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Essays in Industrial Organization

Evren Atiker
eatiker@utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Evren Atiker entitled "Essays in Industrial Organization." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

William S. Neilson, Major Professor

We have read this dissertation and recommend its acceptance:

Matthew Murray, Robert Bohm, Remus Nicoara

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

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Essays in Industrial Organization

A Dissertation Presented for
the Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Evren Atiker
August 2012

Dedication

To my mother

Aysın Atiker,

for her unconditional love and support.

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Abstract

The relationship between acquisitions and investment in research and development can be either directly or inversely related. The three arguments that explain the correlation between the acquisition likelihood and research intensity are managerial myopia, leveraged buyouts and strategic sale of the company motive. In the first chapter of my dissertation, I show that probability of failures and takeovers are negatively associated with firms' research intensity in the biotechnology industry, which supports the managerial myopia argument. The second chapter of my dissertation is based on personality traits as an alternative approach to explain the backward induction failures. In this second essay, we demonstrate that risk taking and assertiveness reduce; self-esteem and intellect traits raise the probability of subgame perfect equilibrium plays in centipede games.

Table of Contents

List of Tables

List of Figures

Introduction

There are three arguments from several studies that explain the effect of acquisitions on the pre-merger research and development activities of the firms. These are managerial myopia, leveraged buyouts and strategic sale of the company motive. Although these three arguments are based on the acquisition likelihood, they can also explain the effect of failure probabilities on firms' research investments. Hence, by including both probability of takeovers and bankruptcies in our analyses, we accurately distinguish between these three theories.

In the first chapter of my dissertation, we use propensity score method and a model analogous to two-stage least squares method to show that the bankruptcy and acquisition likelihood are negatively associated with the research and development intensity of the biotechnology firms. This result implies that there is no evidence of strategic sale of the company motivation by supporting the managerial myopia argument.

The second chapter of my dissertation is based on the effect of personality traits as an alternative explanation of backward induction failures. In this second essay, we use logit models and a poisson model to explain the subject's likelihood of subgame perfect equilibrium plays, their pass rates and their stopping frequencies in centipede games, respectively. We find that high scores on risk taking and assertiveness decreases; intellect and self-esteem increases the probability of subgame perfect equilibrium plays.

Chapter 1

Do Exit Probabilities Affect the Incentives to Conduct R&D?

Abstract: Several studies show that a firm's probability of getting acquired and its R&D intensity can be either directly or inversely related. However, we know relatively very little about the impact of overall exit probability on a firm's investment in research activities in the biotechnology industry, which is not only R&D intensive but also has substantial failures and acquisition activities in the United States. Using 6,465 firm-year observations from the U.S. biotechnology industry between 1985 and 2008, we find a negative correlation between exit probabilities and research intensity.

1. Introduction

The relationship between acquisitions and R&D has been studied by many researchers either to investigate the acquirer's substitution tendency of in-house research activities with the research intensive firm's acquisition[1] or to explore the effect of acquisitions on the consolidated firm's post-merger R&D intensity[2]. However, there are relatively fewer studies[3] that analyze the effect of acquisitions on the pre-merger R&D activities of the firms.

In particular, there are three competing ideas that explain the relationship between the acquisition probabilities and pre-merger research intensity of a firm. These include the managerial myopia argument, strategic sale of the company motive and leveraged buyouts explanation. However, without the effect of failure likelihood we cannot accurately distinguish between these three competing ideas. Hence, we explore the impact of overall exit probability on pre-exit research intensity in a R&D intensive industry. This is our contribution to the literature.

In the biotechnology industry, R&D is an expensive, long term commitment with a high degree of uncertainty. Hence, life sciences firms operate in a highly risky and competitive environment. Among these firms, the ones losing the survival battle are subject to either acquisitions or bankruptcies. Given the intensive mergers, acquisitions and takeover activities in the biotech industry, we argue that, depending on the company's motives, bankruptcy probability decreases, and acquisition likelihood either increases or decreases, corporate R&D. Specifically, if a firm's goal is to be an attractive

[1] see for example Blonigen and Taylor (2001)
[2] see Danzon et. al (2007); Ornaghi (2009)
[3] See Hall (1988), Stein (1988), Arora et al. (2000) and Phillips and Zhdanov (2011)

acquisition target, it should have successful innovation and therefore continue to invest in research. However, if a company aims to avoid or delay an exit through a bankruptcy or an acquisition, it should cut down on its research funds.

As mentioned above, there are three competing ideas in the literature explaining these hypotheses. The first argument is “managerial myopia” by Stein (1988), which states that a company’s decision to invest in research and development activities is a long term commitment. However, takeover pressure and the fear of getting acquired at an undervalued price leads managers to focus on short term profits rather than the firm’s long term goals such as R&D projects. Therefore, by diverting their resources from research projects to strategies for immediate earnings, companies may increase their price and discourage acquirers from a takeover attempt, which enables managers to keep their jobs. This managerial myopia argument can also be used to explain the strategies of managers under the risk of bankruptcy. The second argument, made by Hall (1988), is based on effect of “leveraged buyouts”. If the acquirers buy “cash cows”, the cost of acquisition is financed by the target firms. This gives targets an incentive to reduce their research expenditures and divert it to their debt payments for their acquisition[4]. A third argument, by Phillips and Zhdanov (2011), is the “strategic sale of the company”. According to them, small firms may choose to intensify their research in order to increase the possibility of successful innovation and a valuable acquisition. The strategic sale of the company argument can also explain the firms’ R&D investment decisions under bankruptcy likelihood. Specifically, under this argument, we expect managers to invest

[4] We expect leveraged buyouts to affect the last year of the exiting firm’s R&D in our dataset since for some firms the acquisition agreement is already made during their final year.

more in research in an effort to innovate and save the company from a failure. In summary, R&D investment responses may differ for companies that have a high likelihood of acquisitions and bankruptcies. Hence, by including both probability of takeovers and bankruptcies we can clearly distinguish between these three theories.

Our study takes the analysis of the impact of exits on a firm's incentives to conduct R&D a step further than previous literature via the introduction of some novel elements. First, we make a distinction between the two forms of exit, bankruptcies and acquisitions, in our empirical study. The probabilities of being taken over or going bankrupt are estimated simultaneously by multinomial logit model. To our knowledge, this is the first study to perform this test in this type of framework where the firm exit is defined separately. As a result, this study extends previous literature on the response of research intensity to the likelihood of exits, rather than only to that of take overs in order to accurately differentiate between the three arguments explained above.

Second, we use the most research intensive industry in the U.S., the biotechnology industry, to explore the relationships between the exit probabilities and R&D. This is another factor that makes this study unique, since previous studies considered multiple industries that are merger and acquisition intensive but not necessarily research intensive. Our dataset extends from 1985 to 2008, when failure, merger and acquisition activities are substantial. Compared to other studies, our sample is much richer with respect to internal factors that directly affect research activities, such as intangible assets, patents and financial resources, which enables us to explore cross section variation within the industry.

The examination of our question yields a negative correlation between R&D intensity and acquisition probability. Specifically, firms under the risk of a takeover have lower research intensity compared to non-merging firms. Furthermore, companies under the risk of a failure decrease their R&D compared to their matched controls. These results provide evidence for our managerial myopia hypothesis under which the managers focus on their short term strategies rather than long term commitments such as R&D. Hence, by diverting their resources from research projects to strategies for immediate earnings, companies increase their price and avoid a takeover attempt or a failure which enables managers to keep their jobs.

The rest of the paper is organized as follows. The next two sections discuss in greater detail the exit types and the biotechnology industry. The fourth section explains the relationship between the probability of acquisitions and R&D intensity in the literature. The following sections present the firm characteristics that are essential for survival and research activities in a high technology industry, and they explain the data, our estimation methodology, and empirical results. The final section provides a conclusion.

2. Firm Exit

In the literature, exit is mainly explained by focusing on the plant and firm failures. These studies can be separated into two groups. The first set of studies defines the exit as a failure on the part of the firm and examines the relationship between firm size and the order of exit. The second group of studies describes the firm exit in several forms such as acquisitions, mergers, bankruptcy or voluntary liquidation and then analyzes the impact of the factors causing these types of exit.

Papers such as Ghemawat and Nalebuff (1985), Baden- Fuller (1989), Reynolds (1987), and Whinston (1988) explain firm and/ or plant exit behavior by focusing on declining industries. The order of exit in these models depends on the firm's/plant's size and its cost structure. However, these studies treat all exits as identical events, simply the closing of the plant, or focus on one form of exit, such as bankruptcy, and ignore the fact that different forms of exit have different economic consequences.

In general, with a merger or an acquisition, most of the productive capacity remains in the industry and investors are usually paid a premium for their shares. In voluntary liquidation, capacity is removed from the industry and creditors are often paid fully. In a bankruptcy, productive capacity is removed permanently and the creditors are paid partially or not at all. Because of these important differences, all exits cannot be treated the same[5].

Later studies such as Schary (1991), Harhoff et al. (1998), Wheelock and Wilson (2000), and Buehler et al. (2006) analyze the firm exit in several forms such as an acquisition/merger, a bankruptcy or a voluntarily liquidation and show that exit determinants are not the same for different types of exit. In this study we adopt a similar approach for the distinction of exit types, namely, acquisitions and bankruptcies[6].

Biotechnology, a growing and a competitive industry, is unique with respect to its firms' exit behavior. In particular, for most start-up biotechnology firms, the main goal is

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[5] See Schary (1991) for the discussion on the exit forms

[6] We categorize horizontal and vertical mergers under acquisitions and voluntary liquidation, distress and filings for bankruptcies.

to sell the business to a large company, since they cannot commercialize their product without financial support and experience. Otherwise, these companies are more likely to fail before even reaching the IPO stage. If start-up companies survive and become public through IPO, there still exists a high possibility of exit by acquisitions or failures. Given this risky environment we aim to explore how these life sciences companies respond to exit probabilities when they are in the process of innovation.

3. Biotechnology Industry

In order to stay competitive, many firms try to improve their products and processes by continuously investing in research and development. Currently, investment in R&D is intense among high technology industries. Figure 1 illustrates the R&D intensity over the last five years for the most research intensive sectors in the U.S. According to this graph, the highest research investment is in the Pharmaceuticals and Biotechnology sector.

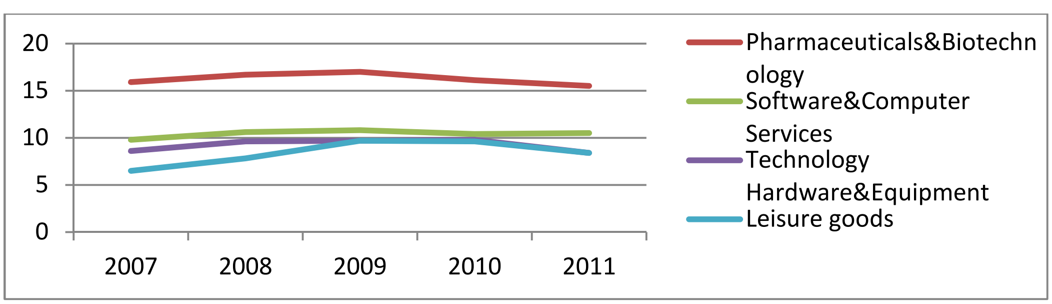

Figure 1.1: R&D Intensity (%) in Top 4 Sectors in the U.S.

Source: The 2011, 2010, 2009, 2008 and 2007 EU Industrial R&D investment Scoreboard. European Commission, JRC/DG RTD

Biotechnology companies conduct a particularly high level of R&D due to the constantly evolving nature of their industries. The life sciences industry is defined not only by the products it creates but also by the technology it uses to make those products. Research in this area focuses on the understanding and the application of the main processes of cellular life to improve medicines, products and processes[7].

Life sciences firms invest more in R&D each year[8] due to the intense rivalry in the industry. A Biotechnology firm's survival depends on its ability to develop a new product that can be commercialized. However, R&D is a very expensive and a long process with no certain success. For instance, according to Pharmaceutical Research and Manufacturers of America (2011), the average cost[9] of developing a biologic drug is 1.2 billion dollars and developing a product takes on average 10-15 years. Hence, research investment in the development of a new product is a very important decision for a life science company and vital to its survival in the market.

4. R&D Investment and Exit Probability: Review of the Literature

Ability to innovate or imitate new products is crucial for a firm's survival in high technology industries. A high-tech firm can use the "make or buy" strategy to either conduct research and innovate, or to reduce research activity and buy a R&D intensive company. In the literature, many researchers investigate the relationship between R&D activities and the firm's acquisition decision in order to understand the strategies of

[7] Bureau of Labor statistics (2012)
[8] R&D spending in biotechnology industry is:47.6 billion in 2004, 51.8 billion in 2005, 56.1billion in 2006, 63.3 billion in 2007, 63.7 billion in 2008, 65.9 billion in 2009 and 67.4 billion in 2010 (PHARMA 2010)
[9] In 2005 dollars

survival in highly competitive industries (see, for example, Blonigen and Taylor, 2000). In contrast, only several studies explore the research activity response of potential targets to a probability of acquisition.

For instance, Hall (1988) investigates whether the probability of an acquisition reduces target firm's research intensity and finds little evidence that acquisitions cause a decrease in research spending. Her data contains manufacturing industries in the U.S., and a solid conclusion on the life sciences industry cannot be drawn from her results.

Furthermore, in his theoretical framework Stein (1988) states that in an environment where takeovers are prevalent, fear of being bought can be damaging because it leads managers to focus on short term, rather than long term, objectives. Using his model to explain the firm's decision to invest in research activities, he concludes that low R&D should be observed in firms for which the ex-ante probability of a takeover is the highest.

In contrast, Arora et al. (2000) finds the impact of net acquisitions to be significant and positive on firm R&D. Their study focuses on the impact of restructuring on U.S., European, and Japanese chemical industry research investment. They test the effect of net acquisitions (acquisitions minus divestures) on research activities, rather than the probability of acquisitions.

