ESSAYS ON ENTREPRENEURIAL RISK PREFERENCES AND CAREER CHOICES

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirement for the Degree of

Doctor of Philosophy

by

Romi Kher

August 2014

Essays on Entrepreneurial Risk Preferences and Career Choices

Romi Kher, PH.D.

Cornell University 2014

This dissertation explores risk preferences and career choice decisions amongst undergraduates and specifically addresses startup challenges facing students and universities. The first paper hypothesizes that undergraduate students from highly ranked universities have strong financial incentives (the "good job" trap) that lead them to pursue traditional, corporate careers *immediately upon graduation*. Analysis of 235 recent graduates from an Ivy League university and a Big Ten university, adjusted for monetary costs, parental preferences and individual ability, shows that the Ivy League graduates are in fact less likely to become entrepreneurs immediately upon graduation due to opportunity cost considerations. Students are also less likely to pursue an entrepreneurial career if they have multiple job offers and conversely, lack of quality job offers is a strong motivator for self-employment. The next paper introduces the concept of "losers' dilemma" and leverages a market driven, dynamic business simulation to specifically study how teams behave in a competitive setting, how they balance personal and team risk preferences, and how competitors can induce riskier behavior. Utilizing a sample of 130 undergraduates participating in a multiple 7-week dynamic simulations, we find that losing teams are dominated by risk averse individuals who avoid conflict, struggle

aligning individual and team risk preferences, and claim to be risk takers but consistently showcase risk averse decision making. These losing teams display high confidence in their business projections but conversely, showcase low self-confidence and a “yo-yo” approach to strategy evolutions. Both papers not only contribute to entrepreneurship literature but also have practical implications for universities and startup incubators seeking to seed the next generation of entrepreneurs.

BIOGRAPHICAL SKETCH

Romi Kher is a doctoral graduate of the Dyson School of Applied Economics and Management from Cornell University with research interests in venture creation and entrepreneurial risk preferences. Romi is also the founder of 10GoodMinutes.com and a co-facilitator of Flip The Switch workshop series. He has previously earned an MBA from UMass Amherst and is interested in venture capital and financing. He is an avid golfer and more importantly, a dog lover. A happy-go-lucky fellow, no one that knew him in high school would ever guess that he now has a PhD from an Ivy League institution.

DEDICATION

To Alfa - the kindest, gentlest soul I have ever met. He taught me the meaning of unconditional love. Nothing I say here can ever come close to how I truly feel.

"No heaven will not ever Heaven be, unless he was there to welcome me"

ACKNOWLEDGEMENTS

It would be foolish of me to ever imply that this thesis is my creation alone. Many have helped, supported and encouraged me through the process and I thank them from the bottom of my heart. As Tim Gunn eloquently said: “Life is not a solo act. It’s a huge collaboration, and we all need to assemble around us the people who care about us and support us in times of strife.”

I would like to publicly thank my committee. They told me what I needed to hear, not what I wanted to hear and without them, I have no idea where I would be.

Dr. Deborah Streeter: It is no secret that I would not be at Cornell were it not for her. Her continued support, mentorship and guidance made my life infinitely easier and made my peers envy me. I have no doubt that my graduate experience would be very different were it not for her guidance and friendship. For that, I am grateful and proud. Thank you.

Dr. David Just: A mentor who pushed me to excel and in his own unique way, molded me into the researcher I have become. I still have a lot to learn but he gave me the head start that all want, but few get. Thank you.

I also want to acknowledge everyone that has ever doubted me - that motivation is special and always welcome. Thank you

TABLE OF CONTENTS

Biographical Sketch	iii
Dedication	iv
Acknowledgements	v
Table of Contents	vi

1. Introduction

1.0	Introduction	3
1.1	Thesis Motivation	5
1.2	Section References	7

2. The "Good Job" Trap: Opportunity Cost as a Deterrent to Immediate Venture Creation

2.1 Abstract
2.2 Background
2.3 Research Hypothesis
2.4 Literature Review
2.4.1 Correlating opportunity cost to general career choices, education and ability
2.4.2 Correlating opportunity cost to entrepreneurial success
2.5 Conceptual Model
2.6 Data Description
2.6.1 Selection of Universities
2.6.2 Choice of University
2.6.3 Background of respondents
2.6.4 Impact of Collegiate entrepreneurship courses on career choice
2.6.5 External impacts on career choice
2.6.6 Career choice upon graduation
2.6.7 Controlling for ability
2.7 Empirical Model
2.7.1 Propensity score matching
2.7.2 Stage 1 Estimation Equation: Selecting a university to attend
2.7.3 Stage 2 Estimation Equations: Determining opportunity costs
2.7.4 Estimation equation: Is entrepreneurship a career choice or no-choice option?
2.7.5 Estimation equation: Factoring in opportunity costs with outside pressures
2.8 Empirical Results
2.8.1 Equation 1 Results: Selecting a university to attend
2.8.2 Equations 2 & 3 Results: Determining opportunity costs
2.8.3 Equation 4 Results: Is entrepreneurship a career choice or no-choice option?

2.8.4 Equation 5 Results: Factoring in opportunity costs with outside pressures
2.8.5 Results Summary
2.9 Conclusions and Discussion
2.10 Section References

3. Estimating the impacts of "certainty in uncertainty" on attitudes and risk preferences in team settings using a dynamic, market based simulation.

3.1 Abstract
3.2 Introduction
3.3 Theoretical Background
3.4 Literature Review
3.5 Data Collection
3.5.1 Experiment Overview
3.5.2 The Simulation – Detailed Outline
3.6 Determining Individual Risk Preferences
3.7 Data Demographics and Risk Perceptions
3.8 Research Hypotheses And Assumptions
3.9 Empirical Model
3.9.1 Estimation Equations
3.10 Empirical Results – Hypothesis 1 and 2
3.10.1 Assumption 1 - Exploring Changes In Individual Risk Attitudes
3.10.2 Assumption 2: Individual versus Group Risk Attitudes
3.10.3 Assumption 3: Personal Satisfaction and Team Conflict
3.10.4 Assumption 4: Impact of Strategy Deviations to Success
3.10.5 Assumption 5: Individual Satisfaction With Results
3.10.6 Assumption 6: Losing And The Dominance of Risk Aversion
3.11 Empirical Results For Hypothesis 3
3.11.1 Equation 2 Results
3.11.2 Equation 3 Results
3.11.3 Equation 4 Results
3.12 Conclusions
3.12.1 Relevance to Entrepreneurship
3.13 Theoretical Implication
3.13.1 Overconfidence in Last Placed Teams
3.13.2 Risk Aversion and Losers Dilemma
3.13 Discussion
3.14 Section References

1.0 Introduction

Since the first class offered in the 1940s, the entrepreneurship discipline has grown and matured across various universities in the U.S. and internationally. The field has its origins in economics, and Cantillon (1755) is credited with coining one of the first definitions of *Entrepreneur* in his "Essai sur la nature du commerce en general." Even Smith dealt with the issue in 1776 in his "An inquiry into the wealth of nations" and Baudeau (1730–1792), the French economist, offered an image of the entrepreneur as an innovator who is able to reduce his costs and consequently raises his profits implementing different innovations.

As an academic discipline, much of its early evolution can be linked to the Austrian economist Joseph Schumpeter who framed the role of the entrepreneur as an agent of economic change. Schumpeter (1947) argued that entrepreneurs excelled in creating "new combinations" of resources that disrupted the competitive equilibrium of existing markets and organizations. Researchers thus began investigating the conceptual aspects of entrepreneurship and viewing entrepreneurs as agents of change.

By the 1970s though, the field evolved to the study of business creation without much social or cultural impacts. These studies generally employed large datasets and a quantitative approach, but little focus on entrepreneurial behavior. The availability of large datasets and advances in computing techniques facilitated this shift. The 1980s witnessed disjointed growth due to "transitory contributors" (Landström, 2001) but the 1990s saw a strong framework emerge. Modern entrepreneurship research (1990s onwards) has renewed its interest in studying the entrepreneur, his or her motivations, and cultural and socioeconomic impacts. Casson (1991, 1995) and his findings on levels of trust in countries and entrepreneurial competence helped jumpstart this new direction in entrepreneurship research.

Today, the subject has grown in legitimacy, particularly in business schools (Cooper 2003) and almost every college or university offers a course in entrepreneurship. As a field, the discipline is still in the final throes in its fight for academic legitimacy, but increased donor funding, growth in courses, conferences and academic appointments is evidence that the field has moved forward (Kuratko, 2003). A 2002 study by Jerome Katz found that the majority of growth in the discipline will likely come from outside the U.S., and that current major problems include a glut of journals, a narrowing focus on top-tier publications, and a shortage of faculty overall exacerbated by a shortage of PhD programs.

This dissertation will investigate two critical entrepreneurship issues leveraging primary data collected specifically for this thesis. The first topic focuses on the impacts of opportunity costs on career choices immediately upon graduation. We test our hypothesis that undergraduate students from highly ranked universities have strong financial incentives (the “good job” trap) that lead them to pursue traditional, corporate careers right after graduation.

The second paper introduces the concept of “losers’ dilemma” and estimates the effects of a business strategy simulation on an individual’s perceived risk aversion towards venture creation. We also estimate how competitive pressures in the business simulation induce individuals to behave in a “more risky” manner and act contrary to their stated risk preferences.

1.1 Thesis Motivation

Kher et al (2012) found that entrepreneurship classes have not only had a statistically significant impact on new venture creation, but are also significant in changing a student’s mindset to favor entrepreneurship. Studying a large sample of 1,520 respondents, they found that the impact of the entrepreneurship program was observed campus-wide and across majors and two primary schools of thought relating to venture creation exist – donors to the entrepreneurship programs want to see students starting their ventures immediately upon graduation while many students prefer gaining work experience before launching a business venture.

This finding motivates our focus on investigating the linkage between risk attitudes, opportunity costs and venture creation. Streeter et al, (2011) found that only 44% of the top 160 programs, as ranked by Entrepreneur magazine, specifically list venture creation as a goal in their mission statements. Yet, this variable is widely used in ranking systems, in program validation metrics and most importantly, in donor expectations. While we have no issue with colleges and universities encouraging student startups, it is critical to study what issues face these students as they pursue career options. This question is the primary motivator for our research into the "good job" trap and the first paper in this thesis.

The final paper studies students undergoing a business simulation and focuses in on their personal risk preferences, team dynamics and decision-making as they participate in an uncertainty and constantly changing market. As facilitators of the simulation, we often hear students say that they changed strategies or took more risks because they observed their competitors making 'big' moves. We witnessed the pressure of competition inducing teams to make moves that were uncomfortable to them and often teams changed strategies or completely abandoned their initial plans solely to counter moves made by their competitors. Such moves also created conflict amongst teammates as team members and a few participants considered some of their team's moves "irrational but necessary to win," and implemented them knowing that the risk-reward ratio was extremely high.

Not surprisingly, startups often pivot and make moves due to market pressures in order to stay relevant and competitive. Often this pivot in strategy is the reason for success and while this concept of pivoting is not new, it has been made popular by Eric Ries, a Silicon Valley entrepreneur and author of *The Lean Startup.* Specifically researching how teams behave in a competitive setting, how they balance personal and team risk preferences, and how competitors can induce riskier behavior, are topics the final paper explores in detail. Findings from this paper will not only contribute to academic literature, but also have practical findings important to universities and startup incubators.

1.2 References

Casson, Mark (1995), "*Entrepreneurship and Business Culture. Studies in the Economics of Trust"*, vol. 1. Aldershot, UK: Edward Elgar.

Cooper, Arnold (2003), "Entrepreneurship: The Past, the Present, the Future," *Handbook of Entrepreneurship Research*. Boston: Kluwer.

Katz J, (2003), "The chronology and intellectual trajectory of American entrepreneurship education: 1876–1999", *Journal of Business Venturing*, Volume 18, Issue 2, Pages 283–300

Kher, R., Just, D., Streeter, D (2011) "Do Entrepreneurship Courses Change an Individual's Attitude Toward New Venture Creation? Results of a Quantitative Assessment of the Cornell Entrepreneurship Program", *International Review of Entrepreneurship*, 9(4)

Kuratko, D.F. (2003), "*Entrepreneurship Education: emerging trends and challenges for the 21st Century"*, Coleman Foundation White Paper Series for the USASBE.

Landstrom, H. (2001), "Who loves entrepreneurship research? Knowledge accumulation within a transient field of research", *Paper presented at the RENT XV Conference*, Turku, Finland, Nov. 22-23.

Schumpeter, J, "The Creative Response in Economic History", *The Journal of Economic History, 7: 149-159.*

Streeter, D., Kher, R., Jaquette, J. (2011), "University-wide trends in entrepreneurship education and rankings: A dilemma", *Journal of Entrepreneurship Education*, Vol 14

The "Good Job" Trap: Opportunity Cost as a Deterrent to Immediate Venture Creation.

