the risky endeavor of choosing the new technological regime or to pass up the potentially attractive opportunity in order to continue under the existing regime. Although there is obviously no infallible solution to this dilemma, our study provides some suggestions regarding how firms could organize when facing disruptive innovations. Table 3.8 summarizes these suggestions.

Our study suggests that to increase the probability of choosing the new technological regime (Column 1 of Table 3.8), the firm should hire specialists and design an organizational structure with more levels of supervision and broader job specifications (i.e., managers with less breadth and a taller hierarchy with less differentiation). To succeed under the new regime (Column 2 of Table 3.8), the firm should hire specialists and structure those individuals into more levels of supervision (i.e., individuals with more breadth and a taller hierarchy). And if the firm chooses to continue under the existing regime (last column of Table 3.8), it should hire inexperienced generalists (i.e., individuals with more breadth but less volume).

More generally, our results (a) suggest how different types of managers and structures fit with different strategies and (b) show that what is advantageous under one strategy can be insignificant or detrimental under another strategy.

3.5.2 Theoretical contributions

Our study contributes on five fronts. First, we show that the strategies of (a) adoption, (b) implementation under the new technological regime, and (c) implementation under the existing one are all affected differently by cognitive and structural antecedents—not all antecedents matter in all cases and not always in the same direction. Acknowledging this is not only important for managers (who need to know when to pull which levers and in what directions) but for researchers, who need to be aware of the contingencies that apply to the phenomena under study. Otherwise, little meaningful empirical progress is possible. For instance, because cognitive breadth can have either a positive or a negative effect depending on the technological regime (see Table 3.7), empirical researchers unaware of this contingency could estimate any effect (positive, negative, or zero) depending on the regime(s) their sample happened to contain. By taking a process-based view of innovation and pointing out differences among the drivers of adoption and implementation, our work contributes toward a contingency theory of adaptation.

Second, we illuminate the question of whether cognition and organizational structure can compensate for each other. Although recent theory papers have hinted that cognition and organizational structure—the two main levels at which firms process information—may compensate for each other (e.g., Gavetti 2005, Csaszar 2014), such a process has not been studied empirically, partly due to the challenges in gathering and measuring both of these antecedents across a large sample of firms. By jointly examining these two antecedents, our study shows that the compensation between cognition and organizational structure is achievable in some cases but not in others (e.g., it is not achievable when implementing under the existing regime; see Table 3.7). In other words, one cannot consider cognition and organizational structure as two independent levers.

Third, our work suggests reevaluating what contributes to adaptation to disruptive innovations. Studies have primarily focused on how adoption of disruptive innovations (e.g., Foster 1986, Christensen 1997) and the firms' complementary assets (e.g., Teece 1986, Tripsas 1997) contribute to adaptation, but have paid less attention to the roles of cognition and organizational structure. Interestingly, in our setting, we find no evidence that adoption and complementary assets influence adaptation, but find evidence that cognition and organizational structure do. This finding, thus, provides empirical support to the growing stream of research that calls for more attention to the cognitive and structural underpinnings of dynamic capabilities and organizational adaptation (e.g., Adner and Helfat 2003, Csaszar 2013, Helfat and Peteraf 2015).

Fourth, and more generally, our study suggests that it may be a good idea to reevaluate common ideas regarding firm innovation. For instance, the common wisdom is that hierarchy deters innovation, yet we find the opposite to be true in our setting (see Row 3 of Table 3.7). That is, hierarchy promotes adopting and implementing disruptive innovations. We theorize this will be the case when the disruptive innovation increases task uncertainty and complexity so as to require a substantial amount of information processing. This suggests that our results are more likely to generalize to the extent that the disruptive innovation poses important information processing challenges.

Lastly, this study introduces a novel empirical method to derive detailed measures of organizational structure and individual cognition for a large sample of firms. Our method employs text analysis on the employees' job titles to produce fine-grained measures of hierarchy (by categorizing those titles into different levels of supervision and counting the unique levels), differentiation (by counting the number of unique job titles), and depth and breadth of experience (by creating and analyzing per-employee experience profiles). This approach can be broadly applied in future empirical research on organization design and managerial cognition.