In addition, a recent paper by Phillips and Zhdanov (2011) conducts a similar analysis of the impact of mergers and acquisitions on the firm's incentives to conduct R&D by using a similar approach to ours but finds a different result. According to their paper, a firm's incentive to conduct R&D increases with the likelihood that it will be taken over, and this effect decreases as firms get larger.

In summary, empirical and theoretical evidence suggest that there is either a direct or inverse relationship between the probability of an acquisition and the research intensity of the target firm. Nevertheless, there is no empirical evidence that we know of on the relationship between the likelihood of failures and incentives to conduct R&D in a research intensive industry. This relationship is explored in this study.

5. Explanatory Variables

I choose the control variables according to the factors that might affect the decision of exit through an acquisition or a bankruptcy and R&D activities such as company's size, age, liquidity, equity, debt, cash flow, value of its intangibles, patents and GDP change. In order to obtain some detail on these characteristics, the relevancy and their consequences for the firm exit is discussed in this section.

5.1 Firm Size and Age:

Many economists have studied the relationship between a firm's size, age and its survival. According to these researchers (see for example, Jovanovic, 1982; Ericson and Pakes, 1987) information gathering is costly and time consuming for an entrant. After the entry, the market conditions change and the entrant has to account for this by changing their actions in order to survive. A company's ability to grow and survive depends on its ability to learn about the environment. If the market is volatile and the learning is slow, then the firms are more likely to fail.

Geroski (1995) states that a firm's survival based on learning abilities is not easy to test empirically because it is not easy to link the knowledge accumulation and the experience with the observable characteristics of the firm. However, empirical studies use figures such as a firm's age to account for experience and size in order to measure knowledge skills (or competitive assets) and learning ability, and therefore, survival of the firms. These studies indicate that there is a positive relationship between the firm's size and age and its survival (see for example Evans, 1987 and Dunne et al., 1989).

In contrast with this fact, a more recent study by Agarwal and Audretsch (2001) suggests that the small firms' lower likelihood of survival cannot be applied to every stage and type of industry. According to them, small firms can survive in the mature phase of industries and in high tech industries because if a small firm finds a strategic niche, it doesn't need to grow in order to survive.

Further analysis of the relationship between firm size, age and exit in the form of acquisitions and/or bankruptcies in the recent literature finds that large firms are less likely to fail and more likely to merge. Moreover, the threat of both acquisitions and bankruptcies decreases with age (Agarwal and Audretsch, 2001; Buehler et al., 2006).

In summary, firm size and age are the most important firm characteristics to be examined. In our study the size of the firm is measured by the logarithm of the number of employees (in thousands), and age is measured by the number of years the company is active starting from the establishment year.

The impact of firm age and size on research intensity has also been examined in various studies of high technology industries. In common, these studies indicate that young firms invest more and larger firms spend less on research activities (Brown et al., 2009; Kim et al., 2009). Thus, we expect the signs of the age and size coefficients to be negatively associated with R&D intensity.

5.2 Financial Sources:

In the literature, the most likely candidates for firm specific constraints on research investment decisions, as well as survival, are liquidity, cash flow, equity and debt (Arora et al., 2000). Cash flow shows whether the firm depends on its own resources or looks for external finance. Equity and liquidity ratios reflect ability to finance long term and short term research investments, respectively, and debt reflects the firm's capital structure.

Financial constraints matter for the biotechnology industry because development of a new product by a life science firm is an expensive and a long process. One pre-clinical phase and three phases of clinical trial are required for FDA approval. These phases necessitate several years and a lot of money. In particular, during the pre-clinical phase, the product's safety is tested on rodents. If the FDA is satisfied by the documented results, the firm can move on to the following three phases. In the first phase of clinical trials, the product is tested for safety on 20 to 100 healthy people who volunteer. In the second phase the drug's effectiveness is tested on 100 to 300 volunteers who have the health condition the drug is intended to treat. In the final phase, the drug is tested on a larger population (1000 to 5000 patients) to confirm the results on effectiveness, safety and best dosage from previous phases. This usually takes place in clinics and hospitals in varying geographical locations. This last stage takes longer than the others and is much more expensive. A failure in the late stage clinical trial phases may cause the company seriously harm.

Anecdotal evidence of cash-strapped companies either going bankrupt or being acquired is common in the biotechnology industry. For instance[10], Vion Pharmaceuticals filed for bankruptcy in December 2009 since the FDA did not approve its anticancer injection product, Origin, due to insufficient late stage clinical trials. The company did not have the money for further clinical trials and had to file for chapter 11 bankruptcy. In another example[11], BioSante Pharmaceuticals had only one year's worth of cash left when they were running the third phase clinical trials on their product Libigel. Hence, in 2009, the company had decided to merge with Cell Genesys. In short, it is often difficult to fund late stage clinical trials, and a company with insufficient cash may consider either M&A or filing for bankruptcy. Therefore, an investigation of the relationship between the financial variables of the firm and bankruptcy and acquisition activities is necessary. In order to test for this in our analysis we use the current ratio for liquidity, total shareholder's equity to measure equity, income before extraordinary items for cash flow, and sum of all corporate debts to measure debt.

[10] See Carroll (2009)
[11] See Johnson (2009)

5.3 Gross Domestic Product:

To control for macroeconomic conditions we use the growth rate of GDP. The previous findings from Swiss and UK data indicate that an increase in GDP growth reduces the likelihood of failures but increases the probability of acquisitions (Buehler et al., 2006; Bhattacharjee et al., 2009). We explore the same correlation using change in GDP to increase the research intensity of the firms. This is explained by the "higher income leads to higher investment in R&D" argument. The principle supporting this argument is called the "acceleration principle of investment" by Schmookler (1966). According to this, rising GDP implies that businesses see increasing sales, profits, cash flow and use of existing capacity. Thus, the companies engage more in R&D to improve profitability. Under this principle investment in research depends on the GDP growth rate.

5.4 Intangible Assets:

These are the patents, copyrights, trademarks, licenses, etc. a firm owns. The value of intangible assets is crucial for the survival of biotechnology firms as well as other high technology firms. Many studies use the number of patents companies own as a proxy for measuring the value of pharmaceutical and biotechnology firms. However, the proper evaluation of a biotechnology firm's intangible assets requires not only the patents the firm owns, but also copyrights, licenses, and so forth. Therefore, we use a variation of Tobin's Q measurement from the Konar and Cohen (2001) study. In their paper, they formulate a firm's market value as the sum of its tangible and intangible assets using the following equation:

$$\mathbf{MV=V_T+V_I} \qquad (1)$$

Dividing each side by V_T:

$$\mathbf{MV/V_T=1+V_I/V_T} \qquad (2)$$

where V_T is the value of tangible assets and V_I is the value of intangible assets.

In the formula, market value is observable but value of intangible assets is not. V_T is measured using replacement costs (RC) of the company's tangible assets through accounting based values for the firm's assets. MV/RC is the Tobin's Q by definition and it is computed as:

$$= \frac{Market\ Value\ (Equity+Debt+Preferred\ Stock)}{Replacement\ Value(Plant+Equipment+Inventory+Short\ Term\ Assets)} \qquad (3)$$

Inserting (3) into (2) and manipulating the equation (2) gives us:

$$\mathbf{(Q - 1) = V_I/V_T} \qquad (4)$$

Hence, we employ equation (4) to test for the value of intangible assets of a biotechnology firm. The higher the ratio, the greater is the value of intangibles. Thus, we predict this variable to be negatively correlated with the exit probabilities and either negatively or positively correlated with R&D intensity.

5.5 Patents:

This variable is constructed using the NBER patent data project[12]. Given the codes of the patent assignees and their affiliations with the firms, we were able to successfully match yearly granted patents with 553 of our Compustat firms. Previous studies find mixed evidence on the impact of the number of patents on R&D intensity. To test this relationship we use number of patents as an explanatory variable for the subsample [13]of our database.

Table 1.1 summarizes all the arguments above. It shows that liquidity, cash flow, equity and GDP change can increase; size, age, debt and likelihood of bankruptcy can decrease; and value of intangible assets, number of patents and likelihood of acquisition either increase or decrease the research intensity of the firm.

Table 1.1 Predicted Effects of Firm Characteristics on Exit Probabilities and R&D

Explanatory Variables	Bankruptcy Probability	Acquisition Probability	R&D intensity
Size	-	+	-
Age	-	-	-
Liquidity	-	-/+	+
Cash Flow	-	-	+
Equity	-	-	+
Debt	+	+	-
Intangible Assets	-	-	-/+
Patents	-/+	-/+	-/+
GDP	-	+	+

[12]The website is https://sites.google.com/site/patentdataproject/
[13] Our patent data is until 2006 and because of this we include the firms from 1985 to 2006 for subsample data examination.

6. Data

Our sample is based on annual data collected from several sources over a six month period. To construct our panel we sample all biotechnology firms listed in the Compustat database with primary Standard Industrial Classifications (SIC) of 2833, 2834, 2835, and 2836 and with continuous financial data[14] for the period from 1985 to 2008.

An accurate record of bankruptcies and acquisition activities is impossible to obtain from the Compustat database[15]. Therefore we used several other resources such as SEC filings[16] and newspapers using Lexis/Nexis for the complete record of mergers/acquisitions and bankruptcies of the firms in our sample.

In our unbalanced panel 108 firms are bankrupt[17], 342 firms are acquired, and 550 firms are surviving. For all firms, the data contains annual information on firm size (number of employees), age, research intensity (R&D expenditure/total assets)[18], liquidity (short term assets to short term liabilities ratio), cash flow, equity and debt, value of intangibles and change of GDP. In addition, yearly granted patent data is matched with a subset of the 553 firms in our database.

[14] All monetary variables are adjusted for inflation using the U.S. manufacturing PPI year of 1987

[15] In the Compustat database most of the firms' inactivity reason is explained with 14 different codes. However, there is no explanation for the most of the inactive firms before 2008. Therefore, we were only able to get the record of bankruptcy and acquisition (and merger) activity of almost one third of the inactive firms from Compustat.

[16] All public firms in the U.S. are required to make regular Securities and Exchange Commission filings.

[17] We use the term bankruptcy to denote the event of filing Chapter 11, Chapter 7 or a corporate dissolution.

[18] We measure R&D intensity as the ratio of research expenditures to total assets since it yields more observations than the ratio of research expenditures to sales. Moreover, we believe that some firms are focused more on research than sales. Our approach in the measure of research intensity is consistent with the studies of Hall 1987 and Blonigen&Taylor 2000.

Table 1.2 illustrates descriptive statistics for our sample of 1000 firms and for the sub-sample of 553 firms. A number of points are noteworthy. First, mean values of firm size and age are largest for acquired companies and lowest for bankrupt firms. Second, both mean value of intangibles and R&D intensity are relatively lower for acquired firms than for bankrupt and surviving companies. Third, the financial variables related to the decision of investment in research are lowest for bankrupt firms.

Table 1.2 Descriptive Statistics

Variables	Bankrupt Companies		Acquired companies		Surviving Companies	
	Mean	**Std.Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Employment	112.91	277.03	3,629.5	11,911.31	3,067.88	13,088.15
Age	16.52	21.06	18.82	24.5	18.37	23.62
Liquidity	7.27	15.43	7.42	31.29	7.38	39.26
Cash Flow*	-12.7	23.2	79.8	513	102	759
Equity*	16.6	36.4	506	1,850	648	3,890
Debt*	16.4	50.1	454	1,960	443	2,380
R&D intensity	0.56	1.46	0.32	0.79	0.48	1.75
Intangible assets	21.63	372.68	4.5	25.85	23.66	303.65
Patents[19]	15.84	5.05	81.50	15.84	49	13.26

** Millions of dollars*

[19] The Compustat firms that are matched with the patent data consists 271 surviving, 226 acquired and 58 bankrupt companies.

6.1 Firm Exit in the Life Sciences Industry

Life sciences firms' survival and success depend on the discovery of new technologies or the use of existing technologies on new products (Goudey and Nath, 1997) which makes the industry highly competitive and risky. Therefore, the companies that cannot survive either become bankrupt or the target of acquisitions. In our sample, if the firm does not exist after a certain year, we code it as bankrupt or merged during their last year of existence (this is explained in more detail under the fourth section).

The yearly mergers and acquisitions in the public biotechnology industry between 1985 and 2008 are as follows:

Table 1.3 Yearly Mergers and Acquisitions

Year	**Active companies**	**Bankruptcies**	**Acquisitions**
1985	161	1	2
1986	181	0	4
1987	195	0	1
1988	205	1	9
1989	217	2	4
1990	252	1	6
1991	285	1	4
1992	321	1	3
1993	352	1	11
1994	376	2	15
1995	444	1	6
1996	477	2	12
1997	478	5	19
1998	518	2	26
1999	546	1	34
2000	544	6	16
2001	549	12	12

Continues on the next page

Year	Active companies	Bankruptcies	Acquisitions
2002	562	6	15
2003	586	0	13
2004	614	8	19
2005	612	5	23
2006	614	10	25
2007	590	15	41
2008	501	25	16

The second column shows the active companies for each year, the third column demonstrates the annual bankruptcies, and the fourth shows the annual mergers and acquisitions of firms. The total number of annual acquisitions in the dataset fluctuates and varies from 1 to 41. On the other hand, bankruptcies do not fluctuate substantially until 2000, and they reach a peak during the 2008 recession.

7. Methodology

The effect of firm exit on the R&D intensity of the firm can be simply measured by a linear regression model where left hand side is the research intensity and right hand side is the dummy indicator of acquisitions and bankruptcies, explanatory variables, year dummies and a random disturbance term. However, the main drawback from this model is that the exit decision is not necessarily an exogenous process. If the exit is a reason of some specific characteristic of these firms, then the estimation of this model would be biased. For instance, if the firms with unskilled managers are more likely to exit through a merger or a failure, then our estimates would be biased. In other words, the exit dummies do not determine the effect of exit probability on R&D intensity if the majority of the companies experience poor performance before their exit compared to the other firms. We control for this endogeneity problem using two approaches namely, propensity score method and a two-stage model analogous to two-stage least square method as in other recent empirical studies (see for example, Ornaghi , 2009 and Danzon et al., 2007).