2.0 Abstract

This paper explores the relationship between opportunity costs and the decision to pursue entrepreneurship among undergraduates as their first career choice. Our hypothesis is that undergraduate students from highly ranked universities have strong financial incentives (the "good job" trap) that lead them to pursue traditional, corporate careers *immediately upon graduation*. Analysis of 235 recent graduates from an Ivy League university and a Big Ten university, adjusted for monetary costs, parental preferences and individual ability, shows that the Ivy League graduates are less likely to become entrepreneurs immediately upon graduation due to opportunity cost considerations. Students are also less likely to pursue an entrepreneurial career if they have multiple job offers and conversely, lack of quality job offers is a strong motivator for self-employment. We argue that it is in fact the sensible choice for students to choose salaried employment rather than venture creation immediately upon graduation, even when they harbor entrepreneurial plans for the future. These findings have implications for programmatic and resource allocation decisions at the university level.

2.1 Background

Entrepreneurship education has seen substantial growth over the past several decades. According to the Kauffman Foundation, the largest foundation in the U.S. with a focus on entrepreneurship, there are currently more than 5,000 entrepreneurship programs in the U.S., up from approximately 250 programs in 1985. To date, the Kauffman Foundation has given more than $50 million to colleges and universities to promote university-wide entrepreneurship. Private donors have jumped on board as well and are actively supporting university entrepreneurship programs, incubators and professorships. Using results reported by participants in the 1999-2000 National Survey of Entrepreneurship Education, Solomon et al. found "evidence that institutions are receiving major endowments for entrepreneurship education in the form of chairs, professorships and centers".

Many of the recipient schools highlight venture creation as a goal of their entrepreneurship programs. For example, a recent study on university wide trends in entrepreneurship found that approximately 44% of the top 160 programs specifically list venture creation as a programmatic goal in their mission statements. The focus on student startups has been encouraged by specific grants the National Science Foundation (NSF) and The National Collegiate Inventors and Innovators Alliance (NCIIA) are awarding to foster the creation of new companies based on student innovations. Furthermore, media outlets such as *BusinessWeek* and *Entrepreneur* have started to publish lists of the "best entrepreneurship programs" that are based on various ranking systems that may vary in terms of approach but share one common metric: student venture creation.

The focus on promoting and quantifying student ventures begs the question – when is starting a venture the "best choice" upon graduation? That is, under what conditions is student venture creation seen as a desirable choice? What roles, if any, do parental pressures, the availability of viable alternatives, the need to pay back college loans and individual risk tolerances play in weighing the choices? And if collegiate rankings have influenced students to pursue a "highly ranked" university out of high school, is the employment vs. entrepreneurship decision influenced by the culture of the university and the opportunity set facing its graduates? Are good jobs forming a trap that prevents students from starting their own companies?

Furthermore, is there an inherent conflict of interest for entrepreneurship programs in their encouragement of student ventures *immediately* following graduation? Programs emphasize the direct pathway to startups in part because it is far easier to do a headcount of the students who started a business just after their senior year than to follow alums across decades and observe new ventures along the way. Are ranking systems and donor expectations inadvertently setting up incentives for programs to favor venture creation without regard to whether a startup is the best option for the individual students? What about opportunity costs of pursuing an alternative and its relationship to rational choice? These questions motivated our interest in researching this subject area.

2.3 Research Hypothesis

Peter Thiel recently created waves with his "20 under 20" fellowship program in which young entrepreneurs are handed $100,000 to pursue their entrepreneurial dreams and are required to skip college for at least two years. As James O'Neill, head of the Thiel Foundation stated, "The broad aim of '20 under 20' is to produce more technological innovation, and in turn faster and more sustainable economic growth. That's best achieved by unleashing the creative and unsullied mind power of young people, before lofty student loans and academic orthodoxy funnel them into safe and risk-averse careers." Simply put, Mr. Thiel is attempting to maximize youth ventures by minimizing the opportunity cost of choosing to pursue an entrepreneurial dream. While we have some reservations with Mr. Thiel's philosophy, his program highlights the importance of opportunity cost in venture creation.

Opportunity cost is defined as the cost of an alternative that must be forgone in order to pursue a certain course of action. The better the alternative choices, the higher the opportunity cost and the less attractive is the option in question. Our hypothesis is that undergraduate students from highly ranked universities have strong incentives towards pursuing a traditional, corporate career versus self-employment. These "top" students have access to relatively high-paying corporate positions and a "track" for succeeding in large firms. For many students from highly ranked universities, the risk of starting their own venture immediately upon graduation, and passing over a corporate opportunity, is just too high. Whether university rankings are a true reflection of differences in candidates' abilities can be debated, but graduates of highly ranked programs do receive better job offers, as seen in Clark (2002) who critiques the ranking systems but cites one study that shows that graduates of the top-ranked US business schools are offered higher salaries even when employers know that lower-ranked schools offer a better education. Since highly ranked universities in the U.S. tend (on average) to be more expensive and may lead to higher levels of student debt upon graduation, we additionally hypothesize that debt obligations coupled with the probability of failure of a startup can serve as strong motivators against pursuing an entrepreneurial career path. Moreover, while not considered as a part of opportunity costs, parental and peer pressures and an upbringing that directs children towards a stable, "high-powered," corporate job (as a first job) can also play a strong role in dissuading students from pursuing an entrepreneurial career path immediately upon graduation.

Thus we see the conflict: programs, funding sources, and donors are incentivized to look for early entrepreneurial successes. However, for any graduating undergraduate student, the opportunity cost of an entrepreneurial path may be too high when compared to a corporate job that not only provides a near-term financial benefit in the face of debt, but also meets cultural norms. Furthermore, the opportunity cost may be considerably higher for graduates of highly ranked institutions due to various factors: higher paying and/or multiple job offers, higher debt levels and the tendency to pursue graduate study.

2.4 Literature Review

Most previous research in this subject examines the correlation of opportunity costs with either: i) general career choices and ability, or ii) success/profitability of entrepreneurial ventures. We were unable to find research that specifically linked opportunity costs to immediate student venture creation. Our paper not only links opportunity costs to immediate venture creation but also discusses student motivations behind such career choices.

2.4.1 Correlating opportunity cost to general career choices, education and ability

Scott Stern explored the relationship between wages and the scientific orientation of R&D organizations by researching the opportunity costs that scientists incur as they pursue research for "the sake of science" versus for the sake of commercialization. Firms were classified as "science" firms if they allowed their scientists to pursue a research agenda and distinctions were made between a scientist's motivations for research. Stern categorized the scientists into two primary groups: scientists who research for the sake of scientific knowledge and the others who pursue science for commercialization purposes. The paper found a negative relationship between wages and the pursuit of scientific research. The paper controls for unobserved productivity bias by looking at how many job offers a post-doctoral biologist received and then adjusting for the different salary levels offered to individual researchers. Stern finds that conditioned on perceived ability, scientists do indeed incur an opportunity cost for pursuing a research career. We adopt this aspect of Stern's approach and adapt it for studying the differences between salaried and entrepreneurial career choices.

Rees and Shah (1986) examined the choice between self-employment and paid-employment and assessed a sample of 4,762 individuals from the General Household Survey for 1978. They found "positive selection bias in the observed earnings of employees, that the probability of self-employment depended positively on the earnings difference between the two sectors and that education and age are significant determinants of self-employment." Chuang and Dellman-Jenkins (2010) surveyed 360 hospitality students and found that future career intentions in hospitality were significantly associated with a student's gender, work experience, transfer status, and outcome expectations in the industry. They also concluded that students focused on intrinsic outcomes regarding career accomplishments, a trait commonly associated with entrepreneurial intentions and decision-making.

Zane and DiRenzo examined the reasons behind why entrepreneurs chose to pursue certain opportunities when compared to others. Cognitive biases affecting risk perception were found in entrepreneurs, with entrepreneurs focused more on potential value, while non-entrepreneurs focused on cost. Their paper proposed a new model whereby opportunity cost and opportunity value mediated the relationship between cognitive biases and risk perception on one hand, and the decision to pursue an opportunity on the other.

Two papers lay the foundation for estimating linkages between opportunity costs and venture creation. Hamilton explored possible explanations for the decision between self-employment and salaried employment, finding the non-pecuniary benefits of self-employment to be substantial. Additionally, Hamilton finds that most entrepreneurs that stayed in business for 10 years had lower earnings when compared to salaried employees. Results indicated a median earnings differential of 35 percent which could not be explained by the selection of low ability employees into self-employment. Hamilton concludes that non-pecuniary benefits closed the gap between salaried employment and venture creation.

Secondly, Amit et. al (1995) used multivariate regression and a large sample drawn from the 1992 Canadian Labor Market Activity Survey. The authors found that paid employees who chose to leave their employment to become entrepreneurs earned, prior to leaving, substantially less on average than those who remained salaried employees throughout the entire period sampled. Specifically, wages of workers who chose to remain paid employees were on average 12% higher than those who left to become entrepreneurs. They found that on average, entrepreneurs earned less than their salaried counterparts in the year following their career switch. The paper did not control for ability, attitudes or any predisposition towards entrepreneurship.

While these studies explain entrepreneurial career choice and explore intentions and risk perceptions among entrepreneurs, they do not explicitly link opportunity costs to actual entrepreneurial outcomes. Furthermore, most of these studies fail to account for environmental and financial pressures facing recent graduates that may force them to postpone their desires to start their own business. While these pressure are not accounted for in determining opportunity costs, they can play an important role in a student's career choice selection.

2.4.2 Correlating opportunity cost to entrepreneurial success

Gavin Cassar investigated how an entrepreneur's opportunity costs influence the intended future size of new ventures. The paper found that the higher opportunity costs an entrepreneur faced in terms of education, household income and managerial experience, the larger the expectations of growth and scale were for the venture. Relating it to this paper, the implications are that students from higher ranked universities would seek to establish higher growth ventures as they would potentially be turning down higher paying positions.

Fear of failure also plays a role in discouraging potential graduating students from starting a business. Arora and Nandkumar's recent paper on innovation-based industries explored this topic and found that entrepreneurs with high opportunity costs tended to focus on cashing out more quickly. This focus on quickly cashing out led to more mistakes, and ultimately more venture failures, as the entrepreneurs were more focused on short-term metrics versus long-term strategy.

Lowell (1999) stated that in order to understand entrepreneurial risk, we must use the lens of cognitive psychology and decision-making. The author argued that entrepreneurs use biases and heuristics, which are likely to lead them to perceive less risk in a given decision situation. In particular entrepreneurs use representativeness to make business decisions and are more overconfident than managers in large organizations. Similarly, Audet (2004) surveyed 512 MIT students to identify the causes of entrepreneurial intent among engineering students. They found that personality traits had a strong impact on the attitude towards self–employment and an "entrepreneurial attitude," was strongly linked to the intention of starting a new venture.

The papers outlined in this section hint at the opportunity costs involved with pursuing an entrepreneurial career choice but deal with intentions and not actual outcomes. Our study looks at actual career choices made, controls for student ability and explores intrinsic differences between students from different universities centered on culture, parental attitudes and university rankings.

2.5 Conceptual Model

Opportunity costs are defined as the value of the next-best foregone alternative, whenever a choice is made. Since our hypothesis is that students from higher ranked universities face a different choice set of alternatives upon graduation when compared to students from lower ranked universities, we need to account for these differences before attempting to make valid comparisons between the two groups. This problem can be viewed as a two-step process where prior to making any comparisons, the actual decision to apply to a certain set of universities must be taken into consideration.

Thus as a first step, we need to understand the reasons why students chose to apply to certain universities. Finding universities that are noticeably different in their rankings is key to establishing and calculating opportunity costs. The next step is to then look at career opportunities a student had immediately upon graduation and the actual choices they made. Actual job offers, number of job offers and the possibility of pursuing self-employment then help determine opportunity costs based on the outcome selected. Controlling for ability and parental pressures can add another dimension to understanding this issue from a holistic perspective. This conceptual model, with our two-step analytic process, is outlined in table 1 as shown below.

Table 1 Conceptual framework behind the analysis

Application choice ->	University decision ->	Individual decision ->	Career choice upon graduation
The decision to apply to a university is based on several factors such as ability, family preferences, distance from home, university ranking, courses offered etc. These are outlined in table 3.	The university decides to accept or reject a candidate based on perceived measures of ability (primarily SAT scores and GPA) and interest.	The individual decides to either accept or decline the universities offer if accepted into the university or keep exploring options if denied admission by the university.	Sometime near graduation, the individual decides on their first career choice. This choice is impacted by available job options, their perceptions of and ability towards entrepreneurship and, outside factors such as family and peer preferences.
Step 1			**Step 2**

2.6 Data Description

Several U.S. universities were contacted based on various characteristics and after careful considerations and negotiations; we reached agreement with two universities; an Ivy League university (ILU) and a Big 10 university (BTU). All data were collected utilizing an online survey. Since our target respondents are geographically spread out, conducting an online survey was the most effective option.

Recent graduates (2005-2010) from both universities were targeted for the survey. We reached out to the alumni offices at both universities and had them email the survey to their graduates. We received a total of 235 responses with 134 responses from our Ivy league university (ILU) and 101 responses from the Big 10 university (BTU). Questions were rated on a 6-point likert scale (strongly agree, agree, neutral, disagree, strongly disagree, N/A) and were designed to elicit attitudes towards venture creation and actual career choices.

