Variability: The effects of variation in power relations within the firm, in its market performance, and in the evaluations of its products

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4. Pushing the boundaries: Determinants of exploration in the video game industry[5]

Abstract

This study examines how trends and variability of past performance predicts organizations' tendency to engage in explorative behavior. The empirical setting is the video game industry. The data refer to 5312 video games from 362 video games developers released in the period between 2000 and 2009. The study finds that a positive trend in performance decreases the likelihood of exploration. This confirms literature that suggests that organizations avoid risk-taking behavior if there is no immediate need. A high variability of past performance increases the probability of organizations to engage in exploratory behavior. By means of exploration, organizations can offset the uncertainty created by high variability in performance. Competitive intensity attenuates the effects of positive performance trends on explorative behavior and intensifies the effects of high variability. The study discusses the theoretical and managerial implications of the findings.

Keywords: Exploration, Performance feedback, Video Games Industry

4.1. Introduction

Organizations have to choose whether they explore new opportunities, exploit their current business or do both. Through exploration, firms can respond to environmental changes and thus ensure future viability (Danneels, 2002; Geroski, Machin, and Van Reenen, 1993; Levinthal and March 1993; March 1991). However, exploration also has a downside since exploration entails activities that embody higher risks (Gupta, Smith, and Shalley, 2006; March, 1991; Voss, Sirdeshmukh, and Voss, 2008). Exploitation, on the other hand, refers to the use and further development of existing knowledge and competences (Danneels, 2002). Returns from exploitation are more proximate and predictable, ensuring a company's current rather than future viability (Benner and Tushman, 2003; Danneels, 2002).

To explain why companies are willing to take the risk of exploration, March (1991) argues that companies have a greater stimulus to search for alternatives (i.e. exploration) "if

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the most preferred known alternative is below the target" (March, 1991: 72). This line of argument suggests that the performance level of the organization is an important rationale or motive for exploration. However, to date, existing literature on exploitation and exploration pays scant attention to performance as an antecedent of explorative and exploitative behavior. Instead, this literature mainly considers the effects of exploration on performance. This paper revisits the argument of March (1991), examining past performance as a determinant of explorative behavior. To do so, this paper examines the influence of performance trends (the general tendency of the changes in performance over time) and variability (the measure of dispersion or instability of performance over time). A dynamic view on performance provides richer information than when focusing on average performance figures alone.

Existing literature on ambidextrous organizations, that is, organizations that engage in both explorative and exploitative behavior, argues that the availability of resources stimulates firms to both explore and exploit (Raisch and Birkinshaw, 2008). However, organization literature suggests that firms tend to avoid risk-taking behavior including exploration, particularly in the case of lack of compelling reasons to do so (Audia and Greve, 2006; Danneels and Sethi, 2010; Lehman and Hahn, 2012).

Next to examining whether a positive performance trend impedes or stimulates explorative behavior of firms, this paper examines the influence of variability of performance on exploratory behavior. Variability of performance creates uncertainty and risks. If this variability results from current activities - and therefore exploitation would only exacerbate this situation-, organizations can attempt to offset this by means of exploration, even though exploration in itself is also uncertain and risky.

Prior research suggests that the competitive environment of an organization influences the strength of the relationship between exploration/exploitation and performance (Calantone, Yeniyurt, Townsend, and Schmidt, 2010; Jansen, Bosch, and Volberda, 2006; Voss et al., 2008). A high degree of competition in general results in lower performance due to competition for resources (Singh, 1986) and pressure to reduce cost (Matusik and Hill, 1998). This study also looks at competitive intensity as a moderator of the main relationships, positing that intense competition will weaken the effects of a positive performance trend on explorative behavior and strengthens the effects of performance variability on explorative behavior.

Exploration can be a result of: (1) developing new technology, (2) entering a new market segment, or a combination of both (Abernathy and Clark, 1985; Benner and Tushman, 2003). In this paper, the focus is on technology-driven firms that develop new technological products for market segments they do not yet serve. Exploring new customers, as opposed to exploiting an existing customer base, requires a proactive market approach (Danneels, 2002), which may be quite challenging, particularly for technology-driven firms. In technology-driven firms, technology exploitation and exploration is, in general, an ingrained part of ongoing business and often necessary for organizational survival (Gilsing and Nooteboom, 2006). Unlike new technology exploration, new market exploration on the other hand is not always necessary for the survival of technology-driven firms and thus can be seen as true risk-taking behavior.

The specific empirical setting for this research on performance and explorative behavior is the video game industry. Video game developers are technology-driven since they have to update their game source code and development techniques continuously to adapt to the new technologies in the console graphical and music processors, operating systems, and new user interfaces (Schilling, 2003). Indeed, video game developers often distinguish themselves not by means of technology from the competition, but through non-technological factors such as graphics, storytelling, world building and leveling (Koster, 2010). When video game developers explore new market segments, they in general do so by means of exploring new video game genres, as particular groups of consumers who constitute specific market segments, tend to buy video games of particular genres (Greenberg, Sherry, Lachlan, Lucas, and Holmstrom, 2010). Serving new consumers by expanding into new video game genres is a type of explorative behavior that is relatively easy to observe. Furthermore objective performance data on video game developers is in the public domain. These factors make the video game industry an excellent empirical setting for this research on determinants of explorative behavior.

The next two parts of the paper present the theoretical framework and the method. Then, a description of the results will be given and the paper concludes with providing implications for both theory and practice and discussing the limitations of the research.

4.2. Theoretical framework

4.2.1. A model for exploratory behavior

Based on a review of the literature, Raisch and Birkinshaw (2008) provide a framework that covers antecedents, moderators and outcomes of explorative and exploitative firm behavior. According to this framework, organizational structure, context, and leadership are important organizational antecedents. In their model, Raisch and Birkinshaw (2008) include performance as an outcome variable rather than an antecedent - as this paper does. Their model does include resource endowments, but as a contingency factor that influences firms' tendency to engage in exploitative and explorative behavior. More specific, based on prior literature, they suggest that firms' ability to engage in both explorative and exploitative behavior "may be contingent on the availability of sufficient resources" (Raish and Birkinshaw, 2008: 395).

Figure 1 presents the model that guides this study. Instead of using performance as the outcome of exploration, the model considers performance as a determinant of explorative behavior. The model makes a distinction between performance trend and performance variability. Financial analysts employ both of these constructs to predict future performance (Bondt, 1993). These two constructs have different functions; variability serves to inform investors about the instability of performance, while trend provides information about the tendency of performance movement into a specific direction over time (Bondt, 1993). Analogously to the literature about stock market investment decisions, this paper will show how performance in terms of trend and variability determines organizational exploratory decisions.