In order to employ both approaches we use the multinomial logit model. Specifically, first we run the multinomial logit model and obtain the predicted probabilities of bankruptcies and acquisitions. Second, we use them as propensity scores in the propensity score model. Third, we include the same predicted probabilities in the second stage of our two-stage model.

In our context, multinomial logit model has two main advantages. First, the specification of the model enables us not only use it for exit prediction (which is used as propensity scores and as an instrument to correct for endogeneity in our two stage regressions) but also analyzes the differences between the factors that drive bankruptcies and acquisitions. Second, the model can be used to assess the effect of a possible rise or a fall in control variables. For example, if an explanatory variable has negative coefficients, a rise in that variable may decrease the probability of acquisitions, and the likelihood of bankruptcy may decrease even more.

The multinomial logit model analyzes the determinants of alternative outcomes (in our case exit types) as a discrete choice problem. The model can be written as[20]:

$$\text{Prob}\,(Yi{=}j) = \frac{\exp(x'i\beta j)}{\sum_{k=1}^{3}\exp(x'i\beta k)} \qquad \text{where} \quad j = 1, 2, 3 \qquad (5)$$

[20] See Greene (2003)

In the model each firm i is faced with j different choices at time t. Choices represent categorical outcomes: survival (Y=1), bankruptcy (Y=2) and acquisition (Y=3). The baseline category is referred to as the comparison group (i.e. "survival" coded as 1 in our data) and x is the vector of the lagged covariates (except for R&D intensity), as explained above, to avoid simultaneity bias.

In our analysis, pooled multinomial logit is used since the model treats each year-observation of the firm as an independent observation. This enables us to analyze the cross sectional variation across firms within the biotechnology industry rather than the time series trend in life sciences compared to the other industries. However, the coefficients from the model are not easily interpretable due to the non-linearity of the model, and therefore, mean marginal effects of the control variables are interpreted. In particular, the marginal effect of a continuous independent variable x_n on the probability outcome j for a company with characteristics x^i can be written as[21]:

$$M_{j,n}^{i} = \frac{\partial \Pr(y=j|x^{i})}{\partial x_{n}^{i}} = \Pr(y = j\,|x^{i})\left[\beta_{n.j} - \sum_{k=1}^{3} \beta_{n.k} \Pr(y = k\,|x^{i})\right] \quad (6)$$

Given equation (6) the mean marginal effects is given by:

$$MM_{j,n} = \frac{1}{N}\sum_{i=1}^{N} M_{j,n}^{i} \quad (7)$$

where the $MM_{j,n}$ is the mean marginal effect of variable x_n on the predicted probability $\Pr(y = j\,|x)$, which is then divided by the number of observations (N) in the sample. In

[21] See Cameron and Trivedi (2005)

other words, it is the mean marginal effect of the independent variable on the predicted probability that a firm is in outcome j that is evaluated over all the sample observations by holding all other independent variables constant.

One of the most important properties of multinomial logit model is its Independence from Irrelevant Alternatives (IIA) assumption. It states that, for a given firm, the ratio of exit probabilities of any two alternatives is unaffected by other alternative's presence or absence. This can be explained with the red bus-blue bus example (Long and Freese, 2000). Suppose one has to choose between a red bus and a car to go to work, and the odds of taking a red bus compared to a car are 1:1. IIA implies that if a blue bus (identical to the red bus) is added to the choice set, the odds between the red bus and the car will remain the same as 1:1 because the blue bus is a perfect substitute for a red bus and it is irrelevant. IIA is tested by Hausman's specification test which is basically a validation of IIA assumption by deleting a category to examine whether the remaining parameters change. The test statistic is:

$$H = (\hat{\beta}n - \hat{\beta}m)'[\widehat{Var}(\hat{\beta}n) - \widehat{Var}(\hat{\beta}m)]^{-1}(\hat{\beta}n - \hat{\beta}m) \qquad (8)$$

where n indicates the estimators based on the restricted model in which one category is eliminated, m indicates the estimators based on the full model, and $\widehat{Var}$ are the estimates of asymptotic covariance matrices. H has a chi-squared distribution with k degrees of freedom, where k is the rank of $\widehat{Var}(\hat{\beta}n) - \widehat{Var}(\hat{\beta}m)$.[22]

[22] See appendix A1 for the Hausman's specification test results

An explanatory variable is endogenous if it is correlated with the error term (Wooldridge, 2001). As explained above, it would be misleading if the dummies for acquisitions and bankruptcies were used in our regressions to examine the exit effect on R&D intensity, because we believe that the firms leave the industry in a non-random manner. For instance, if unobservable factors such as CEO ability are correlated with these exits, then our findings would be biased. In other words, exit dummy coefficients can't assess the actual impact of exit probabilities on the firm's research intensity if these firms are poor performers. In order to correct for this we employ a propensity score method and a two-stage model analogous to two-stage least square method.

Propensity score matching method is about finding a surviving firm for the company which exits with similar pre-exit characteristics. The operating firms are the control group which is a good proxy of what the research intensity of an acquired or bankrupt company would have been had it not exited. We use the multinomial logit model in equation (5) for the calculation of propensity scores (i.e. predicted probabilities). For the control variables, we use the factors that might simultaneously affect the exit decision and research investment such as age, size, financial resources, intangible assets and patents as explained in section five. After obtaining the propensity scores we match the bankrupt and acquired firms with the control firms in a given year. The effects of bankruptcies and acquisitions are estimated using the control group by employing the dummy variable approach in the following section.

Our second approach (see Danzon et al., 2007 and Vella and Verbeek, 1999) also uses the multinomial logit model to account for the endogeneity issue discussed above. In fact, our methodology is analogous to a two-stage least squares (2SLS) regression.

This methodology is generally used by studies that examine both pre-merger and post-merger R&D changes to control for endogeneity (see for example Phillips and Zhdanov, 2011; Danzon et al., 2007).

In the two-stage model, instead of exit dummies, as suggested by Vella and Verbeek (1999), we use the predicted probability of exits obtained from first stage multinomial logit estimations, which are not necessarily correlated with the error term since these probabilities do not always imply actual exits.

I estimate the following econometric model for the second stage, with the year dummies:

$$R\&D_{it}=X`_{it-1}\beta+T\delta+u_{it}, \qquad (9)$$

$$i= 1,\ldots, N;\ t = 1,\ldots, T$$

where $R\&D_{it}$ is research intensity, X_{it-1} contains the lagged explanatory variables of firm age, size, financial variables, value of intangibles, (patents for sub-sample analysis), predicted exit probabilities and an interaction term between firm exit and the probability of exit[23]. The $T\delta$ are time dummies and the u_{it} are typical disturbance terms, assumed to be iid with a zero mean and constant variance.

[23] We use this to check last year effect. However we believe this is endogenous due the reasons explained above and we use propensity matching method as a robustness check.

8. Results

In this section, equation (5) is first estimated using multinomial logit model with three possible outcomes: the firm is bankrupt, is acquired, or survives. The observations are pooled from 1985 to 2008 which creates the unit of observation, a firm-year. Standard errors are adjusted for the clustering within a firm over time and standard robust errors are reported[24]. Table 1.4 shows findings from our multinomial logit estimation.

Table 1.4 Multinomial Logit Model of Bankruptcies and Acquisitions

Independent Variables	**Dependent Variable-Probability of Bankruptcy**	**Dependent Variable-Probability of Acquisition**
Employment	-0.68***	-0.12*
	(0.10)	(0.08)
Age	0.01**	-0.003
	(0.004)	(0.003)
Liquidity	0.002	0.004***
	(0.01)	(0.001)
Cashflow	-1.21***	-0.50*
	(0.26)	(0.30)
Equity	-0.18***	0.03
	(0.07)	(0.11)
Debt	0.44***	0.23***
	(0.10)	(0.06)
Intangible assets	-0.01	-0.05*
	(0.01)	(0.02)
GDP change	-0.23***	0.13**
	(0.09)	(0.06)
Constant	21.43***	3.37
	(6.11)	(6.33)
Observations	6908	6908
R^2	0.035	0.035

*Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses.*

[24] The standard errors for multiple observations are corrected. See Cameron and Trivedi (2009) for details.

The multinomial logit coefficients are not easily interpretable since the model is non-linear and the effects of predictors on the outcome variables depend on the covariates' values at which they are evaluated (Long and Freese, 2001). We instead calculate the post estimation t-statistics to determine whether the coefficients differ between bankrupt and target firms. The results indicate that the coefficients for employment, age, cash flow, equity, debt and GDP change are statistically different whereas liquidity and value of intangible assets are not statistically different from each other for bankrupt and target companies.

In Table 1.5, marginal effects of the probability of exit are reported which show the change in the probability of an event (e.g., the probability of failure) associated with a unit increase in the predictor. Note that the mean marginal effect of a variable sum to zero across all three possible outcomes for each explanatory variable. This means that if the mean marginal effects are known for the other two outcome variables, the marginal effect of the outcome variable of interest can be inferred. Nevertheless in Table 1.5 marginal effects are reported for each category.

In line with our predictions in Table 1.1, smaller firms are more likely to go bankrupt and less likely to survive. A 100 % increase in a firm's size (or an increase of one unit log of its size) is associated with 0.005 percentage point decrease in the probability of failure which is approximately a 0.67 percentage decrease in the bankruptcy probabilities[25]. Age, which is a measure for firm experience in the industry, contrary to expectations, shows that relatively older firms are more likely to go bankrupt.

[25] Because the probability a firm bankrupts in a particular year is 0.0075 (see the bottom row of the Table 1.4)

Table 1.5 Marginal Effects of the Survival, Acquisition and Bankruptcy Probabilities

Independent Variables	**Bankrupt firms**	**Acquired Firms**	**Surviving Firms**
Employment	-0.005*** (0.001)	-0.003 (0.002)	0.008*** (0.002)
Age	0.0001** (0.00003)	-0.0001 (0.0001)	0.00001 (0.0001)
Liquidity	0.00001 (0.0001)	0.0001*** (0.00004)	-0.0001 (0.0001)
Cashflow	-0.010*** (0.002)	-0.010 (0.007)	0.020*** (0.008)
Equity	-0.001*** (0.001)	0.001 (0.002)	0.001 (0.002)
Debt	0.003*** (0.001)	0.005*** (0.002)	-0.008*** (0.002)
Intangible assets	-0.0001 (0.00004)	-0.001*** (0.0003)	0.001*** (0.0003)
GDP change	-0.002*** (0.001)	0.003*** (0.001)	-0.001 (0.002)
Mean of Dependent Variable (percentage points)	0.75	2.2	97.05
Observations (firm-year)	674	1954	4280

*Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses.*

The financial variables predict the likelihood of failure better than the target variables. Specifically, a one unit increase in log cash flow and equity decreases, and debt increases, the probability of bankruptcy. This is consistent with our predictions in Table 1.1 that firms with relatively fewer internal financial sources and funds for long term investments (as reflected in cash flow and equity variables) have a higher probability of bankruptcy. Also, the firms with relatively higher debt are more likely to go bankrupt in the biotechnology industry where competition is intense with regards to investment in research. Furthermore, firms with relatively higher funds for short term investments and more debt have higher probability of being a target as reflected in the liquidity and debt variables, respectively. This result suggests that the target firms are more likely to access cash but have higher debt.

We find that firms with relatively less valuable intangible assets are more likely to be acquired and less likely to survive. This is consistent with the argument about the impact of valuable patents, licenses, trademarks etc. on the survival of a biotechnology firm. A 100% increase in the value of intangible assets is associated with a 0.001 percentage point, or 0.05 percent, decrease in the probability of being an acquisition target. The coefficient on the intangible assets for failing firms is also negative but insignificant. In addition, the macroeconomic indicator, GDP change, shows that a rise in the real GDP growth reduces the likelihood of bankruptcy, and increases the probability of being acquired. This finding is in line with our predictions in Table 1.1 and the findings of Buehler et al. (2006) and Bhattacharjee et al. (2009).

Obtaining the predicted probabilities from the multinomial logit model above, we estimate the propensity score model. Under this approach, R&D of the exiting firms is compared to the surviving firms with similar exit probabilities to illustrate how matched controls respond with respect to their R&D. Specifically, in this method, the predicted probabilities is used to find the firms' closest matches in each year to make sure that the observations of the exiting firms and control firms refer to the same time period.

According to our results, firms which fail in their last year significantly decrease their research intensity by 1.11% compared to the control group with similar characteristics. This finding indicates that failing firms cut their research expenses, highest expenditure of a life sciences company, in an effort to avoid or at least to delay their bankruptcy. Moreover, firms that taken over in their last year have 1.8% lower R&D intensity compared to their matched controls.

These results from propensity score estimations show that in the life sciences industry, firms that are taken over or fail in their last year have lower research expenses compared to their controls which is consistent with the "managerial myopia" argument of Stein (1988). In particular, managers divert their high expenditures from their long term projects such as R&D to their short term goals such as earnings of the firm, in an effort to avoid a failure or discourage the potential acquirers, and therefore, keep their jobs.

Consistent with our first approach, Table 1.6 presents the results for our second approach, two-stage model, using the full dataset. The model yields negative and highly significant coefficients on probability of acquisition. This demonstrates that an increase in the probability of a takeover is associated with lower research and development.