2.6.1 Selection of Universities

The two universities were selected because of several similarities and some key differences. Both universities offer a variety of undergraduate and postgraduate degrees, are close to, but are not in, major metropolitan cities, both have similar sized student populations and both universities focus on entrepreneurship education and venture creation. But, these universities also have several differences that help us estimate opportunity costs for student ventures. Specifically, we leverage the difference in rankings and tuition costs between the two universities. Over the past few years, ILU has been consistently ranked amongst the top 20 undergraduate institutions in the U.S. while BTU ranks outside the top 50 but in the top 100 institutions. Table 2 briefly profiles the two universities on other metrics.

Table 2 Basic comparison statistics between ILU and BTU

2011 Metrics	**ILU**		**BTU**
US News and BusinessWeek rankings	Top 20		70-100
Acceptance rate	Less than 20%		Above 50%
Average tuition and fees (excluding room & board)	$40,000		$15,000
Four year graduation rates	Above 75%		Less than 50%
% receiving financial aid	46%		46%
Average amount of need based financial aid	$30,000		$5,000

2.6.2 Choice of University

Since our hypothesis is that students from higher ranked universities face a different choice set upon graduation as they ponder future career direction, we first wanted to understand why students chose the given university during their high school search process. Table 3 summarizes these responses.

Table 3 A respondents reasons for choosing to attend a particular university. (respondents could select multiple responses)

	Ivy League University				**Big 10 University**		
Choice	**Agree**	**Disagree**	**Neutral & N/A**		**Agree**	**Disagree**	**Neutral & N/A**
Academic reputation	97%	1.5%	1.5%		87%	6%	7%
Alumni contacts	60%	32%	8%		70%	23%	7%
Job prospects	66%	6%	28%		54%	16%	30%
Family tradition	29%	29%	42%		37%	33%	30%
Highest ranking univ. accepted to	66%	16%	18%		8%	44%	48%
Proximity to home	21%	54%	25%		70%	12%	18%
This university was the least cost option	13%	63%	24%		60%	18%	22%
Cost was immaterial to my decision	32%	46%	22%		20%	58%	22%
Offerings in entrepreneurship	9%	40%	51%		9%	47%	44%
Track record of students starting own ventures	5%	25%	70%		7%	49%	44%

As evident from table 3, students at both schools considered similar items as they chose their undergraduate institution: academic reputation, alumni contacts and job prospects. But it is clear that a student bound for ILU places a higher value on the university ranking versus a student considering BTU. Additionally, 70% of BTU students stated that being close to home was a factor in their decision-making versus only 21% of ILU.

With the average cost of attending BTU pegged at approximately $13,000 and the average cost of attending ILU estimated to be approximately $40,000, we needed to explore how cost differences may have impacted a student's decision to attend either university. While BTU was more likely to be the lowest costs alternative for the respondents, costs matter in decision-making for students in both institutions, thus somewhat diluting the common notion that "most Ivy League students don't care about costs."

Finally, since we are interested in venture creation, we also wanted to adjust for a student choosing either university for its entrepreneurship offerings or track record in supporting student ventures. The last two questions in Table 2 outline the responses to this specific topic. At both universities, it appears that students were not overly concerned about the entrepreneurship offerings and instead, were more focused on other characteristics of a university. With factors such as student loans and family commitments factored in along with rankings, the above table lays the groundwork for estimating reasons why students tend to gravitate towards salaried positions versus starting their own ventures, and allows for comparisons between the two universities.

2.6.3 Background of respondents

To allow for decision-making comparisons across universities and majors, it was critical that we cast a wide net and attract students from a variety of backgrounds. In our data, 35% of ILU students are Business majors with Engineering (14%), Sciences (16%), Social Sciences (18%) and Liberal Arts (17%) comprising the rest. Unfortunately for us, the majority of the respondents from BTU were business majors (84%) with Engineering and Liberal Arts making up the rest. We believe that the reason for this imbalance is that the alumni offices at BTU targeted recent Business school graduates versus all recent graduates.

Since a strong SAT score is a requirement for admission at most top ranked universities, it was not surprising to find that 80% of ILU graduates entered the university with a SAT score of 1300 or higher (out of 1600). At BTU, 58% of graduates entered with a similar SAT score. Upon graduation, 47% of ILU graduates finished with a cumulative GPA of 3.5 or higher compared to 25% of BTU graduates. Since many large corporations consider the GPA of an individual during the recruiting process, this data should help us control for differences in post-graduation compensation between graduates of each university and possible opportunity costs they may experience as they decide to pursue a self-employment path versus a salaried one.

2.6.4 Impact of Collegiate entrepreneurship courses on career choice

At ILU, 35% of the respondents did not participate in any entrepreneurship courses or activities compared to 59% of the respondents from BTU. For students that did participate in entrepreneurship offerings, 27% of ILU respondents and 23% of BTU respondents stated that the classes had no impact on their ultimate career choice immediately upon graduation.

2.6.5 External impacts on career choice

As it has been well established in the literature, family pressures, cultural attitudes and risk perceptions towards entrepreneurship impact one's career choice. To account for and control for these measures, table 4 summarizes additional questions that were asked to establish an individual's perceptions towards venture creation.

Not surprisingly, we notice that for a majority of the students, parents do influence career choices and while immediate family members may prefer that an individual pursue salaried employment, respondents generally agreed that if they chose to pursue an entrepreneurial path, they would feel supported by their families.

Table 4 Cultural and familial impacts on career choice (respondents could select multiple responses)

	Ivy League University			Big 10 University		
Choice	**Agree**	**Disagree**	**Neutral & N/A**	**Agree**	**Disagree**	**Neutral & N/A**
My parents influenced my undergraduate education choice.	53%	25%	22%	48%	37%	15%
My immediate family prefers that I pursue salaried employment versus self-employment.	47%	21%	32%	33%	40%	27%
Starting my own business would not be encouraged by my immediate family.	25%	45%	30%	13%	64%	23%
Entrepreneurs are highly regarded in my ethnic culture.	46%	10%	44%	46%	14%	40%
At least one of my immediate family members is a successful entrepreneur.	40%	39%	21%	38%	55%	17%

When asked to rate how respondents felt about venture creation versus pursuing salaried employment, we had nearly identical results for graduates from both universities. 92% of ILU graduates stated that they thought starting their own business was riskier than pursuing salaried employment with only 2% claiming that starting a business was less risky. Amongst BTU graduates, 90% stated that they felt starting a business was riskier than working a salaried position with 2% claiming the opposite. 6% of ILU graduates and 7% of BTU graduates characterized the risk as even.

2.6.6 Career choice upon graduation

As we are seeking to estimate an opportunity cost to pursuing an entrepreneurial career over salaried employment, the survey asked respondents to outline their job choice immediately upon graduation and their current employment status. With respondents being relatively recent graduates (2005 onwards), the chances that a respondent has switched careers multiple times is low. We address and adjust for one career change and Table 5 summarizes respondent career choices from both universities.

Table 5 Summary of career choices made upon graduation and today

	Ivy League University			Big 10 University	
Choice	**Upon Graduation**	**Current employment**		**Upon Graduation**	**Current employment**
Self employed in your own for-profit business	1.5%	8.8%		7.4%	20.8%
Self employed in your own not-for-profit	0.0%	0.8%		1.9%	0.0%
Family business (not founded by you)	3.0%	2.4%		1.9%	2.1%
Salaried employee	69.7%	68.8%		77.8%	70.8%
Enrolled in Graduate (M.D./Law etc.) school	23.5%	15.2%		5.6%	2.1%
Enrolled in the military	0.0%	0.0%		0.0%	0.0%
Unsalaried volunteer work	0.8%	0.0%		3.7%	4.2%
Unemployed	1.5%	4.0%		1.9%	0.0%

What is interesting is that there are a higher percentage of students choosing to pursue entrepreneurship upon graduation at BTU than at ILU. This trend is also reflected in current career choices and lends credence to our hypothesis that students at a higher ranked university face a higher opportunity cost as it relates to venture creation. With higher tuition costs and loans, we believe that students from top ranked universities face a bigger hurdle pursuing the entrepreneurial "gamble." Alternatively, it could also indicate that BTU graduates had fewer job offers and thus chose self-employment. While most of the other percentages are similar amongst the two universities, almost four times as many ILU graduates choose to go on to graduate school, indicating another potential hurdle against pursuing venture creation upon graduation.

Since we expected the majority of respondents at both universities chose to pursue salaried employment, we asked them for reasons why they chose salaried employment upon graduation (table 6) and more importantly, why they chose not to start their own ventures (table 7). The following tables outline their responses.

Table 6 Reasons for choosing salaried employment (respondents could select multiple responses)

	Ivy League University				**Big 10 University**		
Choice	**Agree**	**Disagree**	**Neutral & N/A**		**Agree**	**Disagree**	**Neutral & N/A**
Received the offer I was looking for.	84%	8%	8%		76%	16%	8%
Prefer stability of salaried/corporate career path.	77%	9%	14%		89%	6%	5%
Gaining experience to eventually start my own business.	44%	26%	30%		24%	27%	49%
Never considered any other employment options.	28%	64%	18%		38%	38%	24%
Wanted certain geographical area to be close to family	59%	24%	17%		54%	30%	16%
No funding($) to start my own business.	7%	68%	25%		11%	73%	16%

Overwhelmingly, the majority of the respondents at both universities accepted salaried employment because they received the offer they were seeking and they preferred the stability of paid employment. With the economic downturn that recent graduates are facing, this result is not unexpected. What is unexpected though is that 44% of ILU respondents state that they are using their salaried employment to gain experience to eventually start their own business. Only, 24% of BTU respondents claim that their salaried employment is grooming them for future self-employment. This may lend credibility to the claims of ILU university faculty when they share anecdotal evidence that suggests their students wait a few years to start their own ventures.

Table 7 Reasons for not pursuing an entrepreneurial career path immediately upon graduation – salaried employees only (respondents could select multiple responses)

	Ivy League University				Big 10 University		
Choice	**Agree**	**Disagree**	**Neutral & N/A**		**Agree**	**Disagree**	**Neutral & N/A**
No interest in entrepreneurship.	17%	68%	15%		34%	50%	16%
I believe that I can have greater financial success in the corporate world.	38%	32%	30%		50%	21%	29%
I was worried that failure in my own venture would reflect poorly on me.	16%	54%	30%		16%	55%	29%
Prefer the stability offered by salaried employment versus starting my own business.	64%	16%	20%		81%	9%	10%
No financial resources to start my own business.	62%	12%	26%		74%	13%	13%
Financial obligations (family, loans etc) and was looking for guaranteed income	56%	28%	16%		45%	39%	16%
Not the right time for me to start my own business though I may pursue this at a later date.	71%	12%	17%		58%	16%	26%
I did not have a viable idea.	61%	15%	24%		55%	16%	29%

Differences between student attitudes towards their career choices come to the forefront as we analyze table 7. When compared to ILU graduates, 50% of BTU graduates feel that they can have greater success in the corporate world and 81% of BTU respondents prefer the stability offered by salaried employment. ILU respondents on the other hand, appear to be more willing to pursue self-employment, albeit at a later time. This “later date” hypothesis is one of the causes tested in our model as we believe that it represents the higher opportunity costs ILU graduates face upon graduation as it relates to starting a business.

2.6.7 Controlling for ability

In order to make direct comparisons between graduates from ILU and BTU, we need the ability to randomly assign a student to the other university and then gauge the impact of the assignment. While SAT scores and GPA upon graduation provide some measure of ability and are the primary admissions criteria used by U.S. universities, we also wanted to account for what other universities a student applied to and was accepted to. By determining what other collegiate prospects a particular respondent had prior to choosing either university, we can use publically available university rankings to include other measures of their potential. In addition to including all eight Ivy League members and all eleven Big 10 member institutions, a few other regional universities were also included into the mix to serve as additional controls. Including these additional schools gives us the overall overlap in rankings and geographical proximity that a potential applicant to either of our target universities would consider. In total, 22 universities were used as controls for ability in addition to GPA and SAT scores.

2.7 Empirical Model

Our hypothesis is that undergraduate students from highly ranked universities have strong financial incentives (the "good job" trap) that lead them to pursue traditional, corporate careers immediately upon graduation. These students may also self-select into ILU due to different career motivations. Since data was collected from two target universities, questions of selection bias arise when making comparisons between the two samples. Simply put, selection bias is a type of bias caused by choosing non-random data for statistical analysis. In a regression context, selection bias occurs when one or more of the regressors are correlated with the error term. Random allocation to control (BTU) and treated groups (ILU) can help eliminate this bias.

Ideally, we would solicit responses from individuals that both graduated from, and individuals whose applications were rejected from, the two universities. Since it was not practical to seek out undergraduate applicants that were rejected from either university, we instead proceed by trying to match similar students at the two universities based on the other schools they had applied to, and where they were accepted.