3.5.3 Limitations and future work

Like all research, this study has limitations which can be addressed by future work. First, the empirical analysis is carried out in the context of a single industry, which may not be representative of dynamics in other industries. For example, the dominant organizational form in our context is a project-based organization pursuing a single project. These organizations are ubiquitous in many industries (e.g., construction, film, management consulting) but not in others (e.g., agriculture, retail, transportation). Future research could test the generalizability of our predictions in different industries and using different organizational forms. A second limitation is that the managers' cognition was measured in terms of the volume and breadth of experience. Future research could complement these measures with traditional demographic measures that were not available to us (e.g., age, education, gender) and with more direct measures of the managers' cognitive representations (e.g., causal maps and lens models; Csaszar 2018). Third, although our extensive array of controls and robustness checks gives us confidence on our findings, the observational nature of our methodology cannot ensure causal identification. Hence, future work could revisit our questions using an experimental design (e.g., where hierarchy and differentiation are randomly assigned to same-sized projects). Lastly, cognitive and structural antecedents can affect not only adoption and performance but also other characteristics of decisions that we cannot see in the current setting, such as the speed with which decisions are made. Future research could examine effects on these other outcomes.

3.5.4 Conclusion

Why firms succeed in adapting to disruptive innovations or fail to do so is one of the most critical questions for managers and organizational scholars. To answer this question in a rigorous way, our study dissected adaptation to disruptive innovations into its two constituent phases—adoption and implementation—and disentangled how these two phases depend on the managers' cognition and the organization's structure. Our results underscore the importance of cognitive and structural antecedents and shed light on how they can compensate for each other to promote adaptation. Overall, our work reveals some surprising nuances that emerge when one carefully examines how firms adapt to disruptive innovations, and points out that common wisdom regarding the effects of cognition and organizational structure may not be so wise after all.

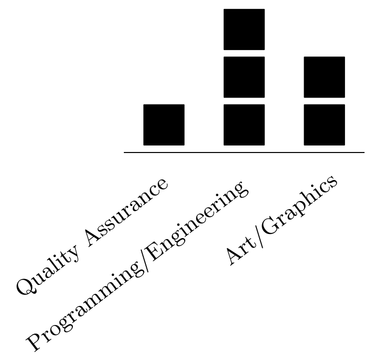
3.6 Appendix

3.6.1 Deriving experience profiles

Figure 3.5 illustrates how an individual's experience profile (panel (b)) is derived from her employment history (panel (a)). To derive an experience profile, we extract from the MobyGames database all the functional domains in which she participated prior to joining the current project, which we then tally.

Project	Functional domain
A	Quality Assurance
B	Programming/Engineering
C	Programming/Engineering
D	Art/Graphics
E	Programming/Engineering
F	Art/Graphics

(a) Hypothetical employment history of a project member.



(b) The project member's experience profile.

Figure 3.5: Deriving an individual's experience profile given her employment history.

3.6.2 Measuring hierarchy

To measure a project team's hierarchy, we first categorize each member's job title into one of the following 11 levels of supervision: "Owner," "President," "VP," "CEO," "CXO," "Head," "Director," "Manager," "Lead," "Supervisor," and "Other." To categorize the job titles, we apply Rules 1 to 11 in Table 3.9 in ascending order until a match is found. That is, we assign a member to a certain level of supervision if her job title includes terms relevant to that level (for the terms, see the third column in Table 3.9). In the list of relevant terms, we include common abbreviations (e.g., "snrvp" is an abbreviation of senior vice president) and typos (e.g., "cheif" is a typo of "chief") that appear in the MobyGames database. Finally, after categorizing all the members in the project into these levels of supervision, we count the number of levels of supervision with at least one member. This number is that team's hierarchy measure.

