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

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March 23, 2020

Forthcoming in *Strategy Science*

*For their useful suggestions, we would like to give special thanks to Robert Axelrod, JP Eggers, Daniel Keum, Jeho Lee, Sunkee Lee, Casidhe Horan Troyer, and the editorial team at Strategy Science. We also thank the seminar participants at the University of Michigan, Boston College, ESSEC, INSEAD Singapore, the 2018 Strategy Science Conference, and the 2019 Academy of Management Annual Meeting. Research support from the Kwanjeong Educational Foundation and the University of Michigan Rackham Graduate School is gratefully acknowledged. All errors are the authors' own.

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Abstract

This paper studies how cognitive and structural antecedents 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.

Keywords: adaptation; innovation; managerial cognition; organizational structure

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 1) and illustrated with cases on how the firms in the photography industry reacted to the arrival 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 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

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

Figure 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.

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 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

[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).

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.

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.

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 1 for a synopsis of 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 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

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 1: Taxonomies describing the phases of adaptation.

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 2 summarizes the mechanisms predicting the positive and negative effects of cognitive and structural antecedents on decision quality. These 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.

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

[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 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.

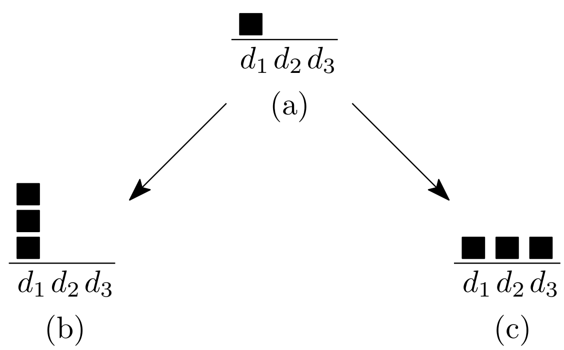

Figure 2: Illustration of volume and breadth of expertise. Panels (a), (b), and (c) characterize three different experience profiles. Each box represents a unit of experience (e.g., having worked in a given functional domain for the extension of a project). The functional domains are denoted d_1, d_2, and d_3.

(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 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).

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 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 technology.

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).

[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).

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.

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]

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–

[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).

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]

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 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?

[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.

[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 2 are occupied), we believe it is more natural not to write down hypotheses in this section.

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.

3.1 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 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). 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.

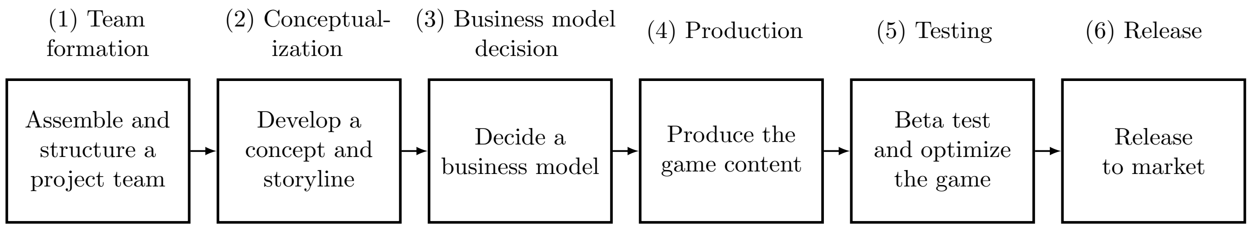

Figure 3: Process of video game development.

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). 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.

3.2 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 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

[8] ThinkGaming estimates revenues using a proprietary model that combines games' prices, number of downloads, and sales data shared by F2P games.

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 (2012) and Rietveld (2018).

3.3 Measurement

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 for details).[9] Thus, formally:

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

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

3.3.2 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.

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 A). 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

[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.

[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.

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

$$Hierarchy_p = \big|\{\text{unique levels of supervision in project } p\}\big|$$
$$Differentiation_p = \big|\{\text{unique job titles in project } p\}\big|$$

To illustrate our measures, consider the hypothetical four-person project team shown in Figure 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 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 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