Additionally, we would have liked a cross section of students of similar backgrounds who had been randomly assigned to ILU or BTU. While we did not find anyone at BTU that applied to ILU or vice versa, we did have overlap with some of our control universities having common applicants from our sample. A university similar to ILU (for example) would have similar academic and admission standards and requirements to ILU. Thus, using this overlap of respondents applying to and being accepted/rejected from our group of control universities serves as an additional method to adjust for ability or ambition of a respondent.

Besides using comparable universities as a control for selection issues, we also asked respondents for their SAT scores entering college, their cumulative GPA upon graduation, starting salary in their first job (for salaried employees, first year compensation for self-employed) and finally, how many job offers they received before selecting their career choice – self employment or salaried employment. These additional variables help control for an individual's ambition and any biases that arise from sample selection issues.

In general, when evaluating the treatment effects of a program (here, the choice of university), we need to address the counterfactual: what is the change in outcomes given treatment Y(1), compared to the potential outcome in the group with no treatment Y(0)? With our non-experimental data, we cannot answer this question just by regressing the observed outcome Y (an indicator of whether a person is an entrepreneur) on a dummy for whether the unit is treated (D = 1) or non-treated (D = 0). This is the problem of selection bias. To address this issue, propensity score matching was used.

In OLS, sample selection bias occurs when data on the dependent variable is missing non-randomly, conditional on the independent variables. For example, if we use OLS to estimate a regression model in which large values of the dependent variable are underrepresented in a sample, estimates of coefficients typically will be biased. Using a dummy for treated/not treated will not account for self-selection as the assignment to the group is non-random. Thus, we have to simulate randomization of our data. Propensity score matching is helpful here.

2.7.1 Propensity score matching

Propensity score matching is a method that estimates the probability of taking a treatment given observed variables. Propensity scores summarize all background information on treatment selection into a scalar and allow us to adjust for selection bias in observational studies of causal effects. When possible, we want to compare control groups and treated groups that are similar in all aspects except for the treatment, which is assigned randomly. Practically, this is not possible. To adjust for this, we use observables to match individuals in the treated (ILU) and non-treated (BTU) samples, and have built our model based on theory to test for multiple covariates.

$$\text{Propensity score} = \Pr\,[\text{treatment} \mid \text{observed variables}]$$

The score is used to match respondents from either group that are similar and allows us to infer the relationship between the treatment and outcome based on observational data. The scores help adjust for selection bias and estimate counterfactual effects. Average treatment effects for the "treated" and average treatment effects for the "untreated" can also be inferred. Simply put, propensity score matching allows us to simulate the random assignment of a student to either university, and then estimate based on the student's characteristics, what the outcomes would be on our variable of interest. For more details, please see Rosenbaum and Rubin (1983).

2.7.2 Stage 1 Estimation Equation: Selecting a university to attend

To estimate opportunity costs as they relate to career choices immediately upon graduation, we need to think of the problem in two steps. In step one, the decision to apply to a certain university has to be accounted for. In the second step, we need to determine if an opportunity cost exists and if it does exist, does it exist due career selection (salaried employment versus venture creation) choices. Thus the model needs to be run in two stages.

In stage one, a Probit model is first used to predict what factors are significant in an applicant's decision as they select a university. A Probit model is used to model dichotomous outcome variables where the inverse standard normal distribution of the probability is modeled as a linear combination of the predictors. Our dependent variable *Ivy* is binary, with "1" representing the decision to apply to ILU and "0" representing the decision to apply to BTU. The independent variables are outlined in table 1 where respondents indicated their agreement on a 6-point likert scale[1]. Ability is controlled for in this equation by adding a list of universities that respondents had commonly applied to as high schoolers. As long as we had an overlap with at least one respondent from each university (ILU or BTU) applying to a "control" university while in high school, that university was included in equation 1 to adjust for ability. All universities

---

[1] An "ordered probit" regression was used here as the variable "y" has an ordered response and the values we assign to each outcome are no longer arbitrary. The fact that 6 (strongly disagree) is a higher rating than 5 (disagree) conveys useful information, even though "y" itself only has ordinal meaning. For example, we cannot say that the difference between 4 and 2 is twice as important as the difference between 1 and 0. This can now be calculated using maximum likelihood and marginal effects can be calculated. N/A were treated as missing data.

that a respondent applied to out of high school were also included, irrespective of whether the respondent was accepted to that university. If a respondent was accepted to a university, their "application to the university" value was not included in the equation.

Equation 1

Pr (y = Ivy) =

f (Academic reputation, Alumni contacts, Job prospects, Family tradition, Highest ranking university, Proximity to home, Least cost option, Cost was immaterial, Offerings in entrepreneurship, Track record of students starting own ventures, Application to comparable universities, Acceptance to comparable universities)

2.7.3 Stage 2 Estimation Equations: Determining opportunity costs

In stage 2, a propensity score matching system was used to match and compare respondents from ILU and BTU to determine what factors were critical in the decision to pursue salaried employment or pursue self-employment. Nearest neighbor matching (nnmatch) was used as it estimates the average treatment effect on our dependent variable by comparing outcomes between treated and control observations using nearest neighbor matching. The program pairs observations to the closest matches in the opposite treatment group to provide an estimate of the counterfactual treatment outcome. In addition, the program also allows for bias correction of the treatment effect, and allows observations to be used as a match more than once, thus making the order of matching irrelevant.

In equation 2, using propensity score matching, an individual's actual decision to pursue an entrepreneurial career path immediately upon graduation was matched between the two groups, and control variables from equation 1 were used for matching. Additionally, we had asked respondents for their undergraduate major and whether they had an entrepreneur in their family. These two variables are used as additional controls in the matching algorithm to account for major and familial impacts.

Equation 2

Entrepreneur career choice =

> *f* (SAT score, Entrepreneur in the family, Undergraduate major, Application to comparable universities, Acceptance to comparable universities)

In equation 3, using propensity score matching once again, a student's total first year compensation was matched with variables from equation 2 to determine if first year compensation impacted the decision to become an entrepreneur. Since the majority of our respondents from BTU were business majors, the equation was run limiting both sets of respondents to business majors only to provide relevant matching between ILU and BTU. If significant, this equation would indicate whether our hypothesis that students from top ranked universities faced a higher opportunity cost held.

Equation 3

Total first year compensation for business majors =

> *f* (SAT, Entrepreneur in the family, Undergraduate major, Application to comparable universities, Acceptance to comparable universities)

2.7.4 Estimation equation: Is entrepreneurship a career choice or no-choice option?

In order to control for the reasons behind becoming an entrepreneur immediately upon graduation, we wanted to explore whether students became entrepreneurs by choice or because they had no other viable job options. All current entrepreneurs were asked questions around their employment decision. The variable *Graduating from Ivy* is binary, with “1” representing ILU graduates and “0” representing BTU graduates. We include total first year compensation and abundance (or lack thereof) of job offers to determine the probability of becoming an entrepreneur conditional on these variables. The term *first year compensation* includes the first year salary and bonuses a salaried employee received. For entrepreneurs, this includes any money they might have withdrawn from their businesses. Only business majors are included in the analysis as the majority of our BTU respondents were business majors.

Equation 4

Pr (y = Entrepreneur) =

f (Graduating from Ivy, First year compensation, No exciting job offers, Lack of any job offers, Business major)

2.7.5 Estimation equation: Factoring in opportunity costs with outside pressures

Finally, a Probit equation was designed around the variables from table 3 to estimate the impacts of opportunity costs (starting salaries) and outside pressures (parental and cultural influences, gender and race) on self-employed respondents to gauge how these factors may have impacted their current career choice. This equation also accounted for a respondent having an entrepreneur in their immediate family.

Equation 5

Pr (y = Entrepreneur) =

f (Graduating from Ivy, First year compensation, Entrepreneur in the family, Parental influence of undergraduate degree choice, Family preferences on self-employment, cultural attitudes towards self-employment, Race, Gender)

2.8 Empirical Results

2.8.1 Equation 1 Results: Selecting a university to attend

Probit results from equation 1 are outlined in table 8. Due to our sample size of 235 respondents, we argue that a 5% level would be too restrictive and may not convey the full story. Variables significant at a 10% level are thus also highlighted. Looking over table 7, we notice that the academic reputation of the university and alumni contacts are significant and with a negative relationship for ILU respondents. This indicates that students applying to BTU are more likely to focus on the academic reputation and potential alumni contacts from their university versus ILU applicants. ILU applicants on the other hand, are more likely to pick a university that is closer to their home.

This may seem counter intuitive but if we subscribe to the argument that ILU applicants are applying to other highly ranked universities, then it is likely that the academic reputation and/or ranking is not a primary concern as most of the other universities are similar high in ranking. This effect also explains the negative coefficient on how important being accepted to the "best ranked" university is to our ILU applicants. The control universities for ILU graduates are likely to bring out this interaction due to their higher rankings as well. Many of our control universities are also significant and generally represent how likely a particular respondent from

ILU was to apply to it, relative to a respondent from BTU. While the equation included all dummy variables for application and acceptance to all the control universities, table 8 does not display these additional coefficients for brevity considerations.

Table 8 Marginal effects from Equation 1 (Probit) showing factors significant to respondents in university choice. Control university results not displayed.

Variables	Coefficient Marginal Effects	Std. Err.	P-value
Academic reputation	- 0.14	0.06	0.028**
Alumni contacts	- 0.11	0.05	0.045**
Job prospects	0.02	0.03	0.490
Family tradition	0.01	0.02	0.539
This university was the least cost option	0.01	0.02	0.597
Highest ranking university accepted to	- 0.05	0.03	0.065*
Proximity to home	0.08	0.04	0.045**
Offerings in entrepreneurship	- 0.004	0.04	0.917
Track record of students starting own ventures	0.01	0.04	0.800
Cost was immaterial to my decision	0.007	0.02	0.677
SAT score	0.01	0.03	0.698
Parental influence on education choices	0.01	0.02	0.563

2.8.2 Equations 2 & 3 Results: Determining opportunity costs

Propensity score matching on equation 2 indicates that pursuing an entrepreneurial career has a negative relationship with graduation from an ILU. Table 9 highlights that students graduating from BTU are more likely to become entrepreneurs immediately upon graduation. Equation 3 matches total first year compensation of business majors and gives even more distinct results. ILU business graduates on average, earn approximately $18,500 more than business graduates from BTU.

This result, coupled with the result from equation 2 on the probability of pursuing a self-employment career, indicates that there exists a higher financial opportunity cost for ILU students. ILU graduates have a higher financial hurdle to jump as they consider entrepreneurial options. Propensity score matching is also run on the entire population of BTU respondents (not limited to just business majors) and results continue to hold, and are significant. We observe that ILU graduates, on average, earn approximately $12,000 more in their first year compensation when compared to BTU graduates.

This result is also reflected in the anecdotal evidence cited by ILU faculty where many students state that they would rather wait, gain experience, payoff loans and then consider starting their own ventures. Based on survey responses, 56% of ILU respondents had financial obligations upon graduation and were seeking guaranteed income to offset these obligations. With the average annual cost of ILU education approximately $25,000 more than the average annual cost of education at BTU, these financial obligations create an additional hurdle for ILU students who may harbor entrepreneurial intentions.

Table 9 Propensity score results from Equations 2 and 3 showing combined effects of opportunity costs. ILU is reference group.
Equation 2: Actual decision to pursue an entrepreneurial career path immediately upon graduation.
Equation 3: Impact of first year compensation on decision to pursue entrepreneurship.

Equation	**Variable**	**Coefficient**	**Std. Err.**	**P-value**
2	Entrepreneur	- 0.18	0.07	0.016**
3	First year compensation (business majors only)	18.45	5.54	0.001***

2.8.3 Equation 4 Results: Is entrepreneurship a career choice or no-choice option?

This equation explores whether students became entrepreneurs by choice or because they had no other viable job options. In line with our hypothesis and opportunity costs results, graduating from ILU has a negative probability on a respondent being an entrepreneur today.

Conversely, not having any job offers at graduation is a positive indicator for being self-employed today. Thus, it can be concluded that pursuing self-employment is a "no other choice" for BTU graduates that pursue self-employment immediately upon graduation as these students tend to have fewer job offers at relatively lower salaries, when compared to ILU graduates. These probit results are outlined in the table below.

Table 10 Marginal effects from Equation 4 (Probit) exploring entrepreneurial career immediately upon graduation – by choice or no other option.

Variable	**Coefficient**	**Std. Err.**	**P-value**
Graduating from Ivy	- 0.15	0.08	0.071*
First year compensation	-0.001	0.00	0.166
Lack of any job offers	0.13	0.07	0.05**
Lack of exciting job offers	-0.12	0.08	0.133
Business major	-0.083	0.06	0.174

2.8.4 Equation 5 Results: Factoring in opportunity costs with outside pressures

Equation 5 results further support our hypothesis that higher starting salaries (opportunity costs) have a negative effect on self-employment as outlined in table 11. Results indicate that for every $1,000 increase in starting salary, the relative probably of pursuing self-employment decreases by 0.2% points. While this may not seem like a large number, it is important to note than this probability is a relative probability and is to be compared to baseline cases of self-employment versus salaried employment for both ILU and BTU respondents.