Rule	Level of supervision is:	If the job title includes any of these terms	Examples of job titles matched by the rule
1	Owner	*owner*, *founder*, *chairman*, *creator*, *created*, or *made*	"Created by," "Created and Developed by," "Chairman," "Made by"
2	President	*president* or *presidente* (but not *vice*)	"President," "President and CEO," "President & CEO," "President, North America"
3	VP	*vp*, *evp*, *avp*, *svp*, *snrvp*, *vice president*, or *vice presidente*	"Vice President," "Vice President of Marketing," "VP of Marketing," "Senior Vice President"
4	CEO	*ceo* or any combination of {*chief* or *cheif*} and {*executive*, *exec*, *exective*, or *executiver*}	"CEO," "Chief Executive Officer"
5	CXO	*cco*, *cdo*, *cfo*, *cho*, *cio*, *clo*, *cmo*, *coo*, *cpo*, *cso*, *cto*, or both *chief* and *officer*	"COO," "CFO," "Chief Creative Officer," "Chief Operating Officer"
6	Head	*head*	"Head of Production," "Studio Head," "Head of Marketing," "Head of Development"
7	Director	*director*, *directo*, *diercto*, *dir*, or *dierctor*	"Art Director," "Director," "Technical Director," "Creative Director"
8	Manager	*manager*, *mgr*, or *gm*	"Project Manager," "Product Manager," "QA Manager," "Production Manager"
9	Lead	*lead* or *leader*	"Lead Programmer," "Lead Artist," "Lead Tester," "Lead Designer"
10	Supervisor	*supervisor*	"Supervisor," "QA Supervisor," "Music Supervisor," "Test Supervisor"
11	Other	(includes none of the above)	"Testers," "Programmers," "Artists"

Table 3.9: Rules to assign a project member's job title to a level of supervision.

3.6.3 Robustness checks

Table 3.10 provides an overview of the robustness checks we performed along with pointers to the tables detailing each specific check.

Empirical concern: The results may be sensitive to ...	**Robustness check**: To validate the robustness of the results, we ran a series of stress tests that ...	**Results**: See ...
... common shock across studios	... use alternative clustered standard errors (i.e., two-way cluster by firm and year)	... Table 3.11 Part A
... one-person businesses	... subsample firms with more than one employee (i.e., *nEmployees* ≥ 2)	... Table 3.11 Part B
... the potential "bad control" bias from including adoption in estimating the coefficients for *Performance*	... exclude *Adoption*	... Table 3.11 Part C
... the variation in experience profiles across the team members	... include standard deviations of both individual-level volume and individual-level breadth	... Table 11 Part D
... certain controls or dummies	... sequentially add controls and dummies	... Table 3.12 for *Adoption* and Table 3.13 for *Performance*

Table 3.10: Overview of the robustness checks.