Table 1.6 R&D with Instrumented Probabilities

Independent Variables	R&D Intensity (with exit dummies)	R&D intensity	R&D Intensity (with interactions)
Employment	-0.390*** (0.04)	-0.393*** (0.05)	-0.392*** (0.06)
Age	-0.006*** (0.003)	-0.010*** (0.003)	-0.010*** (0.003)
Liquidity	0.001 (0.001)	0.007*** (0.002)	0.005*** (0.002)
Cash flow	0.427*** (0.145)	0.059 (0.174)	0.033 (0.172)
Equity	0.213 *** (0.097)	0.248*** (0.083)	0.251*** (0.083)
Debt	0.131 *** (0.032)	0.206*** (0.048)	0.210*** (0.048)
Intangible assets	-0.0002*** (0.0001)	-0.0002*** (0.0001)	-0.0002*** (0.0001)
GDP change	0.008 (0.012)	0.064*** (0.023)	0.069*** (0.023)
Acquisition dummy	0.093 (0.069)		
Bankruptcy dummy	0.432*** (0.193)		
Probability of acquisition		-11.52*** (3.47)	-13.11*** (3.50)
Probability of bankruptcy		2.82 (4.86)	2.61 (4.94)
Probability of acquisition*Acquisition			5.31*** (1.52)
Probability of bankruptcy*Bankruptcy			6.52 (8.89)
Constant	-15.2*** (2.46)	-9.07*** (2.99)	-8.86*** (2.95)
Observations (firm-year)	6465	6465	6465
R^2	0.170	0.173	0.192

*Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses.*

Specifically, the second column shows the results for the linear regression model which accounts for exits using dummy variables. The third column presents the findings from the two-stage model and the last column demonstrates the results from the two-stage model with dummy interactions which accounts for the last year effect.

The second column demonstrates a significant result for only bankruptcies indicating that failing companies would significantly increase their research intensity before the year they exit. However, as expected, this finding is inconsistent with the results presented in fourth column. The two-stage model estimation with exit dummy interactions indicates that the acquisition probability is negatively correlated with the research intensity whereas the bankruptcy probability is insignificant.

In the third column, probability of acquisition coefficient illustrates that a one percent increase in the probability of acquisition is associated with 13.1 % lower research activities of a firm. Hence, firms with a high likelihood of merger appear to have lower research intensity, possibly to avoid an acquisition as suggested by the "managerial myopia" argument of Stein (1988). The interaction variables in the fourth column that test the last year effect on firm R&D yield positive and insignificant coefficients on the acquisition probability and bankruptcy probability interactions, respectively. This means a one percent rise in the likelihood of acquisition is negatively associated with the R&D intensity. In other words, research intensity is 7.8 % lower for the firms that are taken over, compared to non-merging companies. However, the failure probability has no significant impact on the research intensity of the exiting firms.

Differences between the results from our two approaches, propensity score and two-stage model, for the bankruptcy coefficients are not surprising since these are due to two main factors. First, in our two-stage model we use dummy interactions to account for the last year effect. These dummy variables are endogenous and yield biased results. Second, in our propensity score model we limit our observations to exiting firms and their closest matches, and therefore, use a smaller dataset for the estimations. Therefore, using a full dataset for our two-stage model and using a sample that only has exit matches in the dataset for propensity score model may yield different results. Nevertheless, the sign and significance of our coefficients are similar for both approaches testing the relationship between the acquisitions and R&D intensity which supports managerial myopia argument by Stein (1988).

Furthermore, as predicted in Table 1.1, our control variables size and age indicate that smaller and younger firms are more research intensive. Firms spend more on research activities if they have more sources of finance and increase R&D during the times when GDP is higher. As for the effect of intangibles, we find that the higher the value of intangible assets the lower the R&D intensity of the firms. This means, firms with more valuable intangible assets may invest less in research.

Phillips and Zhdanov (2011) conducts a similar analysis of the impact of mergers and acquisitions on the firm’s incentives to conduct R&D by using a similar approach to ours but finds a different result. According to their paper, a firm’s incentive to conduct R&D increases with the likelihood that it will be taken over, and this effect decreases as firms get larger. On the contrary, our results indicate that, a firm's research intensity decreases with the probability of acquisitions even during their final year.

These differences are due to the following reasons. First, their study focuses on a larger sample including 181 three-digit SIC industries compared to ours which is 1 three-digit SIC biotechnology/pharmaceutical industry[26]. They have a variety of industries, and life sciences are only 0.6% of their sample[27]. Compared to other industries, the product development phase is longer for life sciences. Currently, on average, it takes at least a decade and billions of dollars to develop a drug in the biotechnology industry, as explained above. Hence, a biotechnology company facing the possibility of a takeover may decrease research to signal low productivity or to boost short term earnings in an effort to avoid an acquisition and then finish the product development after the threat of acquisition has passes, which may increase its survival chances in the industry. On the other hand, the likelihood of being taken over can have positive effect on firms' R&D in other industries since they can develop a product in a shorter period of time and respond to the opportunity of being taken over by intensifying research in an effort to increase the value of the firm.

The discrepancy of our results may also indicate that firms in our sample of the biotechnology industry are dominated by larger companies when compared to the firms in Phillips and Zhdanov's sample since they find that the probability of acquisition has a negative effect on large firms' research intensity. However, our additional tests suggest

[26] 4 four-digit SIC industries: Medicinal and botanicals; pharmaceutical preparations; prepared diagnostic substances; biological products.

[27] Their database includes agriculture, forestry and fishing; mining; construction; manufacturing; wholesale trade; retail trade; services; public administration and non-classifiable establishments and excludes utilities and financial industries.

that R&D intensity still decreases with acquisition probability for above and below mean size firms. Lastly, they only consider the acquisition effect, rather than the overall exit effect through the probability of acquisitions and failures, which may also bias their results.

For further examination of the differences between the Phillips and Zhdanov's (2011) and our study, we conduct additional analyses to find out whether the response of R&D intensity changes for firms above and below mean size. Results in the Appendix A2 illustrate that, in terms of their R&D responses, the bankruptcy and acquisition likelihood effect on above and below mean size firms differ and stay the same, respectively. The impact of failure probability is significant and positive for companies that are above the mean size, whereas the effect of acquisition likelihood is significant and negative for the firms above and below the mean size. These results suggest that both large and small public biotechnology companies respond to the probability of acquisition by cutting down their research expenses. However, the effect of bankruptcy probability leads large firms to intensify and small companies to either raise or decrease their research investment.

Lastly, we run the same tests for our subsample in which the patent data is matched with 553 biotechnology companies. The findings reported in Table 1.7 have a similar pattern as in Table 1.6. For instance, likelihood of acquisitions and the final year effect of acquisitions are significantly and negatively associated with the R&D.

Table 1.7 R&D with Instrumented Probabilities (sub-sample)

Independent Variables	R&D intensity (exit dummies)	R&D Intensity	R&D Intensity (interactions)
Employment	-0.334*** (0.047)	-0.388*** (0.057)	-0.389*** (0.06)
Age	-0.011*** (0.003)	-0.013*** (0.003)	-0.012*** (0.003)
Liquidity	-0.004 (0.003)	0.001 (0.003)	0.001 (0.003)
Cashflow	-0.248** (0.128)	-0.256 (0.199)	-0.250 (0.198)
Equity	0.094 (0.063)	0.135* (0.074)	0.131* (0.074)
Debt	0.113*** (0.036)	0.247*** (0.055)	0.249*** (0.055)
Intangible assets	0.001 (0.0009)	-0.0003 (0.0008)	-0.0003 (0.0008)
Patents	0.001*** (0.0002)	0.0005*** (0.0002)	0.004*** (0.0002)
GDP change	0.006 (0.012)	0.072*** (0.024)	0.072*** (0.024)
Acquisition dummy	0.095 (0.075)		
Bankruptcy dummy	0.646*** (0.213)		
Probability of bankruptcy		-1.23 (4.61)	-1.62 (4.66)
Probability of acquisition		-16.27*** (4.10)	-16.62*** (4.09)
Probability of bankruptcy*Bankruptcy			5.20 (10.96)
Probability of acquisition*Acquisition			3.47*** (1.55)
Constant	-8.84 (2.66)	-0.40 (3.59)	- 0.47 (3.55)
R^2	0.231	0.231	0.209

*Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses.*

Specifically, a one percent rise in the likelihood of acquisition is negatively associated with R&D for the firms that are taken over, compared to non-merging companies. In addition, the probability of failures and the actual failures do not have a significant effect on the research intensity of all the companies and bankrupt companies, respectively.

One noteworthy result obtained from this sub-sample analysis is that the number of patents has a positive and significant impact on a firm's research and development activities. This shows that the firms with patents tend to invest more in research in an attempt to increase the number of patents they hold. Nevertheless, increasing the value of their intangible assets has no significant effect on firms' research activities suggesting that the firms with valuable intangibles in our subsample may or may not increase R&D intensity.

9. Conclusion

In this study we examine the firm level data for 1,000 publicly traded pharmaceutical/biotechnology companies from 1985 to 2008 to explore whether the probability of exit decreases corporate R&D. We use the multinomial logit model for two approaches that account for endogeneity. The first approach uses predicted probabilities from the multinomial logit model as the propensity scores and the second approach employs the same probabilities in a two-stage model analogous to two-stage least square method. In both approaches we find that the firms have lower research activities when they face the likelihood of acquisitions. The results from the two-stage model reported in Tables 1.6 and 1.7 show that an increase in the probability of being a target is associated with lower research intensity. In addition, our findings from the propensity score model show that higher failure and acquisition probabilities are negatively associated with the R&D of the exiting firms. These results support the managerial myopia argument by Stein (1988).

In particular, when their probability of failure is high, public biotechnology companies cut their research expenditures in order to avoid or delay the bankruptcy. Moreover, when takeover likelihood is high, life sciences firms have low R&D. Hence, we can't accept the strategic sale of the company argument since there is no evidence of pre-planned sale of firms as posited by Phillips and Zhdanov (2011). However, it can be explained by Stein's (1988) managerial myopia. Specifically, managers of the companies with high likelihood of exit, focus on short term survival strategies rather than long term goals (such as R&D projects) and divert their resources from research projects to their short term plans to increase the earnings of the firm in an attempt to discourage acquirers from a takeover and save the company from a bankruptcy, and therefore, keep their jobs.

On the other hand, our control variables such as firm size and age are consistent with the previous studies. Companies invest less in research as they get larger and older. Coefficients of financial sources equity and cash flow are positive and significant in our main and sub-sample analyses, respectively, and consistent with our predictions. The liquidity coefficient is significant and positive in the main sample analysis but insignificant in the sub-sample analysis. Debt, being significant and positive, contradicts our expectations. Hence, life sciences intensify their research activities when they have higher financial resources, but they also use debt as an alternative resource. The value of the intangible assets coefficient is negative and significant for our main sample, which suggests that the biotechnology firms decrease their research investment as they obtain valuable innovations, and the number of patents is positively associated with firms' R&D in our sub-sample. Also, the coefficient of our control variable for macroeconomic conditions, GDP change, is significant and positive as predicted, which means biotechnology firms intensify their research with the GDP.

These results contribute to the understanding of the link between firm exit and research intensity. Several studies provide evidence on the probability (or number of acquisitions) and research intensity correlation. Much literature investigates the impact of mergers on the consolidated firms' research intensity. Our work complements these findings by using pharmaceutical/biotechnology firm level data to look more deeply at the relationship between exit probability, in the form of bankruptcies and acquisitions, and the subsequent decisions on research investment.

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Appendix A

Appendix A1. Hausman Test

The Hausman test for Independence from irrelevant alternatives assumption is performed using the equation in the methodology section. First, acquired firms are left out of the estimations. The parameter estimates should not change systematically if acquired firms are irrelevant. The test statistic yields the following:

$$H = \left(\hat{\beta}n - \hat{\beta}m\right)'\left[\widehat{Var}\left(\hat{\beta}n\right) - \widehat{Var}\left(\hat{\beta}m\right)\right]^{-1}\left(\hat{\beta}n - \hat{\beta}m\right) \;\; = 0.42$$

And the Prob>chi2 = 0.9987 which indicates that the difference in coefficients of full model and restricted model is not systematic by accepting the null hypothesis. Hence this illustrates that the IIA assumption holds and acquired companies should not left out of the estimations.

Second, the bankrupt firms are excluded from the estimations and the test statistic yields: $H = \left(\hat{\beta}n - \hat{\beta}m\right)'\left[\widehat{Var}\left(\hat{\beta}n\right) - \widehat{Var}\left(\hat{\beta}m\right)\right]^{-1}\left(\hat{\beta}n - \hat{\beta}m\right)$ = 0.10 and the Prob>chi2 = 1.000 which shows again the null hypothesis is accepted suggesting that IIA hold again and the bankrupt companies should be included in estimations. These tests suggest that the model is correctly specified when all the exit types are included since IIA assumption holds.

Appendix A2. R&D Response of the Firms Below and Above the Mean Size

R&D Response (firms below the mean size)

Independent Variables	**R&D Intensity**
Employment	-0.26*** (0.07)
Age	-0.01 (0.01)
Liquidity	0.01** (0.003)
Cashflow	-41.19*** (6.85)
Equity	-1.09** (0.46)
Debt	0.09 (0.05)
Intangible assets	-0.0002*** (0.0001)
GDP change	0.03 (0.05)
Probability of bankruptcy	-3.46 (5.34)
Probability of acquisition	-12.70*** (4.27)
Constant	8.93*** (1.46)
Observations (firm-year)	3508
R^2	0.143

*Notes: */**/***significant at 10%, 5% and 1% level. Robust Std. errors in parentheses*

R&D response (firms above the mean size)

Independent Variables	**R&D Intensity**
Employment	-0.41*** (0.10)
Age	-0.01*** (0.003)
Liquidity	0.02*** (0.01)
Cashflow	-0.11 (0.28)
Equity	0.35*** (0.10)
Debt	0.26*** (0.10)
Intangible assets	-0.001 (0.02)
GDP change	0.11** (0.05)
Probability of bankruptcy	16.58** (8.56)
Probability of acquisition	-16.47* (8.99)
Constant	-8.66 (4.33)
Observations (firm-year)	2957
R^2	0.157

*Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses*

Chapter 2

Can Personality Traits of Players in Centipede Games Predict Backward Induction?

Disclosure: This paper is based on a working paper by Atiker, Price and Neilson:

Atiker, E., Neilson W. S, and Price M. K. (2011). "Activity bias and focal points in centipede games." Working paper, University of Tennessee, Knoxville.