In our dataset, the actual percentage of respondents pursuing self-employment immediately upon graduation was 1.5% for ILU and 7.4% for BTU (table 1). A $20,000 higher starting salary for an ILU graduate versus a BTU graduate (for example), leads to a probability decrease of 4% in self-employment for the ILU graduate. With the initial probability of pursuing self-employment itself being low, this 4% difference due to salary considerations on top of the already low probability of self-employment, is relatively high and significant. The previous equation (equation 4) further supports this finding as graduating from ILU is negatively related to self-employment. Additionally, the gender variable is significant indicating that males are more likely to pursue self-employment. In our sample, we had a nearly even split between male-female respondents.

Table 11 Marginal Effects from Equation 5 (Probit). Impacts of salary and outside pressures on self-employment choice immediately upon graduation.

Variable	**Coefficient**	**Std. Err.**	**P-value**
Graduating from Ivy	- 0.04	0.05	0.35
First year compensation	-0.002	0.00	0.01**
Entrepreneur in the family	0.01	0.01	0.47
Family prefers salaried employment	0.015	0.02	0.53
Family would discourage self-employment	0.002	0.03	0.932
Entrepreneurs are highly regarded in my culture	-0.007	0.02	0.47
Gender	0.089	0.04	0.04**
Race	0.011	0.01	0.268

2.8.5 Results Summary

While some of these results individually may not be surprising, combining results from all five equations confirms the existence of higher opportunity costs for ILU graduates, as hypothesized. Essentially, a student considering entrepreneurship and graduating from a more highly ranked university, when compared to a similar student graduating from a lower ranked university, faces an entirely different choice and risk set. This student will likely have (i) a higher paying position, (ii) multiple job interviews and offers, and (iii) parental and peer pressures to interview for and accept "top" corporate positions as these are viewed as "safer" alternatives. With the existence of financial opportunity costs as shown in this section, and the peer/familial pressures outlined in table 3, we claim that pursuing self-employment presents a lower utility option for this student.

In response to the question about having any regrets they may have today about the career choices they made upon graduation, 74% of all respondents stated that they would not change their choices while 12% were unsure at this point. Less than 2% of the respondents stated that they would change their initial choice and instead start their own venture. These numbers strengthen our assertion that students are in fact making an informed and practical choice when faced with a career decision.

The bigger challenge, when conflicted on an immediate career decision, is for students graduating from higher ranked universities. Students from these institutions have access to more salaried employment options and often, higher salaries. These students thus face a higher hurdle of turning down a "sure thing" and considering an entrepreneurial venture. On the other hand, it can be argued that a student without any job offers looks at self-employment as "just another employment option" and views his choices and their risks differently. In this instance, many students may consider starting a venture as a short term option or as a "nothing to lose" option. It is this difference in attitudes that we address in the next section.

2.9 Conclusions and Discussion

The findings confirm that students attending top ranked universities and facing higher financial obligations upon graduation have a tough career choice upon graduation and face a significant hurdle starting their own ventures. Starting their own ventures may be appealing but the financial risks, coupled with the potential of turning down a high paying position, makes it financially unwise for many students to consider self-employment as a "rational" option. This result may come across as “expected” or “not surprising” to some but there are some significant policy implications that matter in a university setting.

For one, the logic of the career decision sheds light on the limitations of *immediate* venture creation as a metric of success for entrepreneur programs (especially in highly ranked universities). Instead of immediate success, programs should be trying to measure longer-term impacts of the entrepreneurship education on the career paths of their graduates. Unfortunately, there is continued pressure to produce immediate startups. Donors who fund professorships and other dimensions of university entrepreneurship programs look for an immediate spike in student venture creation. In informal discussions with several entrepreneurship program leaders, we found that media-fueled examples such as Facebook worsen this trend as donors expect programs to launch the next big exciting venture. With donor expectations and the practical realities of data collection, many entrepreneurship program leaders are simply accepting that they have to use immediate startups as a primary barometer of success.

Secondly, ranking systems for entrepreneurship programs that place a primary weight on venture creation exacerbate the problem. University administrators increasingly pay attention to ranking systems and may even set program targets with the rankings in mind. This is counter productive in settings where students face high opportunities costs when considering *immediate* venture creation. Students with cultural pressures, high debt levels and good job offers often adopt a “later in life” approach to pursuing self-employment. In the absence of other ways to measure this delayed entrepreneurship activity, highly ranked universities face difficult programmatic and faculty resource allocation decisions, and risk disappointing potential donors.

Finally and probably most importantly, there is an even more troubling outcome when universities overemphasize immediate venture creation: large resources may be directed to a very small segment of the university, while ignoring the longer-term outcomes for a larger student population. Business plan contests, incubators, and venture funds to encourage a path directly from undergraduate programs to a new startup benefit only those individuals who either overlook the opportunity costs or do not generate alternative opportunities. In contrast, those who delay their entrepreneurial ventures could benefit from a broader programmatic approach that emphasizes a longer-term outlook.

As mentioned previously, approximately 44% of the top 160 programs (as ranked by Entrepreneur magazine) focus on venture creation in their mission statements. We believe that our results can help put some of these expectations in perspective. In the absence of policies that might minimize the opportunity costs at the time of graduation, we argue that the rational choice for a student is to pursue salaried employment especially if they are graduating from better-ranked institutions. We also argue that the higher the potential opportunity cost a student faces, the more of a "homerun" is needed in terms of immediate and long-term payoffs to equalize the opportunities.

The Global Entrepreneurship Monitor recently found that people over the age of 35 made up 80 percent of the total entrepreneurship activity in 2009. Is the pushing of venture creation out to later in life due to a lack of interest upon graduation, a lack of experience or something as basic as mounting student loans, parental expectations and other aspects of opportunity costs? We argue that one key component of statistic is opportunity cost and as this paper shows, the financial element is significant.

Understanding the opportunity costs faced by their own students upon graduation can help universities in several ways:

1. It can shed light on what the appropriate metrics of success should be. If students tend to be "delayed entrepreneurs" then tracking graduates over time and enumerating and celebrating the later successes will be very important.
2. It can guide curriculum development. For example, students from highly ranked programs may benefit most from broadening the business plan approaches beyond companies that could be launched immediately. Continuing education for entrepreneurs who start ventures later could be developed. Programs could be developed that focus on the development of long term networks to help graduates connect, start and fund businesses later in their career paths.
3. It can point to ways to lower opportunity costs, equalizing choices. Entrepreneurship programs where students face high opportunity costs may want to consider approaches like the one recently established at the University of Rochester, where they now offer a one-year stipend (Kauffman Entrepreneurial Year) to allow a student "extra runway" to pursue additional courses as well as focusing on getting their startup venture off the ground. Sponsored by the Kauffman foundation, this program may have some merit if venture creation is a focus and decreasing the opportunity costs is a desire of the university.

From an economics perspective, universities face a simple dilemma – their entrepreneurship programs are supplying students with encouragement to opt for *immediate* venture creation, but does that choice make economic sense for the student? Are these students actually demanding venture creation opportunities immediately upon graduation? Our research says no. We argue that as long as a high opportunity costs exist for students, the "good job" trap will continue to limit the number of students opting for startups right after graduation.

2.10 References

http://www.kauffman.org/Section.aspx?id=Education

http://www.rochester.edu/entrepreneurship/programs.html

Abadie Alberto, Leber Jane, Imbens Guido W., Drukker David. (2004). NNMATCH: Stata module to compute nearest-neighbor bias-corrected estimators.

Arora & Nandkumar. Cash-out or flame-out! Opportunity cost and entrepreneurial strategy: Theory, and evidence from the information security industry. *NBER Working Papers 15532*, National Bureau of Economic Research, Inc.

Audet, J. 2004. A longitudinal study of the entrepreneurial intentions of university students. *Academy of Entrepreneurship Journal*, 10(1).

Barton H. Hamilton, Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment. *The Journal of Political Economy*, Vol. 108, No. 3 (June 2000), pp. 604-631

BusinessWeek rankings:
http://www.businessweek.com/interactive_reports/top_undergrad_bschools_by_specialty_2012.html

Cassar, Gavin. Entrepreneur opportunity costs and intended venture growth. 2006. *Journal of Business Venturing*, vol. 21, issue 5, pages 610-632

Chuang, N. & Dellman-Jenkins, M. 2010. Career Decision Making and Intention: a Study of Hospitality Undergraduate Students. *Journal of Hospitality and Tourism Research*, 34, 512-530

Clarke, M. (2002). Quantifying quality: What can the U.S. News and World Report rankings tell us about the quality of higher education? *Education Policy Analysis Archives*, 10(16)

Entrepreneur Magazine rankings: http://www.entrepreneur.com/topcolleges/index.html

Hamilton, Barton H. 2000. "Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment," *Journal of Political Economy*, University of Chicago Press, vol. 108(3), pages 604-631, June.

Kher, Romi, Just, David R., & Streeter, Deborah, "Do entrepreneurship courses change an individual's attitude toward new venture creation? Results of a quantitative assessment of the Cornell entrepreneurship program," *International Review of Entrepreneurship, Vol 9: Issue 4, 2011.*

Lowell, B. W. 1999. Entrepreneurial risk and strategic decision-making: It's a matter of perspective. *Applied Behavioral Science*, 35(30), 325-340.

Mueller, E. & Cockburn, I. 1995. Opportunity Costs and Entrepreneurial Activity. *Journal of Business Venturing,* 10(2), 95-106.

Rees, H. and Shah, A. (1986), An empirical analysis of self-employment in the U.K. *Journal of Applied Econometrics*, 1: 95–108. doi: 10.1002/jae.395001010

Rosenbaum, Paul R.; Rubin, Donald B. (1983). "The central role of the propensity score in observational studies for causal effects". *Biometrika* 70 (1): 41–55

Streeter D., Kher R. & Jaquette J., ”University-wide trends in Entrepreneurship Education and the Rankings: A Dilemma”, *Journal of Entrepreneurship Education, Vol 14, 2011.*

Stern Scott. Do scientists pay for being scientists?. *Management Science*, Vol 50, No. 6, June 2004.

Solomon, Duffy & Tarabishy, “The State of Entrepreneurship Education in the United States: A Nationwide Survey and Analysis”, *International Journal of Entrepreneurship Education*, 2002, 65-86

Thiel foundation: http://thielfoundation.org/

Zane, L., De Carolis, D.M., & DiRenzo, M. 2007. An examination of the role of opportunity cost and opportunity value in new venture creation. *Frontiers of Entrepreneurship Research.*

Estimating the impacts of "certainty in uncertainty" on attitudes and risk preferences in team settings using a dynamic, market based simulation.

3.1 Abstract

This paper introduces the concept of "losers' dilemma" and leverages a market driven, dynamic business simulation to specifically study how teams behave in a competitive setting, how they balance personal and team risk preferences, and how competitors can induce riskier behavior. Utilizing a sample of 130 undergraduates participating in a multiple 7-week dynamic simulations, we find distinct differences between winning and losing teams. Losing teams are dominated by risk averse individuals who avoid conflict, struggle aligning individual and team risk preferences, and claim to be risk takers but consistently showcase risk averse decision making. These losing teams display high confidence in their business projections but conversely, showcase low self-confidence and a "yo-yo" approach to strategy evolutions. Findings from this paper not only contribute to risk and team literature, but also have practical importance to universities, industry accelerators and startup incubators seeking to seed the next generation of entrepreneurs.

"Take calculated risks. That is quite different from being rash."
~ General George Patton.

3.2 Introduction

Business decisions often involve comparing alternative courses of action to assess the best way to arrive at the best possible outcome. Economics describes this as evaluating probability distributions over future returns to select one choice from two or more alternatives. Although numerous expected utility models involving experiments and observations have been studied used to effectively describe aggregate behavior, the impact of an individual's risk preferences on group business decision-making has received modest attention in business literature. This is surprising as it is often individual entrepreneurs and managers that make firm level decisions in a group setting (Friedman and Sunder, 1994).

This paper evaluates individual and team risk taking behavior in the context of a simulated, dynamic business simulation. Specifically, this study will investigate two key issues:
(i) How individuals behave in a group setting when forced to make time sensitive business choices while facing uncertain outcomes.
(ii) Whether under competitive pressures, participants can be influenced to make risk-seeking decisions and act outside their stated risk-taking preferences while making business decisions.

Based on informal observations during the business simulation, participants seemed to act in a manner that was more risk-taking than "normal" in an effort to compete more effectively with the other teams in the simulation. This paper takes an assessment approach to estimating how individuals operating in a group setting deviate from baseline risk preferences while making decisions under uncertainty. Risk attitudes were assessed before the business simulation began and then after. After each simulation round, respondents were asked a series of questions to determine if team strategies changed based on actions of competitors and if the focus on winning generated individual and team actions inconsistent with previously stated risk preferences. Surveying students after each round was critical to understanding the risk approaches to actual behaviors. More importantly, participants were asked whether if acting *alone*, they would have made the same choices as made by a team.