In addition to trends in and variability of performance as determinants of explorative behavior, the model includes competitive dynamics as a moderating variable. The expectation is that competitive intensity will create a perception of threat, and as threat increases, organizations should be more willing to risk and invest on exploration (Voss et al., 2008). The next two sections provide arguments for the relationships shown in Figure 4.1.

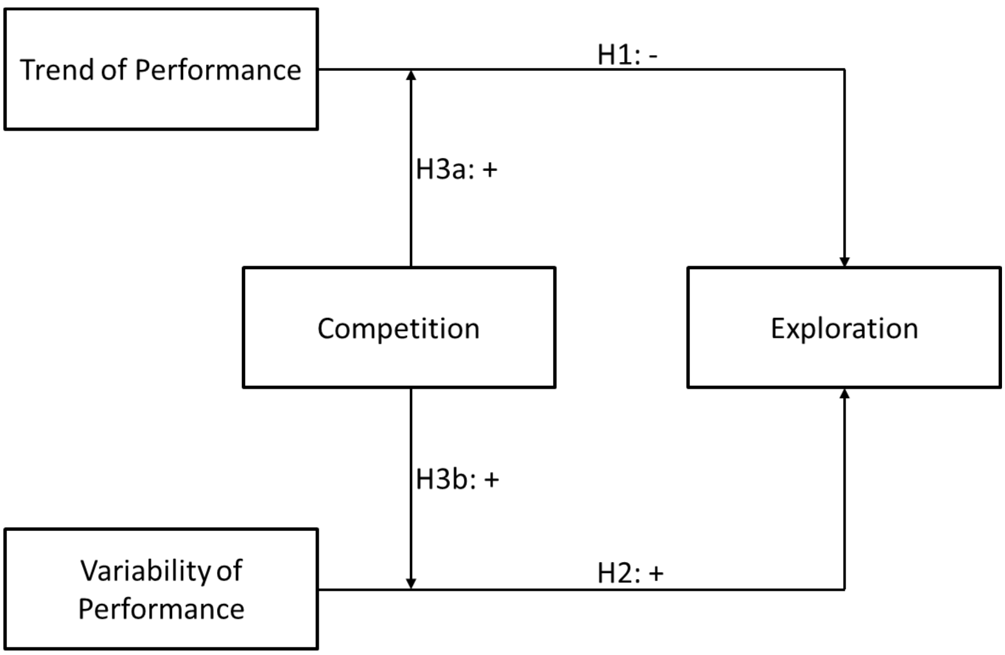

Figure 4.1 Conceptual Model

4.2.2. Trends in past performance and explorative behavior

Literature on organizational ambidexterity tends to study performance in terms of outcomes rather than in terms of antecedents. Studies on the relationship between resource endowments and exploration and exploitation examine how stocks of resources accumulated over time, influence explorative or exploitative behavior or how the simultaneous pursuit of both exploration and exploitation influences stocks of resources (e.g., Ebben and Johnson, 2005; Jansen et al., 2006; Voss et al., 2008). One of the few studies that examine more in-depth how patterns of past performance affect explorative and exploitative behavior is of Lubatkin, Simsek, Ling, and Veiga (2011). In their study, Lubatkin et al. (2011) examine how companies' performance of one year prior (t-1) influences the ambidextrous orientation of SMEs in the subsequent period (t) and find there is no significant relationship. In a similar vein, Wu and Shanley (2009) find that in the US electromedical device industry, firm performance (measured in terms of return on assets) has no significant effect on firms' attempts to explore new knowledge.

Exploration is a risky decision because it involves the development of new technological or marketing trajectories for which returns are unclear, uncertain, and remote in time (Danneels, 2002). Similar to March (1991), other studies in the field of organization theory (e.g., Bazerman, 1984; Audia and Greve, 2006; Daneels and Sethi, 2010; Lehman and Hahn, 2012; Singh, 1986) argue that in particular underperforming entities are likely to engage in risk taking behavior. Singh (1986) for example, finds that organizations with above satisficing performance avoid risky decisions to maintain the status quo and ensure a similar level of satisfying performance in the future. Organizations that lack satisfying performance, on the other hand, tend to take risky decisions in hope to get a better return (Singh, 1986). In their study on nonprofit professional theatre companies, Voss et al (2008) find that having a high number of consumer subscriptions, reduces the theatre group's tendency to explore and take risks by means of new theatre plays and challenging artistic boundaries. Lehman and Hahn (2012) find evidence that the likelihood of risk taking among National Football League teams increases when performance is below the aspiration level.

Exploration may open up new opportunities that can strengthen an organization's position (Miller, Lant, Milliken, and Korn, 1996). However, similar to the reasoning on slack resources and organizational ambidexterity, some studies suggest that in favorable conditions, decision makers tend to engage in risk taking actions (e.g., Staw, Sandelands, and Dutton, 1981; Osborne and Jackson, 1988). In a recent study, Neill and York (2012) find that when managers view situations as favorable due to, for example, market growth, they tend to use more explorative strategies. On the other hand, they also find that when managers perceive the effects of actions as uncontrollable, uncertain or unpredictable, they tend to avoid explorative behavior. Considering these results and evidence that exploration is in general a high-risk strategy (Gupta et al., 2006), this paper predicts a negative effect between a positive performance trend and exploration:

H1. *A positive performance trend is negatively associated with the extent to which organizations engage in explorative behavior.*

4.2.3. Variability of past performance and explorative behavior

The conceptual model suggests that, next to performance trends, the distribution of performance changes –that is, variability –across products within an organization will affect the degree to which organizations engage in explorative behavior. Das and Chen (2007) find that a lack of consistency of stockbrokers' opinion over time has a detrimental effect on stock prices. Varying opinions among stockbrokers create an ambiguous and uncertain view towards the capability of a particular traded stock/commodity to yield favorable return. Such uncertainty negatively affects the sentiment that the stockbrokers have towards that particular share and indirectly their investment decisions with regard to these shares.

When performance is unpredictable and changing constantly, organizations will be likely to adopt diversification strategies to reduce this uncertainty (Bettis and Hall, 1982; Shi, 2004). One strategic option firms can use is to expand, change, or diversify their product portfolio (Shi, 2004). For example, large movie studios tend to co-finance various movie projects at the same time to mitigate risks since performance outcomes of their movies are highly uncertain (Goettler and Leslie, 2005). Another option is to diversify operations by entering a different market segment to reduce demand risk (Kim, Hwang, and Burgers, 1993; Shi, 2004). The study of Kim et al. (1983) of 152 multinational organizations shows how targeting different nations can offset risk and increase the return of investment as the practice reduces the risk exposure as well as offering different investment opportunities.