My primary contributions to this paper include: (i) a new research question, (ii) conduction of the experiments, (iii) analysis of the data, (iv) interpretation of the results, (v) the writing.

Abstract: This paper tests the hypothesis that personality traits explain behavior in the centipede games. Specifically, focusing on seven personality traits, we find that low scores on assertiveness and risk taking, and high scores on self-esteem, and intellect matter the most for subgame perfect equilibrium plays.

1. Introduction

In neoclassical economic theory, the rationality of the decision makers is one of the standard assumptions. This assumption implies that a rational individual can use backward induction, in which the individual can account for all possible outcomes, before making a decision in strategic games. In the literature, whether or not agents are using backward induction in decision making tasks is often tested in experimental laboratories, and the data obtained is further analyzed with cognitive and personality tests.

The failure of cognitive measures to predict certain outcomes prompted researchers to focus on personality characteristics. For instance, Heckman and Rubinstein (2001) show that, given the same cognitive ability, GED recipients have lower schooling, lower wages, and higher job turnover rates when compared to high school graduates. Another study by Heckman et al. (2006) shows that the predictive power of cognitive abilities is less than or equal to the predictive power of personality attributes for schooling, wages, crime, occupational choice, and so on. In other words, they suggest that personality characteristics may be good predictors of economic behavior.

The examination of the link between personalities and backward induction matters because this relationship may have many applications in real life. For instance, personality traits can be used to assign workers to decision making tasks which require the process of backward reasoning. An owner of a company who is searching for a manager would be willing to hire a person with backward induction skills. By gathering applicants' scores on personalities correlated with the success of using backward induction, the owner can select the manager that fulfills his company's needs. It can be also applied to students' early education in schools. Students who have personality traits negatively correlated with backward induction can be trained to use the process of backward reasoning, and therefore, learn to think backwards and plan the sequence of optimal actions ahead to achieve their goals in life.

Many experimental economists have tested the theory of backward induction by using centipede games. Introduced by Rosenthal (1981), the two-person centipede game consists of first and second players who alternate in choosing whether to stay out of the game, by moving down on the first node, or to stay in the game, by moving across on the decision nodes. The total payoff increases as they stay in and continue the game. However, the player who moves down receives a larger payoff, and the other player receives a smaller payoff than he would have if he played down on the previous node. At each node, the other player's incentive to stop at the subsequent node yields a unique subgame perfect equilibrium, where the first player defects down on the first move.

In particular, the backward induction process of a two player centipede game is the following. Figure 2.1 illustrates that the game starts with the first player's decision to terminate the game by moving down or to continuing the game by moving right. If the first player chooses down, and therefore terminates the game on the first node, both players receive the payoffs identified at the corresponding node ($20 for player one and $15 for player two). Otherwise, the game proceeds to the next decision node where the second player makes her decision to either stop or proceed. The second player at the last node stops since we expect her to make a rational decision by taking $38 rather than $25. At the next to last decision node the first player knows that second player will choose down by playing rationally during the next node, and by the same logic she will decide to stop. This thought process will continue until the first player stops at the beginning of the game. Hence, Player 1's decision to terminate the game in the beginning is the Subgame Perfect Nash equilibrium of the game.

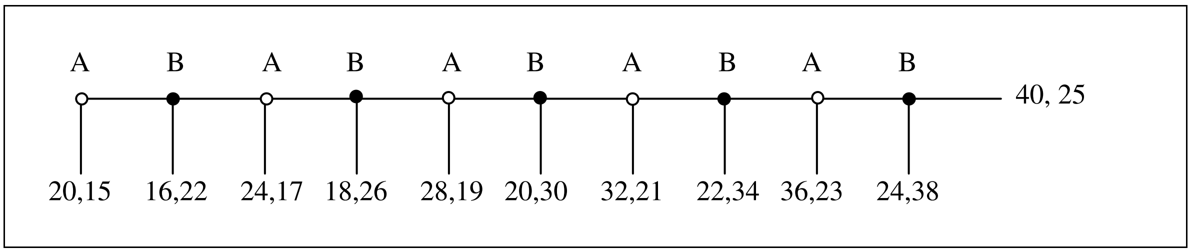

Figure 2.1 Standard Centipede Game

Source: Atiker, E., Neilson W. S, and Price M. K. (2011).

Although the theory predicts that backward induction leads to a Subgame Perfect Nash equilibrium, this is not seen in practice for centipede games. Specifically, the first player must stay out by terminating the game on the first move in order to win. Nevertheless, McKelvey and Palfrey (1992) showed in their four-move, six-move and high payoff versions of the centipede games that first players stop the game by choosing out on the first move in only 7.1 %, 0.7% and 15% of these games, respectively. There are several prominent arguments to explain the failure to play the Subgame Perfect Nash Equilibrium. The first explanation focuses on beliefs about the opponent's rationality. Aumann (1995) states that, a subject's belief about his opponent will deviate him from Nash behavior and lead him to stay in by moving across on the decision nodes. The second explanation for the failure of backward induction is through mistakes. For instance, if the subjects press the wrong button, or misunderstand the game or their roles, they can select in instead of out in their first move and sophisticated players can exploit this situation by continuing the game to increase their payoffs (Fey, McKelvey and Palfrey, 1996). A third explanation by Atiker, Neilson and Price (2011) is due to activity bias and lack of focal points. According to our activity bias argument, the first player desires to stay in the game to give an opportunity to the second player, and therefore, selects in instead of out. In addition, our focal point argument shows that the solution of the centipede game is difficult for subjects because the game lacks focal points and in a standard centipede game all nodes are equally focal. A fourth explanation for the failure of backward induction is altruism. For instance, if the selfish subject believes that the opponent is an altruist, then staying in may be worth losing the payoff since there is a possibility to increase the payoff by cooperating with an altruist (McKelvey and Palfrey, 1992).

To our knowledge, this study is the first to examine the impacts of personality traits such as assertiveness, performance-motivation, self-esteem, self-efficacy, risk taking, intellect, and sociability on behavior in centipede games. We particularly focus on personality traits, because they shape the behavior of individuals and are stable over time but differ across people (Borghans, Duckworth and Heckman, 2008). Specific to centipede games, we believe that there are certain personality attributes that can cause a player’s failure or success in using backward induction. Personality traits that may cause a subject to fail to play the SPE are high levels of assertiveness, self-esteem, risk taking, and sociability. Traits that may cause subjects to play down on SPE include performance motivation, intellectuality, and self-efficacy.

In particular, we presume the assertiveness, self-esteem, risk taking and sociability personality traits will be negatively associated with SPE plays since these traits might be found in players who believe that staying in the game is a strategy to reach a larger payoff on future nodes of the centipede game. However, each trait represents a different motive for a subject to stay in the game. For instance, suppose that the player is a high risk taker. We expect him to stay in the game to receive a higher payoff in the later nodes, rather than end the game by taking a certain payoff, on the first move. Likewise, an assertive player and a subject with high self-esteem will stay in, since an assertive player leads the game and a self-confident player thinks that he can win a high payoff (Benabou and Tirole , 2002). On the other hand, a sociable subject's motivation to stay in the game is different than the other three personalities. Borghans, Duckworth and Heckman (2008) state that sociable people derive pleasure from group activities in a working or learning environment. This implies that sociable players are more likely to cooperate and choose to stay in the game so that they may interact with the other player. Hence, if higher scores on assertiveness, risk taking, self-esteem and sociability are important drivers of a subject's behavior, there should be a higher probability that players stay in the centipede game.

The personality traits that we predict to have a positive correlation with SPE plays are performance-motivation, intellectuality and self-efficacy. We believe that there are different motivations driving this behavior. For instance, if a player's intellectuality score is high, this implies that he has superior cognitive skills. Therefore, he can use the process of reasoning backwards to reach the subgame perfect equilibrium by selecting out on his first move. On the other hand, Judge and Bono (2001) state that high self-efficacy is correlated with searching for more challenging jobs, being persistent on difficult tasks, and not losing motivation when encountering a failure. This indicates that subjects with high self-efficacy can employ backward induction and reach the SPE node by being persistent in the game. Also, Borghans, Duckworth and Heckman (2008) define performance-motivation as the capacity for hard work, ambition, and a tendency to behave in a goal oriented manner. This shows that the ambition and goal oriented behavior of a highly motivated subject can lead him to choose out immediately on the SPE node to eliminate the probability of losing money as they move across the decision nodes. Therefore, players with high scores for self-efficacy and performance motivation should choose out at the SPE node with higher probability in our centipede games.

By measuring the subjects' personality attributes via an International Personality Item Pool (IPIP) personality questionnaire and their strategic decision making using centipede game experiments, we find four traits to be most important. Subjects with high scores on assertiveness and risk taking are less likely to employ backward induction and thus continue across the nodes, whereas subjects with high scores on intellectuality and self-esteem are more likely to use backward induction and stop at the SPE node. Moreover our findings on self-efficacy and performance motivation illustrate that individuals with high self-efficacy are associated with higher frequencies of staying in, and a high score for performance motivation is associated with increased frequencies of staying out by terminating the game on the SPE node. However, these results do not fully explain the use, or failure to use, of backward induction for these characteristics. Finally, sociability is the only trait for which we could not find any statistically significant relation between the SPE plays or terminations on the later nodes.

The rest of the paper proceeds as follows. In the section below we give detailed information on the international personality item pool website, personality scales and the survey we use. We then describe the personality traits, the findings in the relevant literature, hypotheses and the sample statements in the survey. The subsequent sections explain the centipede game experiments, data, methodology and results. The final section provides a conclusion.

2. International Personality Item Pool (IPIP) Database

Subjects in our experiments were asked to complete the paper based personality questionnaire in order to receive a monetary payment after the computer based experiments. All the subjects (except the ones in the pilot session) who participated in the lab experiments completed the survey[28] which was constructed using the international personality item pool (IPIP) database.

The IPIP website has been used by scientific and commercial entities for personality assessment. IPIP scales relate to other well developed measures of similar

[28] We did not give the personality survey in the pilot session which consisted of 18 people. Hence only 184 subjects out of 202 received and completed the questionnaire.

constructs (such as NEO-P-IR[29], CPI[30] and so on) and demonstrate good internal consistency (Goldberg, 1999). The purpose of the website is to provide free access to personality tests created to measure personality and individual differences. The questionnaires consist of statements that are evaluated on a five-point Likert scale as follows: strongly agree, agree, neither agree nor disagree, disagree and strongly disagree.

In our questionnaire we use 42 statements in total to evaluate seven different personality traits, namely, assertiveness, sociability, performance-motivation, self-esteem, intellectuality, self-efficacy, and risk taking. Each trait is evaluated by three positive and three negative statements. Positive statements receive higher scores as the subject agrees and lower scores as he disagrees and the negative statements work the same, vice versa. High scores indicate a high level of the relevant personality characteristic.

3. Personality Traits

The questionnaire constructed from the international personality item pool website assigns personality scores on seven personality attributes. These are self-esteem, assertiveness, sociability, motivation, self-efficacy, intellectuality and risk preference. This section provides detailed information on these traits.

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[29]It contains 240 items which are evaluated on a 5-point Likert scale. Five dimensions of personality are captured using these questionnaires. These are, Openness to Experience, Conscientiousness, Neuroticism, Agreeableness and Extraversion. See Costa and McCrae (1995) for further details.

[30] California Psychological Inventory. See Gough and Bradley (1996) for further details

3.1 Self-Esteem

This is concept about how one evaluates his own worthiness. It involves appraisal of one's own behaviors, appearance, emotions and beliefs and so forth. For instance, a person with high self-esteem thinks highly of himself. According to Benabou and Tirole (2002) overconfidence may give people an incentive to undertake activities that are more risky (such as exploration, combat and so on) than the ones with guaranteed returns. Therefore, in centipede games we expect subjects to play pass instead of down in order to reach a riskier but a higher payoff. The following are examples of questionnaire items that are used to measure the subjects' self-esteem level: "I have a lot of personal ability", "I like to take responsibility for making decisions", "I often think that there is nothing that I can do well" and "I am less capable than most people". Hence we hypothesize the following:

H1: Subjects with high self-esteem are less likely than subjects with low self-esteem to play SPE and more likely to move forward in centipede games.

3.2 Assertiveness

Infante (1987) defines assertiveness as "a person's general tendency to be interpersonally dominant, ascendant, and forceful". We expect this personality trait to lead the subject to risky behavior, and therefore, choose continue in centipede games. In other words, if assertiveness trait is a significant factor that drives the subject's behavior, an assertive subject should aim a higher payoff rather than a guaranteed payoff at the first node and choose to pass on his first move. Examples of statements in the personality survey that measure subjects' assertiveness are the following: "I take control of things", "I express myself easily", and "I wait for others to lead the way". Hence, we can hypothesize the following:

H2: Assertive subjects are less likely than nonassertive subjects to play SPE and move across the decision nodes.

3.3 Sociability

This is about one's preference to affiliate with others and choice of being with others rather than being alone (Cheek and Buss, 1981). Borghans, Duckworth and Heckman (2008) argue that sociability may affect preferences for group activity. Sociable people may receive pleasure and unsociable ones may receive displeasure from group activities in the workplace or learning environment. This may imply that sociable subjects are more likely to cooperate with the other player in centipede games. Because of this, we expect a sociable person to play pass in order to interact with the other player, and therefore, to play fewer SPE. Sociability is tested using the following examples in the personality questionnaire: "I am skilled in handling social situations", "I know how to captivate people", and "I often feel uncomfortable around other people". Hence we hypothesize the following:

H3: Sociable subjects are less likely than unsociable subjects to play SPE and more likely to move forward.