A better understanding of how individuals actually evaluate risky alternatives in a situation where group decision-making occurs can lead to the development of techniques that help entrepreneurs evaluate how risk attitude is impacting the choice among alternatives. Our results can also provide entrepreneurship educators with a relatively simple assessment tool that can give students a more realistic feel for venture creation, the uncertainty involved and how team dynamics can impact success and failure. Finally, in risk literature, the impact of such training programs is under investigated and this paper is a significant step forward.

3.3 Theoretical Background

When studying individual choice behavior, it is often postulated that individuals differ with respect to the amount of risk they are willing to incur in any given situation and thus, two individuals will make different choices when presented with the same alternatives. These different choices attributed to individual "risk attitudes" are determined based on how each individual decides between two or more choices based on personal expectations of outcomes. Expected utility theory is the underlying concept used in mathematical models of choice behavior.

According to expected utility theory, an individual's preferences for any gamble X (e.g., monetary payoffs) can be modeled by a utility function u(X), the shape of which provides information on the individuals risk preferences. The individual is said to be risk averse if $u(X)$ is strictly concave, risk seeking if $u(X)$ is strictly convex, and risk neutral if $u(X)$ is linear (Fischer et al. 1986). Simply put, when facing a number of different choices under uncertainty, expected utility theory prescribes that the decision-maker choose the alternative with the highest expected utility.

To determine a single, underlying risk preference, economists typically use various lottery measures that are modeled on differing financial outcomes. When attempting to determine different risk preferences, the concept of risk aversion is most often used and is tied to an individual's utility of wealth. More formally, risk aversion is defined as a subjective tendency of an individual to reduce unnecessary uncertainty when choosing between alternatives. Risk aversion is subjective because individuals have different perceptions of the amount of uncertainty involved between choices. While this construct explains aversion to large-scale risks, it also implies that people are approximately risk neutral over modest stakes. A commonly used measure of risk aversion is the Arrow-Pratt measure, originally proposed in the early 1960s. This measure uses wealth as the argument in the utility function and for wealth w, the Arrow-Pratt measure of risk-aversion is $[-u''(w) / u'(w)]$. This has become the traditional way in which the measure is used in economics.

However, many psychologists and behavioral economists question whether all of an individual's decisions can be governed by a single utility function. Instead, they argue that risk attitudes are influenced by context. In laboratory experiments, Slovic (1964, 1972a, 1972b) demonstrates that "the domain of risk taking behavior was not conceptually unitary and that risk taking was not a general personality disposition." Binswanger (1980) and Rabin (2000) also criticize the traditional economics approach and find it insufficient in explaining risk behavior over wide ranging domains. They conclude that using expected utility theory, the levels of risk aversion observed over modest payouts would imply extremely high levels of risk aversion over larger payouts. Just and Peterson (2009) show this to be true and find expected utility theory to be applicable only when expected payoffs of gambles are similar, or when more than half of wealth is at risk.

Thus many behavioral economists prefer the prospect theory model, proposed by Kahneman and Tversky (1979), which states that people make decisions using heuristics to assess the potential value of losses and gains versus simply the final outcome. Their model attempts to outline actual decision-making behavior and differs from expected utility theory in two major aspects. First, it posits that people place different relative weights over probabilities and, in fact, most experimental evidence suggests people overweight small probability outcomes and underweight large-probability outcomes. Secondly, differences in utility are determined between outcomes in the context of a reference point, rather than just based on the final payout position.

Our paper combines the different approaches from economics and psychology to analyze risk influences on decision-making, both individually and in a team setting. We utilize the expected utility construct in a series of lottery questions to determine individual risk preferences. To estimate the impacts of non-quantifiable influences on decision-making, we leverage a model of cognition called dual process, attributed to William James, often referred to as the father of modern psychology. This approach, furthered by Sloman (1996), Kahneman (2003) and others, explains decision making involving risk as being governed by two mechanisms: a deliberated, rational, non-emotional mechanism and an emotional, reaction not subject to rationality.

Psychologists, and now some economists, argue that dual process theory provides a better understanding of decision making under uncertainty because it partitions an individual's utility function into two components: an expected utility component and an emotional component. The expected utility portion is based on probabilistic assessments of risk. The emotional component does not involve probabilistic assessment of risk; rather, it is influenced by perceptions of risk. This approach is based on social psychology and is characterized by the work of Slovic (1983); Slovic, Lichtenstein, and Fischhoff (1984); Finucane and Holup (2006); Mukherjee K. (2010) and Schulze, W., and Wansink, B. (2012).

It must be noted here that this paper does not provide empirical evidence to validate the existence of the dual process theory. Instead, akin to Kogler and Kühberger (2007) and Ozdenoren et al. (2012), we leverage the theoretical framework of dual process to model our experiments and use it to better understand the decisions made by respondents in our simulation.

3.4 Literature Review

Economists believe experimental lotteries are the best way to reveal risk preferences and research involving certainty equivalents (Kachelmeier and Shehata, 1992) and pairwise lotteries (Holt and Laury, 2006) in addition to Biswanger's seminal paper (1980) grounded in expected utility theory, have helped establish lotteries as the dominant method for determining risk preferences. Many economists also argue that wealthier people are less risk averse with Holt & Laury (2002) and Schechter (2007) finding that income has a mildly negative effect on risk aversion.

Nonetheless, just as experimental lotteries and expected utility theory have grown in popularity, so has criticism and empirical evidence against their effectiveness. The Allais

Paradoxes shows that in some cases, indifferences curves generated by these lotteries violate the independence axiom and expected utility theory fails to account for loss aversion (Kahneman, 2011). On a national level in the U.S., the Federal Reserve Board, in their Survey of Consumer Finances, has asked a standard question since 1983 regarding investment choices and it is the only risk tolerance question that has been asked of a national sample representing all adults. The question asks what level of risk a respondent is willing to take when saving or making investments. Answer choices range from expecting substantial risk (in anticipation of earning substantial returns) to not willing to take any financial risks (in order to avoid all losses). Utilizing the standard question, Yao et al. (2004) found approximately 23% of the respondents had substantial or above average levels of risk tolerance while 40% said they were not willing to take any risk.

Conceptually, these approaches have shortcomings, which has led to reasonable questions about the applicability of such approaches. On issue is whether respondents truly understand the abstract hypotheticals presented in these questions. Dohmen et. al. (2005) analyzed 22,000 responses from the 2004 Socioeconomic Panel (SOEP) survey, compared various risk measures and found that lottery questions failed to predict risk preferences accurately. They countered that the best overall predictor for any specific behavior is typically a corresponding context-specific measure. Addressing typical laboratory experiments, Cauffman and Steinberg (2000) and Scott et. al. (1995) found similar shortcomings, as these hypothetical scenarios failed to consider the emotional and social contexts in which risk taking actually occurs.

The finance field often uses portfolio allocation models to understand risk preferences and investment decisions. Tobin (1958) hypothesized that agents diversify their savings between a risk-free asset (money) and a portfolio of risky assets based on different attitudes towards risk.

There is an entire literature that discusses the various merits and shortcomings of these models but perhaps most applicable to our research is the finding by Kapteyn and Keppa (2001) which concluded that “in several ways the rational model of choice on which the modern portfolio theory is based appears to be unable to explain several empirical findings.”

Given the shortcomings of portfolio allocation methods, many researchers have turned to more direct and subjective evidence on risk preferences in an attempt to reduce the gap between theory and empirical findings. Barsky et al. (1997) asked a set of hypothetical questions to a large national sample of adults posing different percentage reductions in income to determine risk preferences. While their approach has nice outcomes under CRRA (Constant Relative Risk Aversion) preferences, it falls short when taking difference socio-economic, wealth and risk characteristics into account. Other studies have used hypothetical lotteries and payouts to measure risk preferences in abstract settings. Guiso and Paiella (2001) use a sample of approximately 8000 heads of households from the Italian Survey of Household Income and Wealth (SHIW) survey and Diaz-Serrano and O’Neill (2004) extend the dataset adding another 3000 respondents. Donkers et al. (2001) use a sample of 4,000 respondents from the Netherlands and Barsky et al. (1997) use a large U.S. sample of 14,000 respondents but only focus on individuals between 51 and 61 years of age. These studies help bridge the gap between experimental and survey approaches to estimating risk preferences and provide justification for the approaches adopted in this paper.

Based on the debates and experiments with various approaches, Hanna, et al. (2001) suggest at least four methods for measuring risk tolerance: asking about investment choices, asking a combination of lottery and subjective questions, assessing actual behavior, and asking questions based on hypothetical scenarios. We incorporate this approach and use five different questions to measure risk preferences for all respondents in a dynamic market-driven simulation. Not only do we observe actual decisions made, we also survey decision choices and pose hypothetical scenarios prompting all respondents to choose their ideal outcomes and scenarios.

The use of simulation games is not new in academia; the first practical game was introduced in 1957 (Top Management Decision Simulation). Typically, games are used for teaching purposes, but can also create a “living lab” for research. Most research studies utilizing this tool are found in fields such as finance, engineering and sciences, where a theoretical model can be determined from an algorithm and variety of inputs in laboratory settings. Such studies focus on efficacy, predictability and demand estimations rather than participant behavior. Many management papers that feature simulations debate their effectiveness or recommend approaches for improving their impact (Tjoa et. al, 2011). But using simulations specifically to determine risk preferences is limited to simple lottery experiments (ex: Tecles & Resende, 2011) or use of Monet Carlo simulations to optimize portfolios (ex: Hanna and Chen, 1997). Sahlman and Roberts (1999) found that simulations can help students prepare for failure, learn from and adapt their future activities in a more cogent and efficient manner but they did not use the simulation to actually study participant decisions or behaviors.

Previous studies have investigated the role of using business simulations for student learning (ex: Parish, 1975), for investigating managerial decision making (ex: Lant and Montgomery, 1992), and for developing strategic management behaviors (ex: Sharif and Ranchod, 2009); however,this paper is the first to utilize the study of participant decisions in a business simulation to determine risk behavior under competitive pressures. We focus on observing and analyzing actual decisions made by individuals utilizing a dynamic simulation that encapsulates all business risk. All risk that can impact individual decisions is generated from the participants and their perceptions of the risk involved, not from “acts of God” or other external factors or “shocks.”

3.5 Data Collection

We collected data for this paper in a new, experimental undergraduate business course at the Dyson School of Applied Economics and Management. Pre-requisites for the simulation course included accounting and finance courses and participating in the business simulation is the central activity of the course. Participants entered decisions and the simulation was run 1-2 times each week over a 7-week period, with all decisions being made within the class period. Class met for 150 minutes weekly and data was collected over 2 semesters and 3 class sections (Fall 2012 and Spring 2013). Respondents included a mix of students from business, engineering, economics and sciences.

The 7-week course was offered once in Fall 2012 and twice in Spring 2013. A total of 130 responses were collected and these responses are classified as the treated group. As outlined in Table 12, students in each cohort were surveyed three times during the process to estimate initial risk profiles and any changes which may have occurred due to the simulation: once before the start of the simulation, again after each simulation round, and then a final time after the simulation ended. All surveys were administered electronically through an on-line survey tool.

Table 12 Outline of the experiment and data collection

Date	*Simulation Activity*	*Survey Completed*
Week 1	Introduction & individual practice	Pre-survey
Week 2	Team Practice round	No survey, strategy paper due
Week 3	Round 1 decision (see figure 1)	Round 1
Week 4	Rounds 2 & 3 decisions	Rounds 2 & 3
Week 5	Rounds 4 & 5 decisions	Rounds 4 & 5
Week 6	Rounds 6 & 7 decisions	Round 6 & 7
Week 7	Final Presentations and wrap up	Final post-survey

Concurrently with each class section, the pre- and post- surveys were also run with students not in the simulation class, to serve as our control group. This was done every time a simulation section was run to ensure proper matching. The control group comprised of students enrolled in an excel course, an accounting course and a finance course. These students were incentivized through a lottery that distributed cash prizes every time the control surveys were run. A total of 110 responses were collected from the control group. This group was given the pre survey at the start of week 1 and at the post survey at the end of week 7. This was done to mirror the timing of the simulation for the treated group but weekly surveys were not administered to the control group. The control group was also cross-referenced with the simulation class to make sure no one in the control group had prior (or concurrent) experience with the simulation.

For a simulation to be effective, it must be credible, relevant, and illustrative (Hindle & Angehrn, 1998). This basic yet critical hurdle was easily overcome in our experiments, since the simulation has been developed and refined over 20 years, is accompanied by a detailed handbook, has clear performance outcomes, and makes use of a user-friendly web interface. The business case presented to the participants in the simulation includes a scenario that is highly relevant to the current business climate, with teams able to choose among a variety of products and markets to operate in.

3.5.1 Experiment Overview

The simulation involves a scenario in which each team is taking over a struggling company with two current products for sale. The company is hemorrhaging money with multiple operational issues surrounding R&D, marketing, sales, human resources and manufacturing. The student teams assume the role of a turnaround management team brought in to save a sinking ship. They have to make decisions on current operations and also decide if they want to invest in a new innovative product that would add a third product line to the company's portfolio. All three products target different market segments at different price points. Students are provided with a detailed written business that outlines relevant business, market, and competitor information. We also make two things very clear to the participants: i) market conditions change with every round, based on the cumulative consequences of all the teams' decisions and ii) all changes in market conditions come from actual team decisions and not from external sources manipulated by the course administrators. There is no external source of uncertainty in the simulation.