In sum, prior literature on variability suggests that high variability in performance creates uncertainty. Organizations can reduce this uncertainty by means of developing new products and markets that eventually can provide for a more consistent stream of revenues. Developing new products and markets is, however, also fraught with risk. Thus, when performance variability is high, firms will tend to engage more often in explorative behavior.

H2. A high level of performance variability is positively associated with the extent to which organizations engage in explorative behavior.

4.2.4. The moderating role of competition

Studies on organizational ambidexterity suggest that competitive intensity is an important moderating factor influencing the relationship between exploration/exploitation and firm performance (Levinthal and March, 1993; Lewin, Long, and Carroll, 1999; Auh and Menguc, 2005; Jansen et al., 2006). Empirical results are, however, not clear-cut. Jansen et al (2006) for example hypothesize that, because intense competition usually reduces available resources for exploration, intense competition negatively moderates the relationship between exploration and financial performance. However, in their study of explorative and exploitative behavior of business units of a large European financial services firm, they do not find support for this prediction. To explain this finding, Jansen et al. (2006) point out that, if intense competitive rivalry is long-term, "[t]he only way to refrain from decreasing margins may be to develop radically new products and services for emerging markets or customers." (Jansen et al., 2006: 167).

Studies on industry dynamics and innovation suggest that the degree to which firms innovate is contingent to the degree of competition within an industry (e.g. Geroski, 1994). In highly competitive environments, innovation (i.e. exploration) can offer firms a possibility to escape intensive pressures for higher efficiency and lower prices (Matusik and Hill, 1998). Thus, in environments in which competition is intense, the tendency of firms to engage in explorative behavior may be higher, since this type of behavior can help the organization to escape competitive pressure (Abebe and Angriawan, 2013). This tendency may be more strongly present if organizations have a record of positive past performance, since this will ensure that organizations have sufficient slack resources for explorative innovations. In a similar vein, the urgency for organizations with relative unstable performance outcomes to engage in explorative behavior will even be higher in the case of intense rivalry. They will, however, have less organizational slack than those with a more consistent positive performance track record. Considering the urgency to pursue explorative behavior for long-term viability, they still will have to engage in this behavior.

H3a. *Competitive intensity attenuates the negative relationship between a positive performance trend and the extent to which organizations engage in explorative behavior.*

H3b. *Competitive intensity intensifies the positive relationship between a high level of performance variability and the extent to which organizations engage in explorative behavior.*

4.3. Method

4.3.1. Data and sample

This study uses data from the console video game industry. One of the means to compete in this industry is by the continuous introduction of new video games titles (Williams, 2002). The development of new console video games, however, requires increasing amounts of resources due to sound-, graphical-, and programming complexities. For example, currently new video games for consoles require development budgets of US$ 3 to 10 million on average (Edwards, 2005).

The data for this study comprises of 5312 video games from 362 video games developers (n = 362), released between April 2001 and March 2010 on all major consoles (PS2, PS3, Wii, Xbox, Xbox 360). Video game developers release most of their new games during the second quarter of the year, which coincides with the July and August school holiday season or during the fourth quarter of the year, which coincides with the Thanksgiving-Christmas holiday season. Video games producers' financial year therefore begins at the 1st of April every year instead of the normal calendar year. Using 31 March as the end of the financial reporting year thus better reflects video game developers' annual performance cycle. The study uses Metacritic.com for the name of the developers responsible for the games, game release date, and genres of the games (Arsenault, 2009).

In the video game industry, genre is an important means of classification and examples of popular video game genres are action, racing, or first person shooter games.

Video games of a certain genre share common attributes such as plot similarities, similar visuals, and rules. These common attributes form the basis for audiences' expectations, unique for the genre (Hsu, 2006). Consumers who prefer certain genres of video games often share the same characteristics in terms of gender, personal traits, and personal motives for playing the games (Greenberg et al., 2010). Similar to creative industries such a film and music (Altman, 1999; Schatz, 1981), in the video game industry, genres represent specific market segments (Gartenberg, 2004; Prugsamatz, Lowe, and Alpert, 2010). Video game producers who explore by adding new genres to their product portfolio thus often enter into new market segments by doing so. Organizations' exploration into new genres requires them to understand the needs and preferences of consumers that favor this type of genre.

4.3.2. Model Specification

This study estimates the occurrence of explorative behaviors by organizations. The outcome variable is a binary variable that captures whether organizations explore new genres or not. Given the nature of the dependent variable a binary logistic estimation method is adopted (c.f. Chang, Kao, Kuo, and Chiu, 2012; Larimo, 2003). Similar to other types of regression analysis, the main function in a logistic regression makes use of one or more predictor variables. However, unlike OLS, the logistic method uses a logistic function to accommodate the binary outcomes of the dependent variable (treating the dependent variable as the outcome of a Bernoulli trial).

The main function in our study is a function of the trend and variability in performance, competitive intensity, the number of video game titles already produced, and average past performance (Equation 1). Mathematically the function can be written as follows:

$$f(x_{i,\hat{t}}) = \beta_0 + \beta_1 Trend\ ConsEval_{i,t} + \beta_2 Trend\ ExpertEval_{i,t} + \beta_3 Trend\ Sales_{i,t} + \beta_4 Var\ ConsEval_{i,t} + \beta_5 VarExpertEval_{i,t} + \beta_6 VarSales_{i,t} + \beta_7 Nr.Games_{i,t} + \beta_8 Competition_{i,t} + \beta_9 Avg\ ConsEval_{i,t} + \beta_{10} AvgExpertEval_{i,t} + \beta_{11} AvgSales_{i,t} + \beta_{12} Trend\ ConsEval_{i,t} * Competition_{i,t} + \beta_{13} Trend\ ExpertEval_{i,t} * Competition_{i,t} + \beta_{14} Trend\ Sales_{i,t} * Competition_{i,t} + \beta_{15} Var\ ConsEval_{i,t} * Competition_{i,t} + \beta_{16} VarExpertEval_{i,t} * Competition_{i,t} + \beta_{17} VarSales_{i,t} * Competition_{i,t} + \varepsilon$$

$$p(Expansion_{i,\hat{t}}) = \frac{e^{f(x_{i,\hat{t}})}}{1 + e^{f(x_{i,\hat{t}})}}$$

The second equation is the logistic function that embeds the main function specified in first equation, where *p*(*Expansion*) is the probability that an organization extends operations to at least one new genre. Table 4.1 provides an overview of the variable names and gives short descriptions. The next section gives a more in-depth description of the variables and their measurement.