3.4 Self-Efficacy

Judge and Bono (2001) describe this personality attribute as one's fundamental capability to cope, perform and succeed. They investigate the relationship between the core self-evaluations they developed to measure self-esteem, self-efficacy, emotional stability and internal locus of control and job performance. According to them people with high core self-evaluations have several beneficial behaviors such as searching for more challenging jobs, being persistent on difficult tasks and not losing motivation when they encounter a failure. Their self-efficacy trait defines a general level of ability across a wide range of situations. Nevertheless, their generalized self-efficacy trait is positively correlated with the self-efficacy that is measured with IPIP scale[31]. Sample items in personality survey that measure subjects' self-efficacy are the following: "I am able to think quickly", "I formulate ideas clearly and I never challenge things". We expect higher self-efficacy to be related to a higher number of SPE decisions. Therefore we hypothesize the following:

H4: Subjects with high self-efficacy are more likely to play SPE and less likely to move forward.

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[31] The main difference is International Personality Item Pool (IPIP) uses smaller response scales. IPIP scales have been proven reliability (Goldberg et al. 2006).

3.5 Risk Preference

Risk aversion is defined by Von Neumann-Morgenstern expected utility theorem (1944). According to this, individuals tend to select safer options with lower expected payoffs over riskier options with higher expected payoffs. In the centipede games subjects will make a decision between a guaranteed amount if they terminate the game and a risky one if they continue. This indicates that a risk-averse subject would terminate the game earlier and a risk lover player would move forward for the higher payoffs by staying in the game. Some items from the personality questionnaire that measures the subjects risk preference are the following: “I take risks”, “I am willing to try anything once”, and “I would never make a high risk investment”. Therefore we hypothesize the following:

H5: Risk-lover subjects are less likely to play the SPE and more likely to move forward compared to the risk-averse subjects.

3.6 Intellect

This is generally defined as one’s ability to learn and reason or one’s the capacity for knowledge and understanding. Although this trait is measured using a self-reporting questionnaire rather than cognitive ability tests, we believe that their answers reflects their intellectuality. In centipede games a high intellect subject will decide to stop in the first move by solving the game through backward reasoning. Some examples of the statements in the personality survey that measures this trait are the following: “I like to solve complex problems", "I enjoy thinking about things", and "I am not interested in abstract ideas". Hence, we expect a high intellect subject to understand the backward induction process in centipede games and stop in earlier nodes. Specifically, we hypothesize the following:

H6: Intellectual subjects are more likely to play SPE and less likely to move forward compared to unintellectual subjects.

3.7 Performance Motivation

This is also referred to as "achievement striving" in the IPIP database. It is defined by capacity of hard work, ambition, and a tendency toward goal oriented behavior (Borghans, Duckworth and Heckman, 2008). Some examples of statements in the survey to measure the subjects' performance motivation are the following: "I do more than what is expected of me", "I set high standards for myself and others", and "I put little time and effort into my work". Since we expect motivated students to have a goal of winning the game by understanding the backward reasoning process, we can hypothesize the following:

H7: Motivated subjects are more likely to stop in SPE nodes and less likely to move forward compared to the unmotivated subjects.

4. The Centipede Game Experiments

The experiments were conducted in the experimental research laboratory on 202 students at the University of Tennessee, Knoxville in 2009. Both males and females volunteered to participate in a decision making experiment for monetary payoff based on their performance. These experiments were conducted on computers throughout ten sessions. The experiment was programmed using z-Tree (Fischbacher, 2007). Student subjects were seated at separate cubicles, each containing a computer and written instructions. The students were told not to read the instructions until everybody was present. In each session participants varied from 18 to 24, and sessions lasted approximately 75 minutes on average. Each student received a payment in dollars based on the game we randomly choose at the end of the experiment.

Each session consisted of 12 rounds and the order of games was randomized. For each round, people were randomly assigned to the roles of first and second player and kept their role until the end of the session. For the first player, the nodes of the centipede game, displayed on her computer, were enabled. The second player viewed an identical screen simultaneously however lacked the ability to make a decision before first player. If the first player made a decision to continue, the second player was able to make her choice in the same manner. If either of the player's decision terminated the game, both players were informed on their screen that the round was complete by showing their payoffs at the termination node.

We used 17 centipede games to test for backward induction. The experiment is designed to investigate the reasons that people failed to play the equilibrium, such as beliefs about other player's rationality, joint payoff maximization, activity bias, and lack of focal points. In order to test for these cases, we added an additional one pair and two pairs of node(s) in the beginning of the standard and constant sum centipede games by removing the last two and four nodes of the games (see Atiker, Neilson and Price, 2011 for the details on these games). The personality surveys were given at the end of each session (except for the pilot session 1) and the payment was made after the subjects turned in their surveys[32].

5. Data

We use the same data as Atiker, Neilson and Price (2011) which was obtained from UT students who participated in our laboratory experiment on centipede games. However, in our first (pilot) session we did not distribute the personality questionnaires to the subjects. Hence we have the personality data of 184 students instead of 202 students in our experiment.

During the experiment, subjects played 12 out of 17 different types of centipede games in each session. At the end of the sessions students answered a personality questionnaire that was prepared using the international personality item pool website. In the questionnaire, each subject evaluated 42 statements on a Likert scale by choosing

[32] See the Appendix B2

among strongly agree, agree, neither agree nor disagree, disagree and strongly disagree options.

Each subject's personality characteristics was evaluated by summing the numerical value of each answer for the statements in the questionnaire on self-esteem, assertiveness, sociability, self-efficacy, achievement striving, risk preference, and intellectuality to create the database on subjects' personality attributes. Later, we matched the data on the players SPE and pass choices with the data on their personalities. Descriptive statistics are presented in Table 2.1:

Table 2.1 Descriptive Statistics of Personality Traits

Personality Traits	Mean	Std. Deviation	Min	Average score range	Max
Assertiveness	22.24457	3.127522	14	17.55-26.94	29
Sociability	21.53804	4.046002	11	15.47-27.61	30
Self-Efficacy	23.29348	2.663405	16	19.30-27.29	30
Performance Motivation	23.70109	3.627882	13	18.26-29.14	30
Self-Esteem	23.79348	3.118911	13	19.12-28.47	30
Intellectuality	22.875	3.554513	13	17.54-28.21	30
Risk Taking	20.52717	3.745937	9	14.91-26.15	29

According to Table 2.1, in general, the personality scores range from 9 to 30 out of a possible 30 points. The risk taking trait has the largest range and the self-efficacy trait has the lowest range among all characteristics. Mean value is the highest for the self-esteem and lowest for the risk taking score.

The average score ranges in the 5th column, is estimated by the guidelines in the IPIP database. Specifically, scores that are within one-half standard deviation of the mean score is considered as average score and the scores that are out of this range is interpreted as high and low scores. For our database, the high score on performance motivation has a very narrow range between 29.14 and 30. On the other hand, high score on risk taking has the largest range between 26.15 and 29. In addition, largest range for low scores is between 13 and 19.12 (i.e. self-esteem) whereas the smallest range for low scores is between 13 and 19.30 (i.e. self-efficacy).

6. Methodology and Results

First, we report the bivariate correlations between the scores of personality characteristics and stop choices on each node at Table 2.2. The hypotheses predict that the entries in the first column will be positive for performance motivation, self-efficacy, intellectuality, and negative for assertiveness, sociability, self-esteem, risk taking.

Table 2.2 Pearson Correlation Coefficients

Independent Variables	Dependent Variables: SPE Node	Node 2	Node 3	Node 4	Node 5	Node on Last node
Assertiveness	-0.115 (0.121)	-0.083 (0.262)	0.053 (0.478)	0.137* (0.064)	-0.033 (0.660)	0.129* (0.081)
Sociability	-0.102 (0.170)	-0.015 (0.843)	0.068 (0.362)	0.095 (0.200)	0.003 (0.972)	0.077 (0.302)
Self-Efficacy	0.050 (0.504)	-0.018 (0.813)	0.012 (0.877)	-0.005 (0.944)	-0.017 (0.818)	-0.077 (0.297)
Performance Motivation	0.130* (0.079)	-0.084 (0.257)	0.040 (0.586)	-0.041 (0.580)	-0.087 (0.239)	-0.063 (0.393)
Self-Esteem	0.041 (0.585)	-0.099 (0.180)	0.046 (0.539)	0.034 (0.648)	-0.026 (0.729)	0.004 (0.953)
Intellectuality	0.004 (0.955)	0.094 (0.207)	-0.040 (0.589)	0.006 (0.936)	-0.140* (0.058)	-0.018 (0.810)
Risk Taking	-0.100 (0.176)	-0.135* (0.069)	0.085 (0.251)	0.092 (0.213)	0.069 (0.356)	0.213*** (0.004)

Notes: */**/***significant at 10%, 5% and 1% level. Significance levels in parentheses

As we expected, the table shows a significant and positive correlation between motivation score and SPE plays. Risk taking coefficient is also in line with our predictions. There is a significantly negative correlation between risk taking score and stopping the game earlier. In addition, assertiveness score is positively and significantly correlated with later stops, which is again consistent with our expectation. Intellectuality score is also significantly and negatively correlated with later stops as we predicted.

Next, we tested the effect of a subject's own predispositions on the SPE plays. In order to estimate this we consider the dependent variable to be a binary variable which indicates either a SPE play (1) or non-SPE play (0) of the subject. Therefore, we choose to explore the relationship between the use of backward induction and personality characteristics by employing the Logistic regression model. Although the Probit regression model is an alternative model[33], we prefer to use Logit model. Specifically, the comparison of the goodness of fit of these models using Bayesian information criterion and Akaike information criterion results suggest that the Logit estimation provides a better fit since it has smaller values for the information criterions compared to the Probit model.

In fact, the difference between these two regression models is in their underlying assumptions. Under the Probit model, the error term (ε) is assumed to be distributed normally with Var (ε) = 1 and for the Logit model, the error term (ε) is assumed to be distributed logistically with Var (ε) = $\pi^2/3$.

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[33] Findings from Probit regressions are very similar to Logit regressions. Results from Probit model are contained in the appendix.

However, when the predictions of these models are compared they are similar (Long and Freese, 2001). The Logit model can be written as:

$$\Pr(y=1|x) = \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} \tag{1}$$

$$\Pr(y=0|x) = 1- \frac{e^{\alpha+\beta x}}{1+e^{\alpha+\beta x}} = \frac{1}{1+e^{\alpha+\beta x}} \tag{2}$$

This can be alternatively represented as:

$$P(SPE_{it})=\beta_0+\beta_1(\text{Assertiveness})_{it} +\beta 2(\text{Sociability})_{it} + \beta 3(\text{Self-Efficacy})_{it}+ \beta 4(\text{Performance-motivation})_{it} +\beta 5(\text{Self-Esteem})_{it}+ \beta 6(\text{Risk Taking})_{it}+\beta 7(\text{Intellectuality})_{it} + \text{dummy} + \varepsilon_{it} \tag{3}$$

As explained above for the Logit model, the dependent variable is binary (which indicates 1 if player *i* was able to choose SPE in round *t* and 0 if not) and the explanatory variables are the numerical values computed for each individual's assertiveness, sociability, self-efficacy, achievement-striving, self-esteem, risk preference and intellectuality. Dummy variables represent either the rounds or the games. The coefficients[34] are not readily interpretable from the Logit model, and therefore, we compute the marginal effects after estimation of (3).

Table 2.3 presents the marginal effects after Logit estimation. First, we see that players are more likely to terminate the game on the first node as the role of player changes from first to second. Second there are three traits that are prominent in SPE plays

[34] We also test for the joint significance of the personality characteristics using the Wald test. Our findings suggest that they are jointly significant and have to be included in our estimations.

and these are assertiveness, intellectuality and risk taking. As we predicted, the higher scores on assertiveness and risk taking indicate that the players are less likely to end the game on the first node. On the other hand, higher scores on intellectuality show that subjects are more likely to stop the game at the SPE node. Finally, the round dummies are negative and significant for the second round and positive and significant for the fourth and all the rounds after seventh indicating that the probability of SPE plays increase in later rounds when all the explanatory variables are held constant at their means.

Table 2.3 Marginal Effects of Logit Model

Independent Variables	**Dependent Variable-SPE plays**		
Subject role	0.066** (0.028)	0.070** (0.030)	0.069** (0.030)
Assertiveness	-0.013* (0.007)	-0.014* (0.007)	-0.013* (0.007)
Sociability	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Self-efficacy	0.004 (0.008)	0.004 (0.008)	0.004 (0.008)
Performance motivation	0.002 (0.004)	0.002 (0.005)	0.002 (0.004)
Self-esteem	0.010 (0.006)	0.011 (0.007)	0.011 (0.007)
Intellectuality	0.007* (0.004)	0.008* (0.005)	0.008* (0.005)
Risk Taking	-0.006* (0.004)	-0.006* (0.004)	-0.006* (0.004)
Game dummies			Yes*
Round Dummies		Yes*	
No of observations	2208	2208	2208

Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses.

One important result from this estimation is neither inclusion nor exclusion of round and game dummies make a significant change on our personality traits coefficients. This implies that the subjects' personality traits are stable across games and across rounds. As we discussed above our personality estimation techniques from IPIP database are well enough to capture subjects' personalities that shape their behavior in centipede games.

We also analyze the impact of personalities on the pass rates specifically for the further examination of the hypotheses that suggest a negative and positive relationship between personality traits and SPE plays. For the analyses of the pass rates from the SPE nodes we use the Fractional Logit Model as suggested by Papke and Woooldridge (1996) which is an extension of Logit model. The main reason we use this model is because we treat the dependent variable as $0 \leq y \leq 1$.

Under this method we control for steps. Since different games have different length, we normalize the dependent variable and the following is what we end up with. For instance, a standard centipede game has six options for each player. They can choose to stop on four consequent nodes after the SPE node or choose to continue on their last node. According to this explanation we labeled the first node (SPE) as zero, the second node as 0.20, third as 0.40, fourth as 0.60, fifth as 0.80 and the continue option on the last node as 1.

We used a similar approach for the one-move and two-move games where we added additional one pair and two pairs of nodes by removing the last two and four nodes of the standard and constant sum centipede games. The only difference between one and two-move games are the fractions we use.