	Part A: Alternative clustered standard errors (Two-way clustering by studio and year)			Part B: Subsampling (Exclude one-person businesses)			Part C: Addressing potential bad control bias (Exclude *Adoption*)		Part D: Accounting for standard deviations of individual-level cognition measures		
	Adoption	**Performance**		**Adoption**	**Performance**		**Performance**		**Adoption**	**Performance**	
		Adoption=1	*Adoption*=0		*Adoption*=1	*Adoption*=0	*Adoption*=1	*Adoption*=0		*Adoption*=1	*Adoption*=0
Independent											
Volume (log)	0.39	0.22	-1.12^{*}	0.37	0.19	-0.93^{+}	0.38	-1.20^{**}	1.19^{*}	0.48	-0.79
	(0.29)	(0.59)	(0.45)	(0.30)	(0.62)	(0.48)	(0.59)	(0.45)	(0.49)	(0.80)	(0.68)
Breadth	-4.69^{**}	-11.87^{**}	7.52^{*}	-4.33^{*}	-11.61^{**}	7.04^{*}	-10.81^{**}	6.21^{*}	-5.96^{**}	-9.92^{*}	8.31^{*}
	(1.77)	(3.80)	(3.12)	(1.93)	(4.40)	(2.98)	(3.82)	(3.07)	(2.19)	(4.52)	(3.43)
Hierarchy	0.38^{***}	0.52^{**}	0.10	0.37^{***}	0.51^{**}	0.01	0.48^{**}	0.21	0.39^{***}	0.52^{**}	0.07
	(0.09)	(0.17)	(0.16)	(0.09)	(0.18)	(0.15)	(0.17)	(0.17)	(0.10)	(0.17)	(0.16)
Differentiation (log)	-0.88^{***}	-0.90	0.14	-0.86^{***}	-0.89	0.36	-0.75	-0.21	-0.86^{***}	-0.88	0.20
	(0.23)	(0.55)	(0.49)	(0.24)	(0.57)	(0.47)	(0.54)	(0.52)	(0.24)	(0.56)	(0.51)
Adoption		1.98			2.66^{+}					1.89	
		(1.29)			(1.43)					(1.38)	
Standard deviations of individual-level cognition measures											
sd(Volume)									-0.06^{+}	-0.02	
									(0.03)	(0.03)	
sd(Breadth)									-1.31	-3.63	
									(2.41)	(3.66)	
Controls											
nThemes	0.10	-0.03		0.11	-0.07		-0.02		0.06	-0.03	
	(0.16)	(0.22)		(0.16)	(0.21)		(0.22)		(0.16)	(0.22)	
nPerspectives	-0.52^{**}	0.37		-0.52^{*}	0.39		0.35		-0.52^{*}	0.37	
	(0.20)	(0.27)		(0.20)	(0.28)		(0.27)		(0.20)	(0.28)	
nPlatforms	-0.23^{***}	0.11		-0.23^{***}	0.09		0.11		-0.21^{***}	0.12	
	(0.06)	(0.08)		(0.07)	(0.08)		(0.08)		(0.06)	(0.08)	
Add-on	-1.97^{*}	0.53		-1.96^{*}	0.52		0.47		-1.91^{+}	0.51	
	(0.97)	(1.10)		(0.96)	(1.09)		(1.12)		(1.01)	(1.09)	
3D	-1.18^{+}	-0.39		-1.17^{+}	-0.36		-0.45		-1.16^{+}	-0.33	
	(0.62)	(0.53)		(0.62)	(0.54)		(0.54)		(0.60)	(0.54)	
LicensedTitle	0.14	0.30		0.14	0.28		0.25		0.07	0.26	
	(0.34)	(0.43)		(0.36)	(0.42)		(0.44)		(0.37)	(0.43)	
nEmployees (log)	0.34^{*}	0.83^{**}		0.36^{*}	0.88^{**}		0.85^{**}		0.32^{*}	0.83^{**}	
	(0.16)	(0.31)		(0.16)	(0.31)		(0.33)		(0.16)	(0.32)	
TeamBreadth	-0.11	-3.62^{*}		-0.03	-3.23^{*}		-3.81^{**}		-0.04	-3.30^{*}	
	(0.74)	(1.46)		(0.87)	(1.64)		(1.45)		(0.80)	(1.55)	
Brand	-0.02	0.15^{+}		-0.02	0.15^{+}		0.15^{+}		0.00	0.16^{+}	
	(0.06)	(0.09)		(0.07)	(0.09)		(0.09)		(0.07)	(0.09)	
Console	0.53	0.44		0.52	0.40		0.43		0.53	0.38	
	(0.64)	(0.42)		(0.65)	(0.42)		(0.43)		(0.69)	(0.44)	
nStudios	0.04	-0.65^{*}		0.03	-0.64^{*}		-0.60^{*}		0.06	-0.64^{*}	
	(0.19)	(0.28)		(0.21)	(0.29)		(0.28)		(0.20)	(0.29)	
ExpStudios	-0.09	0.04		-0.12	0.01		0.04		-0.14	0.01	
	(0.15)	(0.19)		(0.17)	(0.19)		(0.19)		(0.16)	(0.19)	
PriorF2PStudios	0.19^{*}	-0.08		0.20^{*}	-0.08		-0.07		0.18^{*}	-0.08	
	(0.09)	(0.07)		(0.09)	(0.07)		(0.08)		(0.09)	(0.07)	
Dummies											
Genre	Y	Y		Y	Y		Y		Y	Y	
Year	Y	Y		Y	Y		Y		Y	Y	
Standard errors clustered by	Studio and year	Studio and year		Studio	Studio		Studio		Studio	Studio	
No. observations	435	461		425	450		461		435	461	
(Pseudo) R-squared	0.22	0.32		0.22	0.33		0.31		0.23	0.32	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Note. Clustered standard errors in parentheses. All models include an intercept and dummy variables for genre and year, which are suppressed for ease of view.