Table 4.1 Overview of the variables

Variable name	Description
$p(Expansion_{i,\hat{t}})$	The probability (odds) of developer *i* expanding into a new genre in the time period $\hat{t}$ (2007-2009)
$TrendConsEval_{i,t}$	The trend of consumer evaluations of games released by developer *i* in the time period *t* (2001-2006)
$TrendExpertEval_{i,t}$	The trend of expert evaluations of games released by developer *i* in the time period *t*
$TrendSales_{i,t}$	The trend of sales of games released by developer *i* in the time period *t*
$VarConsEval_{i,t}$	The variability of consumer evaluations of games released by developer *i* in the time period *t*
$VarExpertEval_{i,t}$	The variability of expert evaluations of games released by developer *i* in the time period *t*
$VarSales_{i,t}$	The variability of sales of games released by developer *i* in the time period *t*
$Nr.Games_{i,t}$	The number of games released by developer *i* in the time period *t*
$Competition_{i,t}$	The number of games in the same genre occupied by developer *i* in the time period *t* that are not developed by *i*
$AvgConsEval_{i,t}$	The average of consumer evaluations of games released by developer *i* in the time period *t*
$AvgExpertEval_{i,t}$	The average of expert evaluations of games released by developer *i* in the time period *t*
$AvgSales_{i,t}$	The average of sales of games released by developer *i* in the time period *t*

4.3.3. Variables

4.3.3.1. Dependent Variable

The dependent variable in this study is whether or not the organization expands into new video game genres (1 = at least one video game released in a new genre, 0 = there are no video games released in a new genre). The timeframe for the dependent variable (t □) is the period from financial year 2007 to 2009. This timeframe is different from the timeframe (t) for the independent variables, which focus on the period from financial year 2001 to 2006.

The main reasoning behind the difference in the timeframe is that video game development is not an instant process. Video game development comprises of different development and testing stages to ensure the quality and stability of the resulting product (Egenfeld-Nielse, Smith and Tosca, 2012; Hall and Novak, 2008). The whole development process requires 24 months on average (Egenfeld-Nielse, Smith and Tosca, 2012; Hall and Novak, 2008). Therefore, if the management team decides to release a game in a new genre and this decision is taken at the end of financial year 2006, the earliest date for the launch date of the new game is at the end of financial year 2007. In order to accommodate for the differences of development time across games, this study extends the timeframe for the outcome variable to financial year 2009.

4.3.3.2. Independent Variable

The independent variables relate to trends and variability in video game performance in the past (2001-2006). To measure video game performance, the study uses three measures at the developer level. The first measurement is worldwide unit sales. Unit sales are a leading performance indicator for most companies as prices are relatively similar (Popova and Sharpanskykh, 2010; Venkatraman and Ramanujam, 1986).

Other performance measures are reviews by critics and end users. Reviews are forms of certification that can have a strong impact on consumer behavior, especially if the quality of the product is difficult to evaluate before consumption (e.g., Basuroy, Chatterjee, and Ravid, 2003; Gemser, Oostrum, and Leenders, 2007; Yang and Mai, 2010). Prior research suggests that expert and end user certification may substantially differ, both in nature and in degree of impact (Gemser et al., 2007; Moon, Bergey, and Iacobucci, 2010; Gemser, Leenders, and Wijnberg, 2008). Thus, contrary to prior research (e.g., Keller, 1993; Hennig-

Thurau, Houston, and Heitjans, 2009), this study makes an explicit distinction between expert and end user evaluations.

To calculate the trend or variability of performance, figures on yearly sales performance, consumer evaluations, and expert evaluations were calculated first. Yearly sales performance is the total sales of all games from a developer in a particular year. Yearly expert (consumer) evaluation is the average expert (consumer) evaluation score of all games from a developer in a particular year. Data on worldwide expert and consumer game evaluations comes from Metacritic.com; data on worldwide unit sales data on video games comes from the on-line database vgchartz.com.

Trend in performance. Yearly performance trends are calculable after obtaining the yearly performance data. Such calculation results into three trend lines: one for sales, one for consumer evaluations, and one for expert evaluations. This study uses the derived slope coefficients of the estimated trend lines as the measurement of trend of performance. These coefficients can be positive or negative; a positive value means the performance is increasing from 2001 to 2006, while a negative value means that the performance is decreasing. If the absolute value of this variable is larger, the trend's slope is steeper (Spicer, 2004: 23).

Variability in performance. This study uses variance as the method to calculate variability. This approach is not uncommon considering that prior literature also uses variance to measure variability and uncertainty (e.g., Dacin and Smith, 1994; Desai, Kalra, and Murthi, 2008). Similar to trend, this study uses the same yearly performance indicators to calculate the variability of performance from 2001 to 2006. After obtaining the yearly performance data, the variance of performance across years are calculated for each type of performance.

Competition. Competitive intensity in a genre is measured from a supply side perspective counting the total number of competing games in the same genres released by the developers in the period 2001 to 2006 minus their own games in that genre. Thus, for example, in the financial period 2001 to 2006, there were 665 games worldwide in the adventure genre, 290 games in the Role Playing genre, and 252 games in the First Person Shooter genre. Developer i produced 5 games in the role playing genre and 2 games in the first person shooter genre. The competition for developer i is (290-5) + (252-2) = 535.

This study controls for several factors. The first control variable is the total number of games from the same developer within the period of 2001 to 2006. This variable (Nr. Games) reflects the differences in resources of each video game developer to produce different products within the time frame 2001 to 2006. The assumption is that the more games a firm develops, the higher the probability this firm engages in explorative behavior. Finally, as an alternative to performance trend, the analyses include the average of consumer evaluations, the average of expert evaluation, and the average yearly sales in the period of 2001 to 2006.

4.4. Empirical results

4.4.1. Descriptive statistics and correlations

Table 4.2 presents the descriptive statistics and the correlations between the variables. In the period 2001-2006, 1812 video games were released in total. On average, each video game developer released 11 games and had a gradual but positive slope in terms of total sales in the specified time frame. Of the video game developers in the sample, 158 developers explore new genres within this period while the majority, 204 developers, remained active in the same genres in the 2001-2006 period.

Table 4.2 shows a negative correlation between the sales trend and exploration ($r = -.12$, $p<.05$). Table 4.2 also shows a positive relationship between exploration and the variability of consumer evaluations ($r = .20$, $p < .01$) and between exploration and the variability of sales ($r=.14$, $p< .01$). The relationship between exploration and trend of expert evaluation is positive but insignificant ($r = .02$, $p > .05$). There is no significant correlation between exploration and variability of expert evaluations either ($r = .09$, $p > .05$). Overall, the correlations between the independent variables do not exceed the $r = .50$ level. Multicollinearity is not a major concern here.