We present the results for the pooled games in Table 2.4 and similar length games in the appendix. We use the personality traits as well as the game and round dummies as explanatory variables and report the marginal effects to interpret the results. The model is similar to the Logit model explained above (see equation (3)). The only difference is the dependent variable which is a fraction.

Table 2.4 Marginal Effect Estimates of Fractional Logit Model

Independent Variables	**Dependent Variable-Nodes as a fraction**
Subject role	-0.075
	(0.022)
Assertiveness	0.003
	(0.005)
Sociability	0.001
	(0.003)
Self-Efficacy	-0.002
	(0.006)
Performance Motivation	-0.0002
	(0.004)
Self-Esteem	-0.009**
	(0.005)
Intellectuality	-0.003
	(0.003)
Risk Taking	0.003
	(0.003)
Round dummies	Yes
Game dummies	Yes
No of observations	2208

Notes: */**/***significant at 10%, 5% and 1% level. Robust std. errors in parentheses

Contrary to our expectations, in Table 2.4 among all seven personalities the only trait that has a significant impact on the percentage of passes is self-esteem. It indicates that, holding all other variables at their means, players with higher scores on self-esteem are less likely to pass the SPE node. We also separately tested the games with similar lengths. However, we found similar results (self-esteem is significant with the same sign) for longer games and no significant result for shorter games[35]. This result implies that given our self-esteem measure, subjects that have a high score in self-esteem are less likely to associate with risky behavior and therefore less likely to pass from the SPE node. This contradicts with the argument on the positive relationship between self-esteem and risk taking behavior by Benabou and Tirole (2002).

Lastly, in order to explore the consistency of our hypotheses throughout the game we consider the frequency of stops at each node. If a personality trait's impact is consistent with our hypotheses, the sign of the personality coefficient on the initial nodes should be different for the later nodes. The Poisson regression model can answer this question as shown below.

To create the dependent variable for the Poisson model we add the number of stops at each node. In particular, we use the total number of stops at the SPE node, and we use 2nd, 3rd, 4th, 5th and continue options on the last node. Note that, since we have different lengths for the games, we add the number of continue choices at the last node whether or not it is the 6th option. In other words, to construct the dependent variable for the number of passes on the last node, we add the number of continue choices on the 3rd

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[35] See the appendix B4

node for two-move games, 4th node for one-move games and 5th node for standard centipede and constant sum games.

In our Poisson model, the number of stops at each node is assumed to have a Poisson distribution with rate parameter λ_i, where i index the node number and λ_i is the expected number of stops on the decision node i. The probability that the number of stops at node i, denoted Y_i, equals y can be written as the following[36]:

$$\Pr(Yi = y) = \frac{e^{-\lambda_i} \lambda_i{}^y}{y!}$$

The model specifies the natural logarithm of λ_i as a linear function of the explanatory variables and can be illustrated as the following:

$$ln\lambda_i = \alpha + \sum_{j=1}^{J} \beta_j X_{ij}$$

where α and β_j are the parameters to be estimated via the maximum likelihood estimation.

Although the model answers the question we want to explore, it has one drawback: an assumption that conditional variance is equal to the conditional mean, which is a very strong assumption because usually variance is not equal to the mean. However, researchers use this model if the conditional mean and variance values are

[36] See Cameron and Trivedi (2005) for details

close. Our conditional means and variances for the explanatory variables are close[37] and our findings show that we have consistent results with the previous two models.

We present the results from the Poisson regressions in Table 2.5. Coefficient estimates can be interpreted as the percentage change in the expected number of stops at the relevant node associated with a one-unit change in the variable of interest (i.e. personality score). According to our findings, assertiveness, motivation, intellectuality, self-efficacy and risk taking traits have a statistically significant relationship with the total number of stops. A unit increase in the assertiveness score is expected to decrease the number of stops by 4.8 percent on the SPE node, whereas a one-unit increase in the performance motivation score is expected to yield 2.7 percent more stops on the SPE node. These two results are not surprising given that the expected direction of the relationship between the SPE plays and assertiveness is negative and the SPE plays and the relationship between performance-motivation is positive. Moreover, a one-unit rise in the assertiveness score is associated with 7 percent and 12.9 percent increases in the expected number of terminations on the fourth node and the continue choices on the last node, respectively. This implies that, our hypothesis on assertiveness trait is consistent throughout the game since subjects with high assertiveness scores are less likely to play SPE and more likely to continue the game, as we predicted. Moreover, the significant and positive association between the performance motivation and SPE plays support our hypothesis but does not yield any evidence on the opposite effect of the performance motivation score in the later nodes.

[37] See the Appendix

Table 2.5 Poisson Regressions

Independent Variables	Dependent Variable-Number of Stops					
	SPE Node	Node 2	Node 3	Node 4	Node 5	Last Node continue
Subject role	0.098 (0.083)	0.014 (0.082)	-0.150 (0.101)	-0.045 (0.138)	-0.013 (0.166)	-0.057 (0.190)
Assertiveness	-0.05*** (0.020)	-0.019 (0.021)	0.001 (0.025)	0.07** (0.035)	-0.014 (0.041)	0.13*** (0.047)
Sociability	-0.010 (0.013)	0.016 (0.013)	0.005 (0.016)	0.003 (0.022)	-0.003 (0.026)	-0.010 (0.031)
Self-Efficacy	0.020 (0.024)	0.010 (0.024)	-0.002 (0.029)	-0.038 (0.039)	0.070 (0.047)	-0.13*** (0.053)
Performance Motivation	0.027** (0.014)	-0.011 (0.013)	0.006 (0.017)	-0.017 (0.023)	-0.041 (0.026)	-0.008 (0.030)
Self-Esteem	0.020 (0.019)	-0.015 (0.018)	0.005 (0.023)	-0.004 (0.032)	0.001 (0.038)	-0.017 (0.045)
Intellectuality	0.005 (0.013)	0.024* (0.014)	-0.014 (0.017)	-0.006 (0.023)	-0.074*** (0.027)	-0.009 (0.032)
Risk Taking	-0.012 (0.012)	-0.021* (0.011)	0.016 (0.015)	0.010 (0.020)	0.031 (0.025)	0.09*** (0.029)
Constant	0.963** (0.433)	1.55*** (0.427)	0.500 (0.525)	-0.144 (0.714)	0.584 (0.867)	-1.148 (0.981)
No of Observations	184	184	184	184	184	184

Notes: */**/***significant at 10%, 5% and 1% level. Std. errors in parentheses.

The results for the second node are reported in the third column of Table 2.5. We find that the intellectuality and risk taking scores are significantly related to the number of stops right after the SPE node. Specifically, a one-unit increase in the intellectuality score is associated with 2.4 percent increase in the expected number of stops on the second node. On the other hand, a unit increase in the risk taking score is associated with 2.1 percent decrease in the expected stops right after the SPE node. These findings are also supported by the significance and signs of the same traits on later nodes. A unit increase in the intellectuality and risk taking scores is associated with 7.4 percent decrease in expected number of stops on the fifth node and 9 percent increase in the expected number of continues on the last node, respectively. The significant and negative coefficient in the second node and the positive on the continue option of last node illustrates the consistency of our hypothesis on risk lover behavior. Evidently, the subjects with high scores on risk taking are less likely to stop on early nodes and more likely to continue on the later nodes of the centipede games. Although we made our predictions based on the likelihood of stops on the SPE node for the intellect trait, this result is not contradictory with our expectations, because they imply that players with a higher intellectuality score are more likely to terminate the game earlier.

Finally, our last significant personality trait, self-efficacy, has a highly significant and negative relationship with the number of continue choices on the last node. Somehow, this relationship is the highest among all traits. Specifically, a one unit increase in the self-efficacy score is associated with 13.3 percent lower expected continue choices on the last node. While this does not yield any evidence on our prediction on the

SPE plays, it implies that subjects with high self-efficacy are more likely to stay in the game rather than to leave it by choosing out on the last node.

7. Conclusion

As shown by many experimental researchers, the real behavior in the centipede games is different than what game theory predicts. Although there are many approaches that explain the failure of backward induction there is no consensus on the proper way to address these differences. We contribute to the literature by using personality differences as an explanatory reason for backward induction failures in centipede games. There are two advantages of this approach. First, research on personality has shown that personality traits are stable across individuals and shape their behavior (Borghans, Duckworth and Heckman, 2008). Second, by using the reliable and simple (Goldberg, 1999) International Personality Item Pool scales that measure personality characteristics, we use the individuals' personality scores to explore the impact of personalities on strategic decision making under the experimental game setting.

In this paper, we have documented how intellect, self-esteem, risk aversion, and assertiveness can predict the implementation of backward induction. Subjects with high self-esteem and intellectuality employ backward induction and terminate the game on the first node. On the other hand, risk loving and assertive players don't use the process of backward reasoning and fail to terminate the game on their first move.

In particular, using binary response models[38], we show that higher scores for assertiveness and risk taking decrease, and higher scores for intellectuality and self-esteem increase, the probability of SPE plays. Moreover, the consistencies of these hypotheses are supported by further analyses of stopping frequencies and pass rates on the later nodes. According to these results, which are mostly consistent with our predictions made in section 3, the assertiveness, intellect, self-esteem and risk taking coefficients change signs from the first node to the last. The summary of all the results indicates that the high scores on assertiveness and risk taking are associated with a lower frequency of stops at the SPE nodes and a higher frequency of stops on the later nodes. Higher scores on intellectuality and self-esteem are associated with a higher frequency of down choices on the SPE node and a lower frequency of down choices on the later nodes. These findings are not surprising for a risk loving subject who prefers the chance of a higher payoff by choosing to continue rather than stopping on a node that offers a guaranteed payoff. The same holds for an assertive subject, since we believe the assertiveness trait is positively correlated with risky behavior. In addition, although we predict the self-esteem trait to be negatively associated with earlier stops on the game, we find the opposite result. Evidently, a player with high self-esteem is more likely to terminate the game on the SPE node and less likely to continue. This is a surprising result since we argue that a high self-esteem subject tends towards risky behavior as suggested by Benabou and Tirole (2002). On the contrary, we believe that the intellectuality score is

[38] Logit and Probit models

correlated with a subject's cognitive abilities. Hence, an intellectual can understand the process of reasoning backwards in the game and end on the SPE node.

Furthermore, high scores on self-efficacy and performance motivation are associated with staying in and out of the game, respectively. Subjects with high self-efficacy choose out less frequently, and players with high performance motivation choose down on the first move more frequently. Apparently, players with high self-efficacy are persistent in the game and do not give up easily by leaving the game as suggested by Judge and Bono (2001). However, our prediction on their high likelihood of SPE play is not supported by this result. Moreover, high performance motivation leads subjects to stay out of the game by choosing down on the SPE node. While this single result supports our hypothesis, it does not fully support the use of backward induction by the highly motivated subjects. As suggested by Borghans, Duckworth and Heckman (2008) performance motivation represents the subjects' ambition and goal oriented behavior, since they end the game without giving themselves any chance to lose money.

In this study, our findings clearly show that players with different personality traits make different decisions while facing the exact same games. In our strategic games, low scores for risk taking and assertiveness, and high scores for intellect and self-esteem lead subjects to have closer decisions to the game theoretic prediction. This implies that an owner of a company who wants to hire a manager for a position which requires decision making tasks using the process of backward reasoning should prefer the risk averse, unassertive, intellectual and self-assured applicants to the risk lover, assertive, unintellectual and low self-esteem applicants. Moreover, teachers who would like to train their students on backward induction should target the students with low self-esteem, ignorance, risky behavior and assertiveness.

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Appendix B

Appendix B1. Instructions and the Games

INSTRUCTIONS

Thank you for participating in this experiment on decision-making behavior. You will be paid for your participation in cash at the end of the experiment. Your earnings for today's experiment will depend partly on your decisions and partly on the decisions of the player with whom you are matched.

It is important that you strictly follow the rules of this experiment. If you disobey the rules, you will be asked to leave the experiment.

If you have a question at any time during the experiment, please raise your hand and a monitor will come over to your desk and answer it in private.

Description of the task

You will be participating in a simple game. The game requires 2 players, one of whom will be called Player A and the other Player B. Prior to the start of the session, you will be randomly assigned the role of either Player A or Player B and will remain in this role throughout the experiment.

Each player has to choose between two decisions:

STOP

or

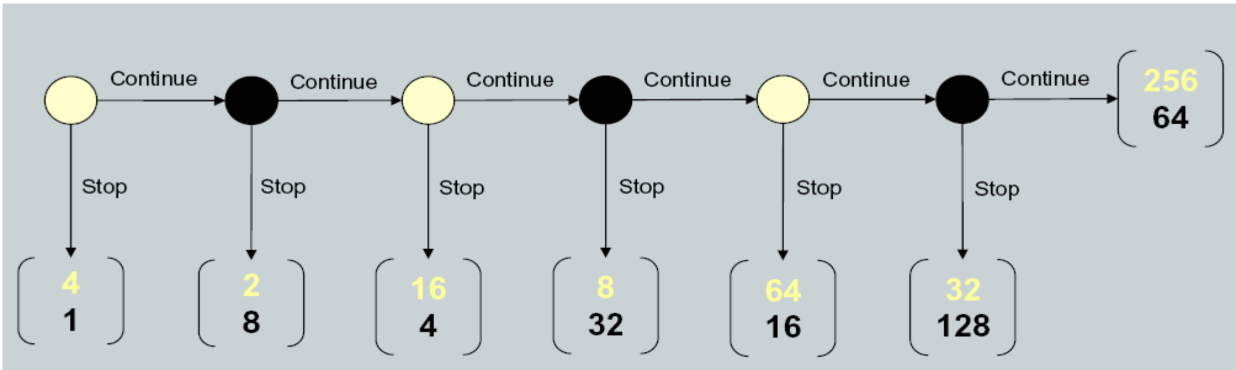
CONTINUE

for each of 5 decision nodes. As soon as any player chooses to STOP, the game ends. If a player chooses to CONTINUE, the other player will be faced with the same choice: STOP or CONTINUE. If he is the last player in the sequence, the game will end regardless of what decision he makes.