Table 3.11: Checking robustness with respect to: (A) alternative clustering of errors, (B) subsample of studios with more than one employee, (C) "bad control" bias, and (D) standard deviation in individual-level cognition measures. Signs and significance levels are consistent with the main results (Table 3.6).

	Sequentially adding controls and fixed-effects														
	Adoption														
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Independent															
Volume (log)	0.48	0.48	0.48	0.43	0.44	0.42	0.40	0.42	0.47	0.45	0.44	0.44	0.35	0.34	0.39
	(0.32)	(0.32)	(0.32)	(0.30)	(0.30)	(0.29)	(0.29)	(0.27)	(0.28)	(0.29)	(0.29)	(0.29)	(0.27)	(0.26)	(0.30)
Breadth	−5.66**	−5.60**	−5.55**	−5.55**	−5.53**	−5.42**	−5.29**	−5.13**	−5.51**	−5.50**	−5.50**	−5.48**	−5.36**	−4.74**	−4.69**
	(1.84)	(1.85)	(1.86)	(1.71)	(1.71)	(1.69)	(1.68)	(1.59)	(1.78)	(1.79)	(1.79)	(1.79)	(1.69)	(1.63)	(1.81)
Hierarchy	0.29***	0.28***	0.30***	0.29***	0.31***	0.32***	0.31***	0.33***	0.33***	0.33***	0.33***	0.32***	0.33***	0.35***	0.38***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Differentiation (log)	−0.43**	−0.43**	−0.43**	−0.37*	−0.39*	−0.37*	−0.38*	−0.80***	−0.81***	−0.81***	−0.81***	−0.81***	−0.83***	−0.86***	−0.88***
	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.23)	(0.23)	(0.24)
Controls															
nThemes		−0.10	−0.14	−0.19	−0.18	−0.17	−0.16	−0.18	−0.19	−0.18	−0.19	−0.19	−0.20	−0.19	0.10
		(0.13)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)
nPerspectives			−0.50**	−0.44*	−0.47*	−0.47*	−0.47*	−0.50*	−0.50**	−0.51**	−0.52**	−0.52**	−0.50*	−0.45*	−0.52*
			(0.18)	(0.18)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)	(0.20)	(0.20)
nPlatforms				−0.27***	−0.27***	−0.28***	−0.28***	−0.28***	−0.28***	−0.28***	−0.28***	−0.28***	−0.28***	−0.27***	−0.23***
				(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)
Add-on					−1.77*	−1.81*	−1.81*	−1.93*	−1.90*	−1.91*	−1.91*	−1.91*	−1.88*	−1.81*	−1.97*
					(0.74)	(0.75)	(0.74)	(0.79)	(0.79)	(0.78)	(0.78)	(0.79)	(0.80)	(0.83)	(0.97)
3D						−1.07*	−1.08*	−1.07*	−1.07*	−1.06*	−1.08*	−1.08*	−1.10*	−1.14+	−1.18+
						(0.49)	(0.50)	(0.50)	(0.50)	(0.51)	(0.51)	(0.51)	(0.52)	(0.59)	(0.62)
LicensedTitle							0.23	0.14	0.14	0.13	0.13	0.13	0.18	0.17	0.14
							(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.36)
nEmployees (log)								0.38*	0.36*	0.36*	0.36*	0.36*	0.34*	0.39*	0.34*
								(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.16)
TeamBreadth									0.43	0.43	0.43	0.43	0.45	0.57	−0.11
									(0.81)	(0.82)	(0.82)	(0.81)	(0.81)	(0.82)	(0.76)
Brand										0.02	0.02	0.01	−0.01	0.02	−0.02
										(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
Console											0.34	0.33	0.36	0.29	0.53
											(0.64)	(0.64)	(0.62)	(0.63)	(0.64)
nStudios												0.04	0.02	0.13	0.04
												(0.18)	(0.18)	(0.19)	(0.20)
ExpStudios													0.10	−0.14	−0.09
													(0.12)	(0.14)	(0.16)
PriorF2PStudios														0.16*	0.19*
														(0.07)	(0.09)
Dummies															
Genre															Y
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	461	461	461	461	461	461	461	461	461	461	461	461	461	461	435
(Pseudo) R-squared	0.08	0.08	0.09	0.13	0.14	0.15	0.15	0.16	0.16	0.16	0.16	0.16	0.16	0.18	0.22

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Note. Standard errors clustered by the set of studios in parentheses. The intercepts and dummy variables for genre and year are suppressed for ease of view.