Table 4.2 Bivariate Correlations and Descriptive Statistics

		Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11
1	Exploration	.44	.50											
2	Trend Cons. Eval.	-.05	1.41	-.10										
3	Trend Expert Eval.	-.07	.61	.02	.37**									
4	Trend Sales	.95	2.09	-.12*	.32**	.01								
5	Var. Cons. Eval.	3.98	5.14	.20**	-.26**	.01	-.21**							
6	Var. Expert Eval.	1.06	1.98	.09	-.14**	-.02	-.07	.36**						
7	Var. Sales	45.73	80.26	.14**	.08	-.20**	.39**	-.12**	-.04					
8	Nr. Games	11	10.66	-.20**	.07	-.04	.21**	-.09*	.05	.31**				
9	Competition	459	318.01	.25**	.17**	.06	-.09*	-.02	.06	-.03	.45**			
10	Avg. Cons. Eval.	5.83	2.37	-.26**	.03	-.03	.25**	-.04	-.09*	.32**	.33**	.20**		
11	Avg. Expert Eval.	4.88	1.57	.13*	.07	-.07	.27**	.10*	-.10*	.38**	.27**	.17**	.46**	
12	Avg. Sales	.80	.74	-.27**	.10*	-.22**	.31**	-.12**	-.11*	.37**	.43**	.05	.46**	.41**

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

4.4.2. The determinants of explorative behavior

Two logit models are estimated to explain the occurrence of explorative behavior at the organizational level: Model 1 is the default model that only contains the control variables; Model 2 is the complete model that includes all of the main constructs. Model 2 will be used to test the hypotheses. Model 1 explains 82.3% of the variance in explorative behavior (Nagelkerke R^2 = .56); Model 2 explains 92.5% of the variance in behavior (Nagelkerke R^2 = .80). The significant decrease of -2*log-likelihood between Model 1 and Model 2 signifies an improvement of predictability in the complete model (164.39) from the default model (300.50). Table 4.3 shows the results.

The results show that a positive performance sales trend and a positive consumer evaluations trend have a negative effect on the probability of explorative behavior (B = -.3.35, p < .05 for consumer evaluations; B = -3.44, p < .05 for sales). A positive trend of expert evaluations has, however, no significant effect on the probability of explorative behavior (B = .39, p = .09). These results suggest that organizations are less likely to explore when consumers support their products, both in term of sales and evaluations. Support from experts seems to influence firms' tendency to explore in a positive way rather than a negative way, as predicted. However, this relationship is only marginally significant (p< .10) and thus these findings should be interpreted with care. In sum, the results of the analysis partly support Hypothesis 1.

Table 4.3. Results Exploration Models

Variable	Model 1					Model 2				
	Coefficient	S.D.	t		VIF	Coefficient	S.D.	t		VIF
constant	1.13	.54	2.08	*		-2.51	.82	-3.07	**	
Competition	.01	.00	7.02	***	1.01	.02	.00	6.33	***	3.37
Nr. Games	-.21	.03	7.70	***	1.36	-.35	.06	-6.42	***	1.62
Avg. Cons. Eval.	-.21	.05	-4.06	***	2.23	-.40	.18	-2.25	*	2.52
Avg. Expert Eval.	.71	.42	1.60		2.45	.90	1.13	.81		2.69
Avg. Sales	-.34	.05	-6.40	***	1.16	-.12	.03	-3.84	***	1.38
Trend Cons. Eval.						-3.35	1.56	-2.15	*	2.38
Trend Expert Eval.						.39	.20	1.69		2.12
Trend Sales						-3.44	1.51	-2.28	*	2.70
Var. Cons. Eval.						.29	.09	2.90	**	1.94
Var. Expert Eval.						.20	.13	1.51		2.03
Var. Sales						.00	.00	2.09	*	1.93
Trend Cons. Eval.* Competition						.01	.00	2.91	**	1.94
Trend Expert Eval.* Competition						.00	.02	.07		2.59
Trend Sales * Competition						.01	.00	3.62	***	2.60
Var. Cons. Eval.* Competition						.01	.00	4.52	***	1.67
Var. Expert Eval.* Competition						.55	3.83	.14		1.66
Var. Sales* Competition						.00	.00	3.25	**	1.45
Nagelkerke R^2	.56					.80				
c^2square	195.48	***				331.58	***			
-2*log-likelihood	300.5					164.39				

***. is significant at the 0.001 level (2-tailed). **. is significant at the 0.01 level (2-tailed). *. is significant at the 0.05 level (2-tailed).

Note1: Binary Logit Model, the dependent variable is: Market Segment Exploration (Yes/No: Binary), 2007-2009

Note2: The reported coefficients are not standardized due to the binary nature of the dependent variable (c.f. Chang, Kao, Kuo, & Chiu, 2012; Larimo, 2003)

Variability in evaluations signals a lack of stability of expert and consumer support for the products released by organizations over time. Hypothesis 2 suggests that in the case of high performance variability, firms will engage in explorative behavior to diversify operations and reduce risks.

This study indeed finds positive effects of variability of consumer evaluations (B= .29, $p < .01$) and variability of sales (B = .00, $p < .05$) on the probability of explorative behavior. However, variability of expert evaluations again has no significant effect on explorative behavior (B = .20, $p = .13$). These results partly support Hypothesis 2.

Competitive intensity has a positive relationship with the probability of explorative behavior (B = .02, $p < .01$). This result is similar to other studies who find that environmental dynamism is an antecedent of explorative behavior (Jansen, van den Bosch, Volberda, 2005). Furthermore, competitive intensity moderates the effects of trend of consumer evaluations (B= .01, $p < .01$), trend of sales (B= .01, $p < .001$), variability of consumer evaluations (B= .01, $p < .001$), and variability of sales (B= .00, $p < .01$). However, the study does not find significant coefficients for the moderating effects of competition towards the effect of expert evaluation trend nor variability. The results thus partly confirm Hypotheses 3a and 3b.