Player A will make the first decision. As indicated above, the game ends as soon as one player chooses to STOP. Below is a pictorial representation of the game. The color of the circles (WHITE or BLACK) identifies which player makes a decision (either STOP or CONTINUE) given that the game has progressed to that circle. The arrows pointing right and down represent the two decisions. The terminal brackets contain the payoff information. The game will end at one of the eleven terminal brackets.

All of the payoffs are in U.S. dollars. The top number in each bracket identifies the payoff in $'s for Player A. The bottom number in each bracket identifies the payoff in $'s for Player B.

The game will start with Player A at the farthest left decision node. Please take some time now to study the structure of the game.



The experiment consists of 12 games. In each game you are matched with a different player of the opposite type. That is, if you are Player A you will be matched with a different Player B for each subsequent game. Importantly, you will not know the identity of the players with whom you will be matched, nor will the person with whom you are matched know your identity.

Procedure for Playing the Game:

Indicate on your computer screen at which node you would first like to choose STOP by pressing the button that corresponds to that particular node. If you wish to play continue for all five of your nodes, please press the None option. Once you have made your selection, please press the submit button to record your final decision.

Once all subjects have made their decisions, the computer will randomly match the decisions for each Player A with the decision for a unique B Player.

Using the decisions for each player, the game will be played out as follows. The computer will examine the decision at the first node for Player A. If he selected STOP for this node, the game will end. If not, the computer will examine the decision at the first node for Player B. Again, if he selected STOP for this node, the game will end. If not, the computer will examine the decision at the second node for Player A. These sequential choices continue until we reach either a node where STOP was selected or the final node – the one farthest right – is reached.

Once the outcome of the game has been determined by the computer, you will be informed of the outcome of the game (the node at which STOP was first selected) along with the associated payoff.

This same basic procedure will be followed for each of twelve games.

Determining Final Payoffs

You will only be paid your earnings for one of the twelve games you will play during today's session. After all twelve games have been completed, we will randomly select one of the games by selecting an index card that is numbered from 1 to 12. The number on the card which is selected will determine which game will determine your earnings for today's session.

Even though you will make twelve decisions, only one of these will end up affecting your earnings. You will not know in advance which decision will hold, but each decision has an equal chance of being selected.

Games

G1: Standard centipede (n=202)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	36, 23	24, 38	--	40, 25
G2: Constant sum centipede (n=202)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
22, 22	**20, 24**	26, 18	15, 29	31, 13	11, 33	34, 10	7, 37	40, 4	2, 42	--	44, 0
G3: One-sided error one move standard 1 (n=102)											
A1 D	B1 D	**A2 D**	**B2 D**	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
12, 9	17, 14	**20, 15**	**16, 22**	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	--	36, 23
G4: One-sided error two moves standard 1 (n=102)											
A1 D	B1 D	A2 D	B2 D	**A3 D**	**B3 D**	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
8, 5	10, 7	12, 9	17, 14	**20, 15**	**16, 22**	24, 17	18, 26	32, 21	22, 34	--	36, 23
G5: One-sided error one move standard 2 (n=100)											
A1 D	B1 D	**A2 D**	**B2 D**	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
8, 5	10, 7	**20, 15**	**16, 22**	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	--	36, 23
G6: One-sided error two moves standard 2 (n=100)											
A1 D	B1 D	A2 D	B2 D	**A3 D**	**B3 D**	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
12, 9	14, 10	15, 12	17, 14	**20, 15**	**16, 22**	24, 17	18, 26	32, 21	22, 34	--	36, 23
G7: One-sided error one move constant sum 1 (n=102)											
A1 D	B1 D	**A2 D**	**B2 D**	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 19	22, 21	**22, 22**	**20, 24**	26, 18	15, 29	31, 13	11, 33	34, 10	7, 37	--	40, 4
G8: One-sided error one move constant sum 2 (n=100)											
A1 D	B1 D	**A2 D**	**B2 D**	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
16, 15	22, 21	**22, 22**	**20, 24**	26, 18	15, 29	31, 13	11, 33	34, 10	7, 37	--	40, 4
G9: One-sided error two moves constant sum (n=202)											
A1 D	B1 D	A2 D	B2 D	**A3 D**	**B3 D**	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
16, 15	18, 17	20, 19	22, 21	**22, 22**	**20, 24**	26, 18	15, 29	31, 13	11, 33	--	34, 10

G10: Activity bias standard (n=202)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
B chooses 19,10 or 20, 15	**16, 22**	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	36, 23	24, 38	--	40, 25
G11: Activity bias constant sum (n=202)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
B chooses 21, 20 or 22, 22	**20, 24**	26, 18	15, 29	31, 13	11, 33	34, 10	7, 37	40, 4	2, 42	--	44, 0
G12: Early beliefs 1 (n=102)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	-5, 44	45, -5	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	--	36, 23
G13: Late beliefs 1 (n=102)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	24, 17	18, 26	28, 19	20, 30	-5, 56	57, -5	32, 21	22, 34	--	36, 23
G14: Early beliefs 2 (n=100)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	12, 9	17, 4	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	--	36, 23
G15: Late beliefs 2 (n=100)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	24, 17	18, 26	28, 19	20, 30	12, 9	17, 14	32, 21	22, 34	--	36, 23
G16: Early focal point (n=202)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	39, 0	0, 40	24, 17	18, 26	28, 19	20, 30	32, 21	22, 34	--	36, 23
G17: Late focal point (n=202)											
A1 D	**B1 D**	A2 D	B2 D	A3 D	B3 D	A4 D	B4 D	A5 D	B5 D	A5 R	B5 R
20, 15	**16, 22**	24, 17	18, 26	28, 19	20, 30	51, 0	0, 52	32, 21	22, 34	--	36, 23

Appendix B2. Personality Survey

Subject # ____________________

Confidential Survey: These questions will be used for statistical purposes only. THIS INFORMATION WILL BE KEPT STRICTLY CONFIDENTIAL and WILL BE DESTROYED UPON COMPLETION OF THE STUDY.

	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
I do more than what is expected of me	❑	❑	❑	❑	❑
I talk to a lot of different people at parties	❑	❑	❑	❑	❑
I just know that I will be a success	❑	❑	❑	❑	❑
I often think that there is nothing that I can do well	❑	❑	❑	❑	❑
I seek adventure	❑	❑	❑	❑	❑
I am not interested in theoretical discussions	❑	❑	❑	❑	❑
I hold back my opinions	❑	❑	❑	❑	❑
I take control of things	❑	❑	❑	❑	❑
I formulate ideas clearly	❑	❑	❑	❑	❑
I do just enough work to get by	❑	❑	❑	❑	❑
I am able to think quickly	❑	❑	❑	❑	❑
I question my ability to do my work properly	❑	❑	❑	❑	❑
I undertake few things on my own	❑	❑	❑	❑	❑
I can handle a lot of information	❑	❑	❑	❑	❑
I misjudge situations	❑	❑	❑	❑	❑
I express myself easily	❑	❑	❑	❑	❑
I avoid dangerous situations	❑	❑	❑	❑	❑
I am not interested in abstract ideas	❑	❑	❑	❑	❑
I have a lot of personal ability	❑	❑	❑	❑	❑
I am skilled in handling social situations	❑	❑	❑	❑	❑

I never challenge things	❑	❑	❑	❑	❑
I am not highly motivated to succeed	❑	❑	❑	❑	❑

	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
I cannot come up with new ideas	❑	❑	❑	❑	❑
I take risks	❑	❑	❑	❑	❑
I enjoy thinking about things	❑	❑	❑	❑	❑
I have difficulty expressing my feelings	❑	❑	❑	❑	❑
I often feel uncomfortable around other people	❑	❑	❑	❑	❑
I set high standards for myself and others	❑	❑	❑	❑	❑
I seek to influence others	❑	❑	❑	❑	❑
I come up with good solutions	❑	❑	❑	❑	❑
I put little time and effort into my work	❑	❑	❑	❑	❑
I like to take responsibility for making decisions	❑	❑	❑	❑	❑
I would never make a high risk investment	❑	❑	❑	❑	❑
I like to solve complex problems	❑	❑	❑	❑	❑
I wait for others to lead the way	❑	❑	❑	❑	❑
I am less capable than most people	❑	❑	❑	❑	❑
I am willing to try anything once	❑	❑	❑	❑	❑
I have little to say	❑	❑	❑	❑	❑
I demand quality	❑	❑	❑	❑	❑
I know how to captivate people	❑	❑	❑	❑	❑
I avoid philosophical discussions	❑	❑	❑	❑	❑
I stick to the rules	❑	❑	❑	❑	❑

Appendix B3. Probit Estimations

Marginal Effects of Probit Model

Independent Variables	Dependent Variable-SPE plays
Subject role	0.071**
	(0.030)
Assertiveness	-0.013*
	(0.007)
Sociability	0.002
	(0.004)
Self-efficacy	0.004
	(0.008)
Performance motivation	0.002
	(0.004)
Self-esteem	0.011*
	(0.007)
Intellectuality	0.008*
	(0.005)
Risk Taking	-0.006
	(0.004)
Game dummies	Yes
Round dummies	Yes
No of observations	2208

Notes: */**/***significant at 10%, 5% and 1% level. Robust Std. errors in parenthesis

Appendix B4. Fractional Logit Estimates for Separate Length Games

Marginal Effects Estimates of Fractional Logit Model (one and two move games excluded)

Independent Variables	**Dependent Variable-Nodes as a fraction between 0 and 1**
Subject role	-0.063***
	(0.025)
Assertiveness	0.004
	(0.005)
Sociability	-0.001
	(0.004)
Self-Efficacy	-0.003
	(0.007)
Performance Motivation	-0.001
	(0.004)
Self-Esteem	-0.010**
	(0.005)
Intellectuality	-0.003
	(0.004)
Risk Taking	0.004
	(0.003)
Round dummies	Yes
Game dummies	Yes
No of observations	1472

Notes: */**/***significant at 10%, 5% and 1% level. Robust Std. errors in parentheses.

Marginal Effects Estimates of Fractional Logit Model for one-move games

Independent Variables	**Dependent Variable-Nodes as a fraction between 0 and 1**
Subject role	-0.010***
	(0.037)
Assertiveness	0.009
	(0.008)
Sociability	0.001
	(0.005)
Self-Efficacy	-0.003
	(0.011)
Performance Motivation	0.002
	(0.006)
Self-Esteem	-0.011
	(0.008)
Intellectuality	-0.003
	(0.005)
Risk Taking	-0.0002
	(0.005)
Round dummies	Yes
Game dummies	Yes
No of observations	368

Notes: */**/***significant at 10%, 5% and 1% level. Robust Std. errors in parentheses.

Marginal Effects Estimates of Fractional Logit Model for two-move games

Independent Variables	**Dependent Variable-Nodes as a fraction between 0 and 1**
Subject role	-0.010***
	(0.032)
Assertiveness	-0.005
	(0.008)
Sociability	0.004
	(0.005)
Self-Efficacy	0.005
	(0.011)
Performance Motivation	-0.008
	(0.005)
Self-Esteem	-0.002
	(0.007)
Intellectuality	-0.006
	(0.005)
Risk Taking	0.003
	(0.005)
Round dummies	Yes
Game dummies	Yes
No of observations	368

Notes: */**/***significant at 10%, 5% and 1% level. Robust Std. errors in parentheses.

Appendix B5. Means and Variances for Poisson Model

Variable	Mean	Variance
Total stops at SPE	3.33	5.79
Total stops at 2	3.34	3.69
Total stops at 3	2.24	1.95
Total stops at 4	1.21	1.52
Total stops at 5	0.84	1.22
Total out	0.65	1.26

In the table above we have 184 valid observations for each outcome variable. The unconditional mean and variance of our outcome variable, number of stops at each node and continue choices at the last node, are not very different. Hence, our model assumes that these values conditioned on the predictors, will be roughly equal. Additionally, the means and variances for the first and second player roles, which show the conditional means and variances, are similar as shown below.

Subject Role	**Mean**	**Variance**	**N**
1	3.16	5.19	92
2	3.50	6.38	92
Total stops at SPE	3.33	5.79	184
1	3.38	4.00	92
2	3.30	3.42	92
Total stops at node 2	3.34	3.69	184
1	2.38	2.04	92
2	2.11	1.83	92
Total stops at node 3	2.24	1.95	184
1	1.23	1.85	92
2	1.18	1.21	92
Total stops at node 4	1.21	1.52	184
1	0.80	1.06	92
2	0.87	1.39	92
Total stops at node 5	0.84	1.22	184
1	0.66	1.19	92
2	0.64	1.33	92
Total out	0.65	1.26	184

Conclusion

Takeover probability and firm's research investment can be either directly or inversely related. In this dissertation, I examine three arguments on the relationship between the exit probabilities and the research and development intensity. These are managerial myopia, leveraged buyouts and strategic sale of the company motivation.

In the first chapter of my dissertation, I examine the impact of failures and acquisitions on firms' research intensity using a propensity score model and a model similar to the two-stage least squares. The evidence shows that the correlation between the exit likelihood and research intensity is negative. This finding suggests that managerial myopia plays an important role in firms' research investment decision when they are under the risk of a takeover or a failure.

The second chapter of my dissertation is based on the personality traits as an alternative explanation for the backward induction failures. The second essay examines the impact of risk taking, assertiveness, sociability, intellect, self-efficacy, performance-motivation and self-esteem on the subgame perfect equilibrium plays in centipede games. Using logit models and a poisson model we find that, subjects' high scores on intellect and self-esteem are positively associated whereas risk taking and assertiveness are negatively associated with the likelihood of subgame perfect equilibrium plays.

Vita

Evren Atiker was born in Izmir, Turkey. She received her Bachelor of Arts degree in Finance from Eskisehir Osmangazi University, Turkey, in 2004. After graduation, she entered the University of Tennessee to pursue PhD in economics in August 2006. Her doctoral degree would be received in August 2012.