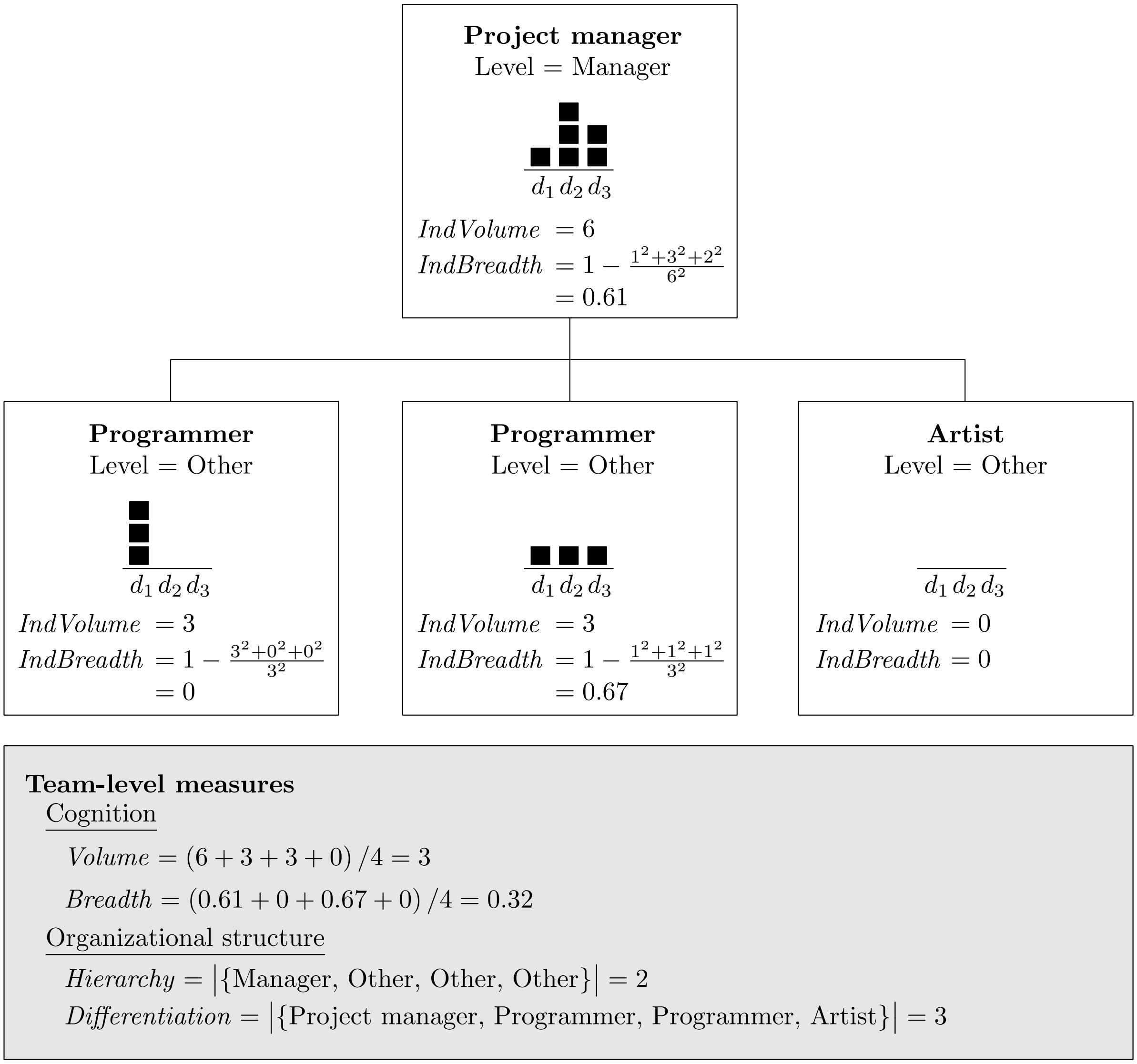

Figure 4: Computing the cognitive and structural measures for a hypothetical four-person project team.

control variables described in Table 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

[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: Description of the control variables.

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).

	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 4: Descriptive statistics.

3.4 Descriptive statistics and correlation matrix

Table 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*).

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 5 displays the correlation matrix, which shows a high level of correlation (larger than 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.

3.5 Model specification

Because the video game development process is sequential (as shown in Figure 3), we can specify our empirical model using two equations—one to estimate the probability of adoption and the other

[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 $Breadth = 0.34$ ($= 1-(8^2+1^2+1^2)/10^2$).

	(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 5: Correlation matrix.

to estimate performance. Thus, our empirical model is specified as follows:

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

$$\begin{aligned}\mathbb{E}[Performance] = \beta_0 + \quad & Adoption \quad \times (\beta_1 Volume + \beta_2 Breadth + \beta_3 Hierarchy + \beta_4 Differentiation) \quad (2)\\ & + (1 - Adoption) \times (\beta_5 Volume + \beta_6 Breadth + \beta_7 Hierarchy + \beta_8 Differentiation)\\ & + \beta_9 Adoption + Controls\end{aligned}$$

where $L(\cdot)$ is the logistic function and *Controls* stands for the control variables (described in Table 3) in both equations. Equation 1, which specifies the probability of adoption as a function of cognition and organizational structure, is estimated using logistic regression. In turn, Equation 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 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.

4 Results

Table 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 1). In turn, Models 3 and 4 present the OLS estimates for implementation (Model 3 is a baseline and Model 4 replicates Equation 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

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

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) 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).

4.1 What determines the probability of adoption?

Recall that, as summarized in Table 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.

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).

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

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

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 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.

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 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 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.

4.5 Interesting non-results regarding adoption and complementary assets

An interesting observation from Table 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 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.

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 C) 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

	(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 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., $p > 0.05$).

findings.

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 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.

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 8 summarizes these suggestions.

Our study suggests that to increase the probability of choosing the new technological regime (Column 1 of Table 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 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 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.

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 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 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 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.

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 and Laureiro-Martinez 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.

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.

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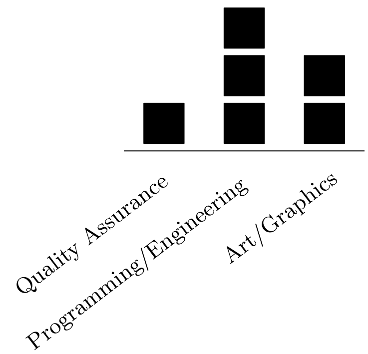
A Appendix: Deriving experience profiles

Figure 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 5: Deriving an individual's experience profile given her employment history.

B Appendix: 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 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 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 9: Rules to assign a project member's job title to a level of supervision.

C Appendix: Robustness checks

Table 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 11 Part A
… one-person businesses	… subsample firms with more than one employee (i.e., *nEmployees* ≥ 2)	… Table 11 Part B
… the potential "bad control" bias from including adoption in estimating the coefficients for *Performance*	… exclude *Adoption*	… Table 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 12 for *Adoption* and Table 13 for *Performance*

Table 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 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 6).

	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
	Sequentially adding controls and fixed-effects														
	Adoption														
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 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 13: Checking robustness by adding controls sequentially in estimation of *Performance*. Signs and significance levels are stable as variables are added.