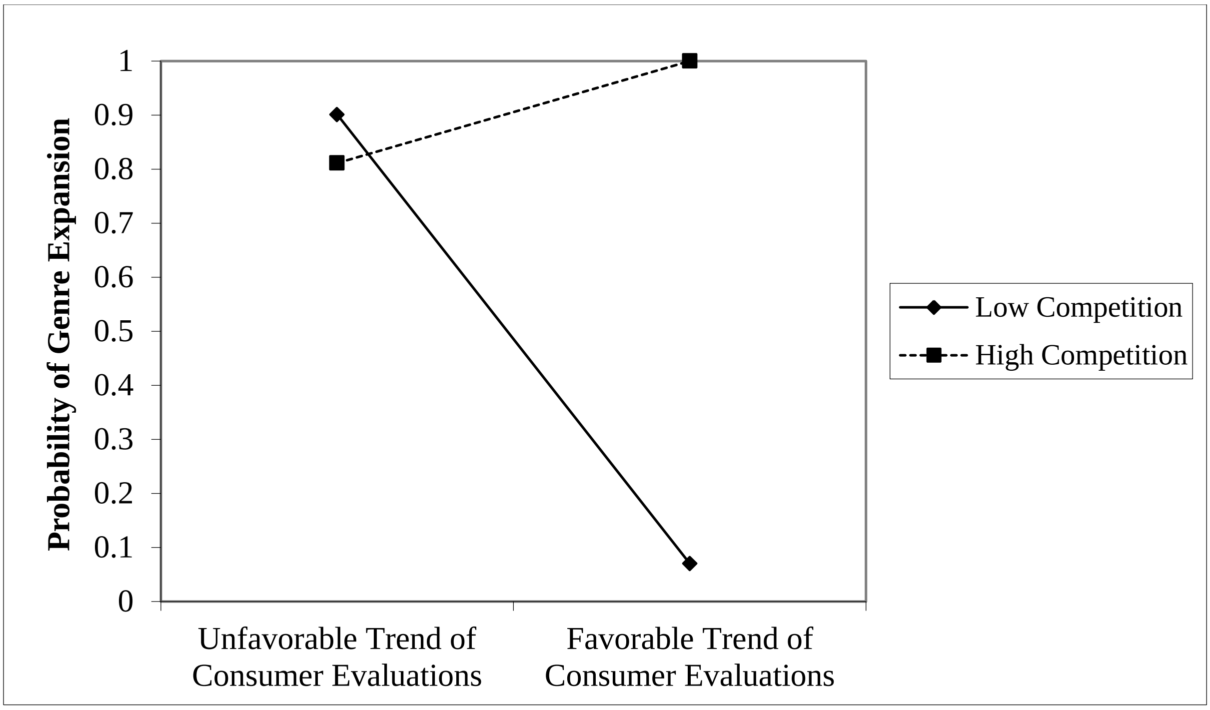

Figure 4.2 The probability of genre expansion affected by trend of consumer evaluations and competition

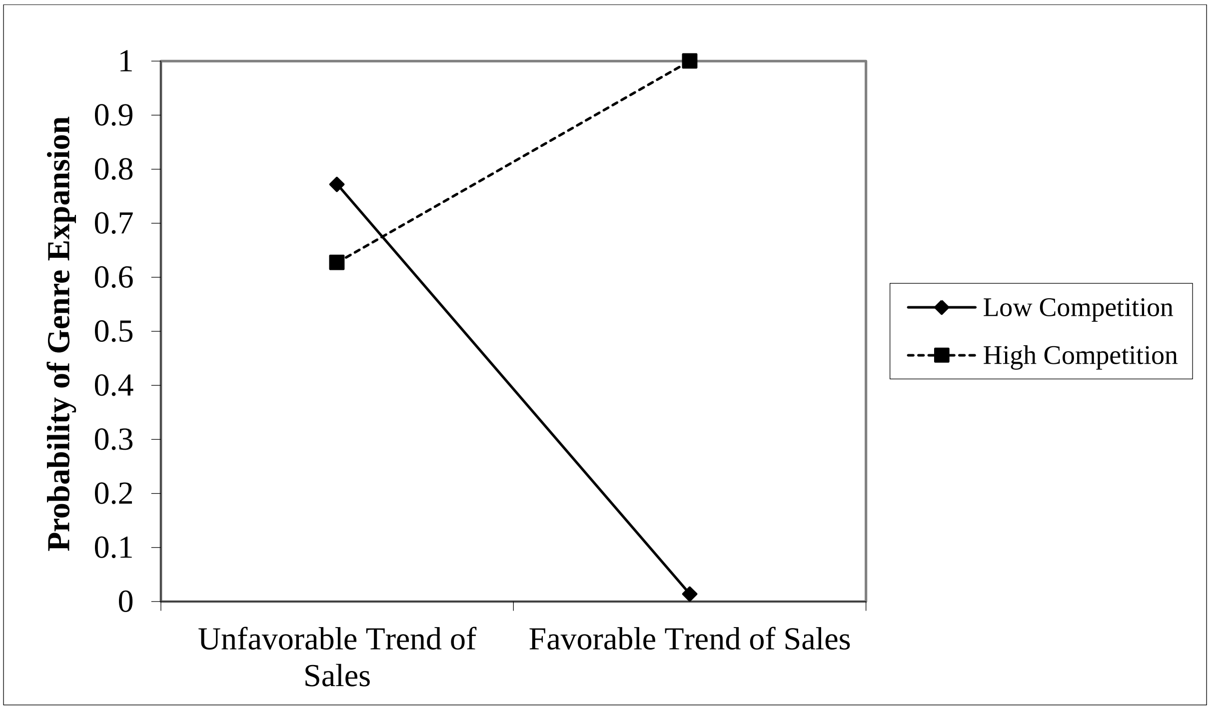

Figure 4.3 The probability of genre expansion affected by trend of sales and competition

Figure 4.2 visualizes how the underlying trend in consumer evaluations has a negative effect on explorative behavior. When competition is intense, the line is higher than when competition is low, indicating a positive moderating effect of competition on the trend of consumer evaluations. This effect is more prominent for the trend of sales (see Figure 4.3). Figure 4.4 and Figure 4.5 visualize the effects of variability in consumer evaluations and sales respectively on firms' probability to explore. The figures show a positive moderating effect of competitive intensity. Figure 4.5 suggest that whenever sales are highly variable over time, organizations will be more likely to engage in explorative behavior.