Students are randomly divided into diverse and balanced teams (gender and major) of 4-5 individuals and compete with other teams in an attempt to turn around business operations and achieve profitability. The simulation runs for 7 rounds (each round represents one fiscal year in the simulation), but teams are not told how many rounds the simulation will run so as to prevent any "gaming of the system" as the end is approached. Each team is allocated 60 minutes to make decisions for each of the first two rounds and starting with round three, teams are given 45 minutes to submit final decisions. Late submissions are penalized $5 Million and this amount is deducted from net profits.

Teams are given updated market information after each round and then base their upcoming decision on how they and their competitors performed in the previous round. Teams quickly realize that not only do their own decisions impact their results, but also the collective actions of other teams. Thus, all teams make decisions under aggressive time constraints and based on imperfect information regarding target markets, manufacturing, pricing, sales force allocation and financing.

For participants, the overall goal of the simulation is simple – meet all financial targets and beat the other teams to win the startup strategy challenge by procuring the highest stock price. The educational goal of the course is to provide students with experience applying key business principles, such as those they learned in finance, accounting, marketing, manufacturing and human resources in a simulated, real world setting.

A critical point to reiterate is that the source of all risk and uncertainty is team decision making; there is no external source of uncertainty. Other business simulations often have an "act of God" element or a random variable generator that inserts an additional component of uncertainty to the game that serves as a "shock" to the economic system. For our simulation, because we do not incorporate any external source of uncertainty, it allows us to hone in on the decision making process of the participants, and the participants alone.

3.5.2 The Simulation - Detailed Outline

In the first meeting, as instructors, we provided a detailed overview of the business case and course expectations. Students were then given two days to review the business case and decide if they wanted to take the course. They were informed that weekly surveys were a part of the course but the research focus and purpose behind the surveys is not shared with them. Students were also informed that the availability of a laptop or tablet during the weekly course sessions would be critical to the learning process during the simulation. Those that expressed their interest in staying in the course were sent an electronic pre-survey designed to capture their demographic information, career interests, proclivity towards entrepreneurship and their risk attitudes. They were also sent an individual login to get familiarized with the simulation interface.

Since the course instructors control the composition of the teams, we divided the class into balanced teams of 4-5 students with each team, taking into account diversity in gender, major, and class year. Once teams were created, 4-5 teams made up the "industry" in which those teams competed. To maintain a competitive environment and ensure learning outcomes, each industry was limited to 5 teams, with a maximum of 5 students per team. Thus, the simulation was always run with two industries, comprised of 4-5 teams, with each industry operating completely independent of the other.

In the second class meeting, students were introduced to their teams and given the entire class time to focus on three tasks: i) getting familiar with their teammates, ii) discussing their business strategy on how they will turn the company around, and iii) submitting a practice round decision to get a feel for the process before the simulation began in earnest. It was announced that the winning team would receive a cash prize, a message that added to the competitive environment for the course. Figure 1 outlines the general simulation process.

Armed with this knowledge, students left the classroom and found their own working space in the building. As a reference point, the building used for the simulation was adjacent to the library which offers ample meeting space and breakout rooms. When the students came back from their breakout meetings, practice round results were processed and the results (in the form of profit figures) were shared with the class. The facilitators also provided a brief overview of how the market evolved after just one round, further helping the teams understand the dynamic nature of the simulation. The overview session also served as an opportunity to answer any lingering questions about the interface, the business case or "rules of the game," and to make sure teams fully understood the competitive nature of the simulation. Since all teams begin the simulation from the same scenario in terms of market share, product lines, cash on hand etc., just one practice round demonstrated how the different strategies employed by each team in the practice round contributed to the evolution and "new look" of the industry. After the practice round, the simulation was set back to the initial baseline conditions and the students were prepared for the competition.

By the third class, the classroom was primed for a competitive environment. By now, everyone knew his/her teammates, had a stated business strategy for moving forward, had experienced a practice simulation round and had witnessed the dynamic nature of the market. They now focused on competing and winning their industry and subsequently, the cash prize. Following a short 15-minute overview lecture, teams were sent out to make real decisions for the first round of operations in their industry. Students were reminded that the practice round results had been wiped clean and the game had been reset and that each round of the game would simulate one year of operations.

At the end of the third class, actual round 1 results were shared with the class, followed by a quick debrief. Teams privately received detailed financial metrics on their own company's performance and general "publically available data" for their competitors. No team-specific strategic information was discussed but a general conversation took place with the class to ensure all teams clearly understood the dynamic nature of the simulation. The weekly risk survey was also administered, instructing students to review their team performance results and answer various questions on the following topics:

- Assessments of the results of the team.
- Individual risk preferences during decision-making.
- Team risk dynamics.
- Team strategy vis-a-vis competition.
- Expectations for future rounds.

Starting in the fourth class (round 2), teams were given 60 minutes to meet, discuss and submit their final decisions and two rounds were completed in the allocated class time of 150 minutes. Once decisions were submitted, teams were given a 5-minute break during which results were processed. Teams were then given 10 minutes to review their performance and complete another weekly risk survey. Once this was done, they were sent off to discuss and submit decisions for the next round.

Round 3 served as a critical tipping point for teams that decided to launch a third product line. Based on simulation specifics, two (simulated) years are needed to launch the new product line, so effectively any team that decided to enter a new market had to make two years worth of investments before they could sell the new product. Consequently, it is only in year 3 that other teams potentially discovered if a certain competitor entered a new market. In running the simulation, the third round is when we often saw teams evolve, pivot, or completely change their initial strategies as the markets look very different from the first couple rounds.

It is worth noting here how the simulation provides an effective environment for studying risk attitudes. The simulation presents teams with the task of choosing from among a wide variety of strategies and there are inherent risks in any one of them because the outcomes depend on the decisions make by other teams, since it is the aggregation of decisions that determines market sizes and market share. For example, given the way the simulation operates, the introduction of the new product can be a game changer but it does not always have a positive impact on profitability in the short or long term. There is no guarantee that launching the new product implies success, as the team has to spend money on engineering a new product and at least initially, new products have limited market demand and others may also pursue the market, leading to a smaller market share for each. Teams can choose to invest millions reengineering and repositioning their product lines but may create with a daunting task for future rounds if the market size and share is not what was suggested.

On the other hand, early investments in new products may lead to long-term success, as they may set up the conditions for dominating an entirely new market segment in which other teams are not prepared to participate. Therefore, early "wins" do not predict the future; a team leading the simulation for the first couple rounds may find itself out of the lead as competitors make operational moves to reposition current product offering.

The dynamic nature of the simulation enables us to use it to determine risk attitudes and behavior of the participants as there is no predetermined path to winning the game. Over the many simulations we have run, individual teams have tried many different operational strategies and there is no systematic model that serves as the “best” or “winning” formula. The simulation cannot be “reverse engineered” as there is no optimal mathematical model that can be predetermined, so the dynamic and market-driven nature of the simulation makes it an ideal research and learning tool.

Returning to our experiments, in classes 4-6, teams completed two decisions (rounds) per class and completed a survey after each round. Once we completed round 7, we informed the teams that the simulation was over and promised to share the final in the final class. The final post-survey was completed and each student was asked to complete the same questions asked in the pre survey designed to estimate their individual risk profile. In addition, we asked to them to comment on their overall experience with the simulation, including: overall satisfaction with their performance, the level of team conflicts, the nature of risk taking, and ways the team responded to competitors as strategies and outcomes emerged.

The final class was a debrief session and involved each team giving a brief presentation on their experience, explaining the evolution of their strategies and commenting on team dynamics. Once all presentations were complete, we shared final team results and the winning team was announced. Winning team members were given their cash prize and the course officially ended.

3.6 Determining Individual Risk Preferences

Refining current approaches that emphasize lottery measures or laboratory experiments to determine risk preferences, we use five different risk questions to measure an individual’s risk perceptions and preferences. Another advantage over other research approaches is that our experiment provides respondents a context for “risk taking” (the simulated business setting) and allows us to adjust for team pressures and dynamics.

Previous research has shown that independently, our questions provide a viable method to determine risk preferences and a validated method of risk assessment. Our approach not only establishes a risk baseline for respondents but also allows us to make comparisons across groups. The five questions, outlined in table 13, were asked pre- and post- simulation and measured on a 7-point likert scale. Both groups of respondents, the control group, and the simulation participants were asked to respond to the risk assessment questions to ensure proper controls.

The first question asks respondents to state what they find more risky – salaried employment or starting a business and is a self-assessment question adapted from Guillemette et al (2012). Questions 2 and 3 help elicit an individual’s Arrow-Pratt measure of risk tolerance specifically outlined in Guillemette et al (2012). These questions are attitudinal in nature and are designed to assess the risk perceptions versus quantifiable risk preferences. The fourth question resembles standard lottery measures used in economics and is adapted from Dohmen et al (2005). Here, the respondent is told that he has won $100,000 in a lottery and is then asked what fraction of the $100,000 he would choose to invest in an offer from a reputable bank. This common lottery question presents an individual with explicit stakes and probabilities and holds risk perceptions constant across individuals. Because beliefs are held constant, differences in responses are more clearly attributable to risk preference alone, as compared to the other measures above, which potentially incorporate both risk preferences and risk perceptions.

The final question, as proposed by Hanna and Lindamood (2004), is a sequential choice question and involves an investment setting where the respondent chooses between two different pension options. It is designed to measure an individual’s subjective risk preferences and the final outcomes range from extremely low to extremely high-risk preferences. Based on responses from 152 students, previous studies found a significant correlation between relative risk aversion estimates based on this survey measure and income gambles related to optimal portfolio choices.

Table 13 Five different questions used to determine risk perceptions and preferences

Q#	***Questions asked to all respondents pre- and post- simulation***
1.	When comparing starting a business to pursuing salaried employment, what statement do YOU personally agree with? Choices: Starting a business is riskier → Salaried employment is riskier.
2.	If you had a choice between: (i) a job with more security but with a potential for smaller pay increases and (ii) a job with less security but with a potential for bigger pay increases, which would you choose? Choices: Definitely more job security with smaller pay increases → Definitely less job security with larger pay increases
3.	Suppose you were in a job where you could be paid all salary, all commission or a mix of both. Which would you choose? Choices: All salary → All commission
4.	Imagine that you have won $100,000 in a lottery! Almost immediately after you collect, you receive the following financial offer from a reputable bank, the conditions of which are as follows: There is a 50% chance to double any investment you make, in two years. It is equally possible that you could lose half of the amount invested. What fraction of the $100,000 will you invest? Choices: $0, $20,000, $40,000, $60,000, $80,000, $100,000
5.	Suppose that you are about to retire, and have two choices for a pension: - Pension A gives you an income equal to your preretirement income. - Pension B has a 50% chance your income will be double your preretirement income, and a 50% chance that your income will be 20% less than your preretirement income. You will have no other source of income during retirement, no chance of employment, and no other family income ever in the future. All incomes are after tax. Which pension would you choose? Choices: Questions adapted sequentially to converge to an individuals risk profile.

3.7 Data Demographics And Risk Perceptions

A total of 130 responses were collected from the treated group (students undergoing the simulation) and 110 responses were collected from the control group. Table 14 briefly outlines the demographic background of respondents for each group. The control group was nearly evenly distributed in terms of gender. In the treated group, males made up a majority of participants but the teams were assigned (rather than allowing students to form by choice) in order to produce teams that were balanced in terms of gender. Teams were also constructed to maximize diversity in terms of majors. Amongst the other variables, the treated and control groups were well-matched, allowing us to tease out the effects of the treatment (simulation) on the risk perceptions of the treated group.

Table 14 Demographic overview of the background of respondents

Background information	Treated Group	Control Group
Responses collected	130	110
Gender breakdown: Male / Female	69% / 31%	55% / 45%
Degree status: Undergraduate / Graduate	94% / 6%	92% / 8%
Dominant major amongst respondents	63% Engineering	50% Engineering
Respondents between 19-21 years old	84%	79%
On-campus part time or full time job: Yes / No	40% / 60%	48% / 52%
Percentage funding some portion of their education on their own (grants, loans, aid etc.)	54%	52%
Total entrepreneurship courses taken (Treated group was asked to not include current course)	54% - None	59% - None

Note: ANOVA tests were used to determine that both groups are from the same population. *p-values* are not provided in the interest of brevity.

A majority of respondents from each group were undergraduate engineering majors, between the ages of 19-21 and more than half had not taken any entrepreneurship courses. The students in our experiment were asked to exclude the current simulation course from their answer while estimating the total number of entrepreneurship courses they had taken. Since undergraduate engineering majors have limited course flexibility in taking electives, it is not surprising the most had not taken an entrepreneurship elective. More than 50% of the respondents are also funding their own education in some way and this could give some insight into respondents' career choices post graduation. It can also be argued that since it is likely that these students do not come from wealthy families, they seek more stable employment options in order to meet loan obligations or fulfill family obligations. For loan-bearing students, entrepreneurship options that include lower short-term returns (but the possibility of higher long term returns) are likely to be less attractive than more stable, more highly remunerated alternatives. The impact of financial positions of individuals is critical as we analyze risk attitudes.