Table 3.12: Checking robustness by adding controls sequentially in estimation of *Adoption*. Signs and significance levels are stable as variables are added.

	Sequentially adding controls and fixed-effects															
	Performance															
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Adoption=1																
Volume (log)	0.83	0.59	0.60	0.60	0.63	0.64	0.62	0.53	0.45	0.08	−0.04	−0.04	0.08	0.36	0.37	0.22
	(0.66)	(0.66)	(0.65)	(0.65)	(0.65)	(0.65)	(0.65)	(0.66)	(0.65)	(0.66)	(0.65)	(0.65)	(0.64)	(0.63)	(0.62)	(0.60)
Breadth	-14.85^{***}	-15.77^{***}	-15.45^{***}	-15.48^{***}	-15.40^{***}	-15.48^{***}	-15.35^{***}	-14.56^{***}	-14.37^{***}	-10.44^{*}	-10.48^{*}	-10.48^{*}	-11.76^{**}	-12.49^{**}	-13.18^{**}	-11.87^{**}
	(3.84)	(3.89)	(3.92)	(3.95)	(3.95)	(3.97)	(3.96)	(4.00)	(4.07)	(4.31)	(4.31)	(4.34)	(4.28)	(4.25)	(4.23)	(4.01)
Hierarchy	0.45^{**}	0.50^{**}	0.50^{**}	0.48^{**}	0.48^{**}	0.47^{**}	0.47^{**}	0.42^{*}	0.48^{**}	0.47^{**}	0.44^{*}	0.44^{*}	0.47^{**}	0.46^{**}	0.44^{*}	0.52^{**}
	(0.17)	(0.18)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Differentiation (log)	0.01	−0.19	−0.19	−0.16	−0.19	−0.18	−0.18	−0.19	-0.90^{+}	−0.84	−0.82	−0.82	-0.90^{+}	−0.85	−0.82	−0.90
	(0.37)	(0.41)	(0.41)	(0.42)	(0.42)	(0.42)	(0.42)	(0.42)	(0.53)	(0.55)	(0.55)	(0.55)	(0.54)	(0.52)	(0.53)	(0.55)
Adoption=0																
Volume (log)	-1.01^{*}	-0.90^{*}	-0.93^{*}	-0.92^{*}	-0.91^{*}	-0.92^{*}	-0.92^{*}	-0.94^{*}	-0.83^{*}	-1.18^{**}	-1.29^{**}	-1.29^{**}	-1.35^{**}	-1.25^{**}	-1.24^{**}	-1.12^{*}
	(0.42)	(0.41)	(0.41)	(0.40)	(0.41)	(0.41)	(0.41)	(0.41)	(0.40)	(0.44)	(0.44)	(0.44)	(0.44)	(0.45)	(0.45)	(0.46)
Breadth	2.37	4.07	4.18	4.28	4.24	4.28	4.19	4.30	4.68^{+}	6.84^{*}	6.92^{*}	6.91^{*}	7.01^{*}	7.25^{*}	6.98^{*}	7.52^{*}
	(2.70)	(2.69)	(2.67)	(2.65)	(2.67)	(2.67)	(2.68)	(2.65)	(2.62)	(2.87)	(2.84)	(2.84)	(2.80)	(2.86)	(2.85)	(3.11)
Hierarchy	0.11	−0.03	−0.04	−0.04	−0.04	−0.06	−0.05	−0.07	−0.02	0.02	−0.00	−0.00	0.05	0.06	0.04	0.10
	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)	(0.17)	(0.17)	(0.16)	(0.16)	(0.16)	(0.15)	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)
Differentiation (log)	0.71^{+}	1.11^{**}	1.13^{**}	1.11^{**}	1.09^{**}	1.09^{**}	1.10^{**}	1.06^{**}	0.24	0.26	0.23	0.23	0.24	0.29	0.30	0.14
	(0.37)	(0.37)	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)	(0.34)	(0.50)	(0.51)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)	(0.50)
Adoption		2.40^{+}	2.32^{+}	2.36^{+}	2.38^{+}	2.39^{+}	2.37^{+}	2.40^{+}	2.24^{+}	2.04	1.96	1.96	2.26^{+}	2.26^{+}	2.33^{+}	1.98