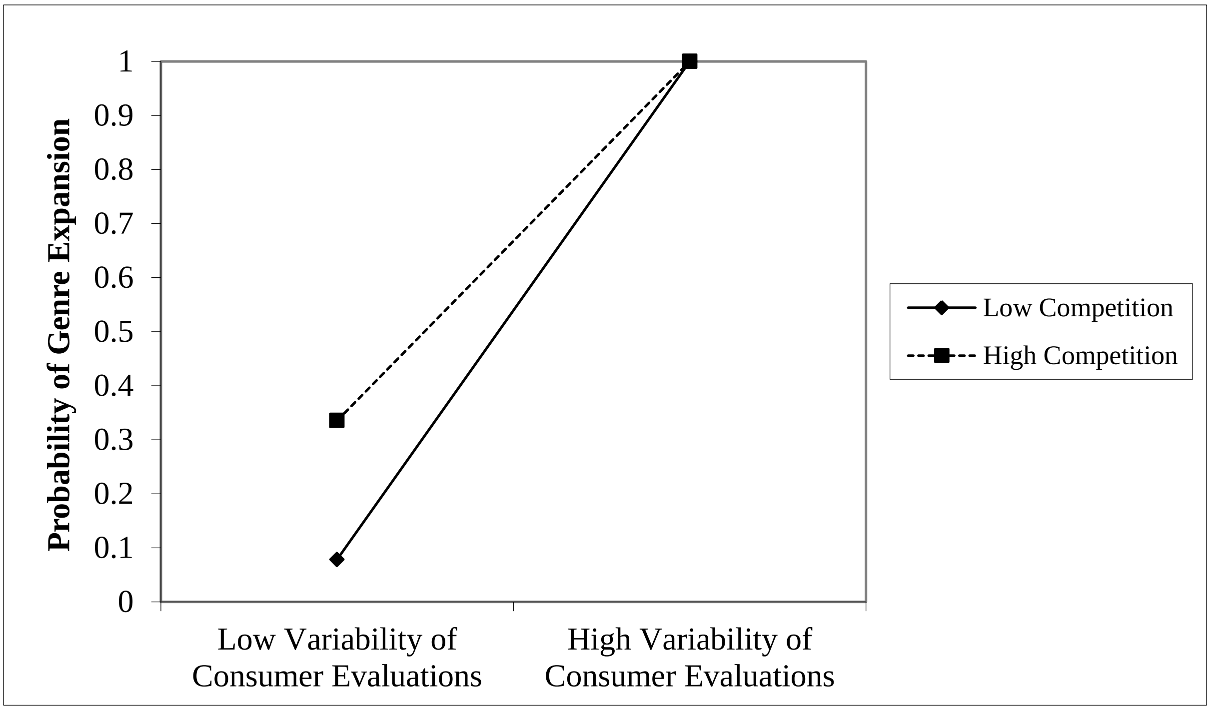

Figure 4.4 The probability of genre expansion affected by variability of consumer evaluations and competition

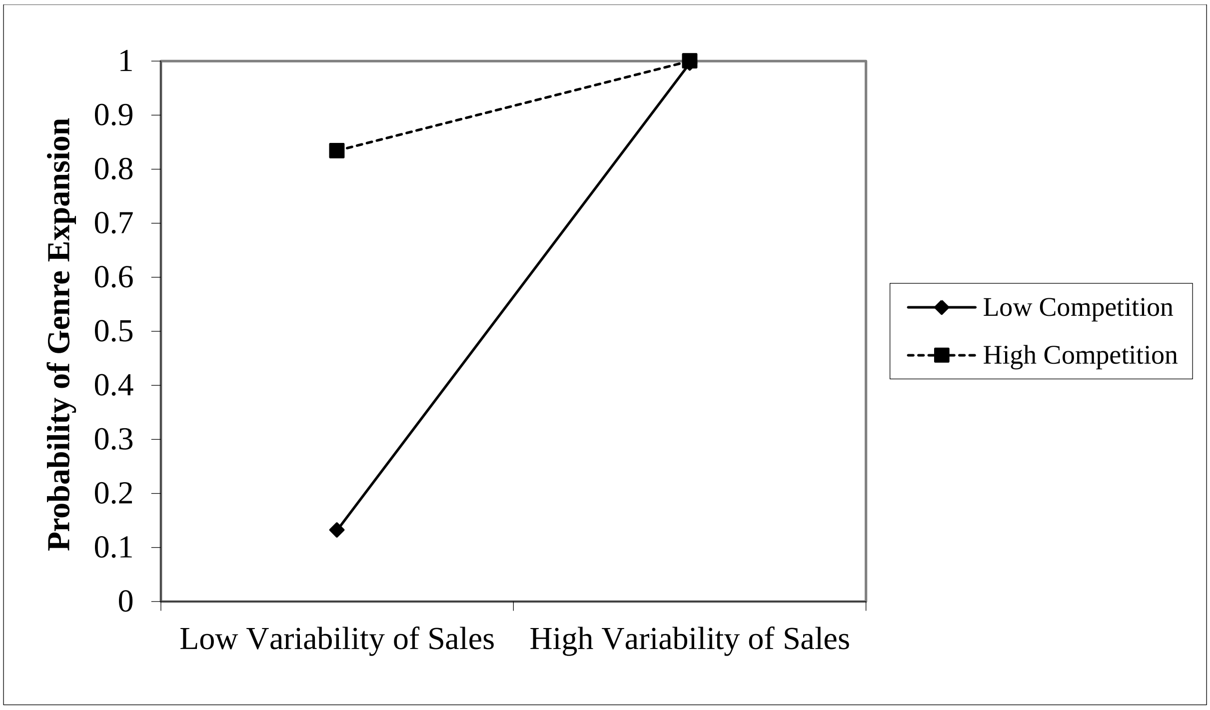

Figure 4.5 The probability of genre expansion affected by the variability of sales and competition

The variables that measure average performance (of sales, consumer evaluations, and expert evaluations) have the same sign and significance level as the trend indicators. The number of games produced by organizations has a significant effect on their tendency to explore (B = -.35, p < .001). Although significant, the sign is unexpectedly negative, which indicates that companies who produce more games are more likely to exploit the segments that they already occupy rather than entering new ones.

Table 4.4 Results Exploitation Model

Variable	Model 3				Model 4			
	β	t		VIF	β	t		VIF
constant	.46	2.08	*		.58	1.98	*	
Competition	.93	49.53	***	1.01	.94	49.33	***	3.37
Nr. Games	.04	1.74		1.36	.04	1.95		1.62
Avg. Cons. Eval.	.09	2.63	**	2.23	.10	2.97	**	2.52
Avg. Expert Eval.	-.01	-.34		2.45	-.02	-.51		2.69
Avg. Sales	.20	9.42	***	1.16	.29	7.64	***	1.38
Trend Cons. Eval.					.03	1.37		2.38
Trend Expert Eval.					.02	1.24		2.12
Trend Sales					.12	3.79	***	2.70
Var. Cons. Eval.					-.05	-2.54	*	1.94
Var. Expert Eval.					-.03	-1.61		2.03
Var. Sales					-.17	-4.43	***	1.93
Trend Cons. Eval.* Competition					-.04	-2.04	*	1.94
Trend Expert Eval.* Competition					-.05	-2.64	**	2.59
Trend Sales * Competition					-.07	-2.42	*	2.60
Var. Cons. Eval.* Competition					-.01	-.25		1.67
Var. Expert Eval.* Competition					-.01	-.63		1.66
Var. Sales* Competition					-.09	-3.47	***	1.45
R^2	.86				.88			
Adj. R^2	195.48	***			.87	***		
F	300.5				121.03			