		(1.40)	(1.40)	(1.40)	(1.41)	(1.41)	(1.41)	(1.40)	(1.35)	(1.34)	(1.34)	(1.34)	(1.34)	(1.35)	(1.36)	(1.38)
Controls																
nThemes			−0.32	−0.28	−0.26	−0.27	−0.26	−0.25	−0.26	−0.22	−0.20	−0.20	−0.17	−0.16	−0.16	−0.03
			(0.20)	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.22)
nPerspectives				0.52^{*}	0.51^{*}	0.52^{*}	0.52^{*}	0.54^{*}	0.50^{*}	0.50^{*}	0.43^{+}	0.43^{+}	0.45^{+}	0.39	0.36	0.37
				(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.28)
nPlatforms					0.10	0.10	0.10	0.10	0.08	0.08	0.08	0.08	0.10	0.09	0.08	0.11
					(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Add-on						0.86	0.85	0.85	0.73	0.57	0.55	0.55	0.78	0.74	0.67	0.53
						(0.85)	(0.86)	(0.88)	(0.87)	(0.88)	(0.89)	(0.89)	(1.00)	(1.04)	(1.03)	(1.10)
3D							−0.61	−0.63	−0.62	−0.66	−0.52	−0.52	−0.33	−0.31	−0.28	−0.39
							(0.55)	(0.55)	(0.54)	(0.55)	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)	(0.54)
LicensedTitle								0.84^{*}	0.68^{+}	0.69^{+}	0.59	0.59	0.62	0.51	0.51	0.30
								(0.41)	(0.41)	(0.40)	(0.39)	(0.39)	(0.40)	(0.41)	(0.41)	(0.43)
nEmployees (log)									0.67^{*}	0.84^{**}	0.82^{**}	0.82^{**}	0.85^{**}	0.88^{**}	0.85^{**}	0.83^{**}
									(0.29)	(0.29)	(0.30)	(0.30)	(0.29)	(0.29)	(0.29)	(0.31)
TeamBreadth										-3.45^{*}	-3.48^{*}	-3.48^{*}	-3.51^{*}	-3.62^{*}	-3.69^{*}	-3.62^{*}
										(1.51)	(1.50)	(1.50)	(1.51)	(1.50)	(1.48)	(1.47)
Brand											0.16^{*}	0.16^{*}	0.21^{**}	0.26^{**}	0.25^{**}	0.15^{+}
											(0.07)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)
Console												−0.03	0.17	0.12	0.16	0.44
												(0.38)	(0.40)	(0.40)	(0.40)	(0.42)
nStudios													-0.59^{*}	-0.55^{*}	-0.64^{*}	-0.65^{*}
													(0.27)	(0.27)	(0.27)	(0.29)
ExpStudios														−0.24	−0.07	0.04
														(0.15)	(0.18)	(0.19)
PriorF2PStudios															−0.11	−0.08
															(0.07)	(0.07)
Dummies																
Genre																Y
Year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	461	461	461	461	461	461	461	461	461	461	461	461	461	461	461	461
R-squared	0.15	0.16	0.17	0.18	0.18	0.18	0.18	0.19	0.21	0.23	0.23	0.23	0.25	0.25	0.26	0.32

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$

Note. Standard errors clustered by the set of studios in parentheses. The intercepts and dummy variables for genre and year are suppressed for ease of view.

Table 3.13: Checking robustness by adding controls sequentially in estimation of *Performance*. Signs and significance levels are stable as variables are added.

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