***. is significant at the 0.001 level (2-tailed). **. is significant at the 0.01 level (2-tailed). *. is significant at the 0.05 level (2-tailed).
Note1: OLS Model, the dependent variable is: The quantity of sequel titles in the same genre from the same developer, 2007-2009
Note2: The coefficients are standardized (beta)

4.4.3. Robustness test: The determinants of exploitative behavior

To examine whether the results are valid, the model is re-estimated using an exploitation measure instead of exploration measure as dependent variable. Exploitation is measured as the quantity of sequels or spin off titles in the same genre produced by the same developer in the period of 2007 to 2009. The Exploitation Model uses the same independent and control variables as the Exploration model (Model 2) (c.f. Voss et al., 2008). Since the model measures quantity of sequels and spin offs, the nature of the dependent variable is not binary. This situation allows for the use of the OLS estimation rather than logistic regression. Table 4.4 presents the results. The exploitation model explains 88% of the variability of its dependent variable (R^2 = .88). The results indicate some opposite effects compared to the exploration model. For example, the effect of trend of sales on exploitative behavior is positive and significant (p < .001), while it is negative and significant in the Exploration Model. The contradicting signs of the coefficients in exploration and exploitation models confirm prior studies which also find similarly contradicting effects of exploration and exploitation antecedents (Voss et al., 2008).

4.5. Discussion

The results of this study provide insight into the effects of organizational performance on explorative behavior. The study builds on literature on organizational ambidexterity that predominantly studies organizational performance as an outcome of explorative and exploitative behavior rather than an antecedent. The study also builds on organization theory literature on firms' risk taking behavior which suggests that companies will only engage in risk taking behavior if this behavior is really necessary, for example because of unsatisfying or unpredictable performance results.

The results of the study suggest that organizations will not risk disturbing the status quo by making changes when the market signals satisfaction with the quality of products delivered. A positive sales trend and consistent positive customer evaluations result in a reduced propensity to engage in explorative behavior. These findings do not confirm the results of Lubatkin et al. (2011) who examine how companies' performance of the previous year influences the ambidextrous orientation of SMEs and find no significant relationship. Lubatkin et al. (2011), however, use a rather restricted time period of one year. This paper uses a longer time frame, and looks at trends, to better and more fully assess influences of past performance. Furthermore, Lubatkin et al. (2011) measure explorative and exploitative behavior as a joint construct, while this study examines exploration and exploitation separately.

Interestingly, a positive trend of expert evaluations seems to stimulate rather than to hinder explorative behavior by organizations. Perhaps positive evaluations from experts provide organizations sufficient confidence to enter into new areas. Organizations operating in the creative industries often use critical acclaim as evidence of organizations' success in creating a high quality product. In the video game industry, for example, it is not uncommon to boast critical acclaims in the promotion materials of a new game, similar to the movie or music industry. However, since the relationship between a positive trend in expert evaluations and explorative behavior is only marginally significant ($p<.10$), the results should be interpreted with care.

Overall, the findings suggest that the source of the performance indicator (either the end user or the expert) plays a role in how decision makers use these indicators in making decisions to explore or exploit. Other recent findings show that quality signals such as reviews or awards originating from different types of evaluators can have very different effect on the behavior of consumers (Gemser et al. 2008) or investors (Ebbers and Wijnberg, 2012). This study adds to this stream of research by showing that quality signals originating from different types of evaluators can have very different effects on the behavior of producers.

The study finds that variability of performance has a positive effect on explorative behavior, when performance is measured in terms of sales trend and consumer evaluation trend. These results and the results on performance trends suggest that using types of measurements that reflect changes, such as trends, growth, and variability rather than static representations of the constructs can help to explain phenomena. Indeed, the models in this study explain much of the variability of the dependent variable.

Competitive intensity is an important moderating variable that influences the relationship between past performance and exploratory behavior. Competitive intensity weakens the effect of performance trend and increases the effect of performance variability on firms' tendency to explore –when performance is operationalized in terms of market acceptance. These findings provide support for competition as an important environmental moderator.

The model is valuable for managers to be able to better predict explorative behavior of their competitors by simply using sales, consumer evaluations, and expert evaluations records of those organizations. Managers who are able to predict their competitors' actions and who are able to develop strategy that anticipate these actions should find themselves in a better position in administering their organization. Besides business managers, market analysts or investors can also use the results to develop a forecast of future strategic decisions of the firms that they investigate.

4.5.1. Limitations and future research

The sales data used in this study are from Vgchartz.com. This website records sales data of video games if these game have, at minimum, sold 10.000 copies worldwide. Thus the data may be skewed towards larger video game developers. Research that also covers small developers can be difficult and expensive to conduct. However, future research may benefit from technologies like web-crawling to obtain such data.

The focus of the study is on antecedents of explorative behavior, rather than striving for a balanced portfolio of exploitative and explorative behavior. The study examines antecedents of exploitative behavior and finds that, similar to prior research, the results are opposite to the results of the antecedents of explorative behavior. Future research is however, needed to examine how trends and variability in past performance affect organizational ambidexterity.

The use of objective performance data rather than self-reported data from large scale surveys is a strength of this study. Future studies may, however, want to provide a more complete model that uses both performance data and organization attributes data to predict explorative behavior. In the current study only one organizational attribute was included, namely the number of games produced as a proxy for firm size.

The research uses data from the video games industry. The results should be generalizable to other creative industries where exploration by developing new genres is common, such as book publishing, the movie, theatre, and music industries.

Appendix 4.A The list of genres used in this research

Genre	# Titles Financial Year 2001-2009
Action	540
Adventure Games	665
Alternative Sports	104
Baseball	63
Basketball	79
Car Combat	23
Card Battle Games	16
Combat Sims	39
Compilations	112
Exercise / Fitness	20
Fighting Games	167
First-Person Shooters	252
Football	73
Futuristic Combat Sims	36
Golf	49
Hockey	35
Miscellaneous	202
Other Driving Games	66
Other Shooters	404
Other Sports Games	245
Other Strategy Games	75
Parlor Games	180
Party Games	83
Platformers	339
Puzzle	263
Racing	399
Real-Time Strategy	50
Rhythm Games	179
Role-Playing	290
Simulations	24
Soccer	49
Tactical Shooters	46
Turn-Based Strategy	62
Virtual Life Games	48
Wrestling	35
Total	5312