Looking at the psychological makeup of respondents, risk perceptions and proclivity towards entrepreneurship, we find a wide dispersion of interests and attitudes. Table 15 outlines any prior disposition towards entrepreneurship (self-employment) that may exist in both groups. We see a small percentage of respondents from either group are considering starting their own venture and this percentage drops by 2% for the treated group, post simulation. This could be considered an initial indicator that the simulation succeeded in exposing the uncertainty that surrounds business (in general) and the lack of control over market outcomes despite best intentions of the management team.

Table 15 Proclivity and predisposition towards entrepreneurship

Question: What do you foresee yourself doing immediately upon graduation?	Pre - Simulation		Post - Simulation	
	Treated	Control	Treated	Control
Salaried Employment	64%	71%	67%	62%
Self Employment	7%	3%	5%	3%
Family Business	1%	10%	1%	12%
Graduate School	18%	3%	15%	11%
Academic Job	1%	0%	1%	1%
Unsure	9%	14%	11%	11%

Both groups were also asked to answer several questions relating to their appetite for uncertainty and risk preferences both pre- and post- simulation. These questions are outlined in table 2 and responses are outlined in table 16. An initial change in attitude is observed from question one helps set the stage moving forward. The control group was unchanged but for the treated group, following the simulation experience 2% of the group agreed that pursuing salaried employment was slightly riskier than starting their own business, compared to 0% in the pre-survey. We theorize that this increase in perception of uncertainty was driven by the simulation and is a topic we wanted to further explore in the analysis.

Table 16 Risk perceptions and preferences pre- and post- simulation
(Responses collected on a 7-point likert scale but condensed here for brevity)

#1 When comparing starting a business to pursuing salaried employment, what statement do YOU personally agree with?

Control Group

	Starting a business is riskier	→ Both Equally Risky	→ Salaried employment is riskier.
(Pre)	94%	5%	1%
(Post)	94%	5%	1%

Treated Group

	Starting a business is riskier	→ Both Equally Risky	→ Salaried employment is riskier.
(Pre)	94%	6%	0%
(Post)	92%	6%	2%

#2 If you had a choice between:
(i) a job with more security but with a potential for smaller pay increases and
(ii) a job with less security but with a potential for bigger pay increases,
which would you choose?

	Control Group More job security → Indifferent → Bigger pay increases. (Pre) 38% 13% 49% (Post) 39% 11% 50% **Treated Group** More job security → Indifferent → Bigger pay increases. (Pre) 24% 11% 67% (Post) 30% 8% 62%
#3	Suppose you were in a job where you could be paid all salary, all commission or a mix of both. Which would you choose? **Control Group** All salary → Indifferent → All commission. (Pre) 58% 25% 17% (Post) 50% 32% 18% **Treated Group** All salary → Indifferent → All commission. (Pre) 66% 19% 15% (Post) 50% 23% 27%
#4	Imagine that you have won $100,000 in a lottery! Almost immediately after you collect, you receive the following financial offer from a reputable bank, the conditions of which are as follows: There is a 50% chance to double any investment you make, in two years. It is equally possible that you could lose half of the amount invested. What fraction of the $100,000 will you invest? **Control Group** $0 $20,000 $40,000 $60,000 $80,000 $100,000 (Pre) 8% 23% 40% 20% 5% 4% (Post) 5% 17% 46% 25% 5% 2% **Treated Group** $0 $20,000 $40,000 $60,000 $80,000 $100,000 (Pre) 10% 23% 31% 22% 5% 8% (Post) 7% 12% 40% 26% 5% 10%
#5	Sequential question adapted to converge to an individuals risk profile. (Risk profiles ranged from extremely low to extremely high) **Control Group** Extrm low V. low Low Mod Mod high V. high Extrm high (Pre) 4% 8% 5% 40% 20% 16% 7% (Post) 6% 3% 5% 33% 27% 17% 9% **Treated Group** Extrm low V. low Low Mod Mod high V. high Extrm high (Pre) 4% 2% 4% 31% 28% 20% 11% (Post) 2% 3% 3% 26% 30% 24% 12%

Questions two and three were asked to gauge self-confidence and a respondent's willingness to tolerate uncertainty in their careers. As outlined in table 16, the control group was relatively unchanged in its preferences for job security and compensation structure. The treated group does show movement towards preferring more job security and preferring a compensation structure that relies more on commissions versus pure salary. We contend that these numbers are an early indication that respondents prefer to exert more control on their careers. Due to the volatile nature of business decision-making and lack of control on external factors, choosing a compensation structure that involves more commissions indicates a growing self-confidence in their abilities.

Questions four and five are standard lottery and risk profile questions from economics and business. They help establish baseline risk profiles and the amount of risk a respondent is willing to take in situations involving financial gains and losses via lottery. As evident, there is not much movement in the both sets of respondents, which could indicate that respondents stay true to their baseline risk preferences and profiles. For the treated group, this indicates that despite experiencing uncertainty in decision-making and possibly acting outside their comfort zones during the simulation, respondents did not inherently change their risk preferences and instead, risk perceptions are contextual. This postulation is further explored in the paper.

3.8 Research Hypotheses And Assumptions

Risk preferences are conceptualized as variables that moderate risk decisions (Rohrmann, 2005). We assume that a person's risk tolerance influences how they view the amount of risk incorporated in a decision with societal and cultural factors helping shape risk perceptions in various contexts. This paper focuses on two broad issues of how individuals behave vis-s-vis their risk preferences and how competitive pressures that force individuals to act outside their risk-preference comfort zones. We investigate behavioral and attitudinal changes on how individuals behave when forced to make business choices while facing uncertain outcomes.

When investigating the impact of outside forces that may impact an individual to act in a "more risky than normal" manner, much can be learned from behavioral economics and psychology. In their study of 306 participants, Gardner and Stenberg (2005) found that participants took more risks and focused more on the benefits than the costs of risky behavior when making decisions in peer groups, versus making decisions alone. The roles of teams and the interactions of strategy with performance have been studied (Durham et al., 1997; Durham, Locke, Poon, & McLeod, 2000; Weldon et al.,1991) and provide some of the theoretical basis for our research.

Conversely, Slattery and Ganster (2002) simulated a dynamic task with uncertain outcomes and found that decision makers that failed to reach goals, set lower less risky goals moving forward in subsequent decisions. Smallman and Smith (2003) determined that business managers focused in on a narrow band of organizational risks that arose from the processes of management and failed to adequately consider and act upon externally generated risks. Informed with these findings, we design and test our three hypotheses and how they relate to risk attitudes and decision-making under uncertainty.

Jensen & Meckling (1976) conclude that risk and expected financial returns are positively correlated because rational decision makers will take greater risks to achieve higher expected returns. Due to the competitive nature of the simulation, the cash prize, and the desire to win prompts us to hypothesize that:

Hypothesis 1: Undergoing a dynamic business simulation under time pressures forces individuals to behave in a "more risky than normal manner," which is likely inconsistent with their stated, baseline risk preferences.

Bandura (1997) suggests that meeting goals not only serves as a motivator for continued performance, but also helps build and strengthen a sense of efficacy, both amongst individuals and teams. We propose that teams possessing greater confidence in their ability to perform should be more willing than others to undertake risky strategies, because they believe they can implement them successfully. Conversely, we hypothesize that:

Hypothesis 2: Inability to align personal and team risk preferences will lead to poor team performance, increased team conflict, and low self-confidence.

Prospect theory (Kahneman & Tversky, 1979) suggests that people will be more risk averse when choices or alternatives are framed as potential gains than they will be when choices are framed as potential losses. Knight et al. (2001) investigated this hypothesis utilizing a computer simulation to study the relationships between team goals, incentives and performance. They found evidence that teams facing difficult goals chose risky strategies that maximized performance in the presence of a monetary reward. A losing team in a competitive environment can be considered to be facing a difficult turnaround goal and thus we hypothesize that:

Hypothesis 3: Regularly updated leaderboards will influence poorly performing teams to make risk-seeking decisions and over adjust strategies to match their competitors' better performance.

Due to the competitive nature of the simulation, we expect good performance to positively impact team dynamics, individual self-confidence and strategy implementations and poor performance to have the opposite effect. These six assumptions help us determine hypotheses 1 and 2 and set the stage for investigating hypothesis 3.

Assumption #1 – The simulation will force respondents to frequently strategy changes and this will likely not appeal to individuals and teams. Teams may behave in manners inconsistent with their baseline risk preferences but baseline preferences should not change.

Assumption #2 – Teams that finish in first place will begin the simulation starting off 'in sync' due to good alignment in risk preferences when comparing individual versus team preferences. Losing teams will have much more disagreement in risk preferences.

Assumption #3 – Last place teams have many disagreements between individual and team risk preferences, resulting in increased conflict among team members. The lack of alignment should lead to poor round-by-round business projections, further increasing the rift amongst last place team members.

Assumption #4 – Losing teams tend to change business strategies often and struggle to follow the agreed upon team strategy set prior to the simulation. While first place teams are expected to tweak their strategies based on previous round performances, in contrast, losing teams tend to adopt a more drastic, yo-yo approach.

Assumption #5 – We predict individuals on last place teams will show lower satisfaction and confidence with their performance when they reach a point in the simulation when it seems that losing is inevitable.

Assumption #6 – Once a team finds itself losing, we expect individuals with stronger risk-loving preferences to dominate team decision-making, in an effort to turn things around.

The following sections outline the empirical model, estimation equations, results, and conclusions. The final section discusses the impact of our findings and avenues for future research.

3.9 Empirical Model

Before we outline the empirical model, we must address the issue of "narrow bracketing" as we conduct the simulation over a finite time period. Narrow bracketing can be defined as the phenomenon that occurs when an individual makes a decision without taking into account the long-term consequences of their actions. Similar to gamblers who swear that their run of bad luck just means that their luck is about to change, individuals who are tasked with breaking up a series of decisions over a number of days do not always take the long view when making their judgments. Gertner (1993), Kahneman & Lovallo (1993), Benartzi & Thaler (1995), Read et al. (1999) have explored this topic to find that individuals tend to be more sensitive to losses versus gains. We address the bracketing issue in the overall design of the simulation, the repeated in-class emphasis on long-term results during debriefs, the uncertainty of when the simulation ends to prevent "end-gaming," and the nature of questions asked after each round that focused on long-term goals.

To investigate the various relationships outlined in the assumptions for hypothesis 1 and 2, Pearson's correlation coefficients (simply called correlation coefficients) are used to measure the dependence between two variables. The correlation coefficient between two random variables *X* and *Y* with covariance (X,Y) and standard deviations σ_X and σ_Y is defined as:

$$\text{corr}(X,Y) = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}$$

The degree of dependence between variables *X* and *Y* does not depend on the scale on which the variables are expressed but is sensitive to range of values. Dependence is stronger when viewed over a wider range of values and can indicate the possible causal relations that exist between variables. To this extent, all responses in our surveys were collected over a 7-point likert scale to provide a wider range of values and stronger relationship indicators.

An ordered probit regression is used to estimate the relationships outlined in hypothesis three. This regression model, a generalization of the probit model that involves more than two outcomes of an ordinal dependent variable, is used to estimate relationships between an ordinal dependent variable and a set of independent variables where the outcomes can be ordered or ranked. An underlying score is then estimated as a linear function of the independent variables and a probability of observing the outcome is calculated along with cutpoints or threshold parameters. Cutpoints in the ordered probit model can be regarded as similar to intercepts, in a regular regression model.

The central idea behind the ordered probit is that there is a latent continuous metric underlying the ordinal responses observed and thresholds partition the real line into a series of regions corresponding to the various ordinal categories. The latent continuous variable, y^* is a linear combination of some predictors (x_i) plus an error term that has a standard Normal distribution:

$$y_i^* = X_i\beta + \varepsilon_i, \qquad \varepsilon_i \sim N(0,1), \forall \; i = 1 \ldots N$$

Here y_i, the observed ordinal variable, takes on values 0 through m as defined by:

$$y_i = j \iff \mu_{j-1} < y_i^* < \mu_j \qquad \text{where } j = 0 \ldots m$$

Since we are concerned with how changes in the predictors translate into the probability of observing a particular ordinal outcome, we can generically solve for $\Pr[y_i = j]$ such that,

$$\Pr[y_i = j] = \phi(\mu_j - x_i\beta) - \phi(\mu_{j-1} - x_i\beta)$$

If j = m (maximum value), the generic probability form reduces to:

$$\begin{aligned}\Pr[y_i = m] &= \phi(\mu_m - x_i\beta) - \phi(\mu_{m-1} - x_i\beta) \\ &= 1 - \phi(\mu_{m-1} - x_i\beta)\end{aligned}$$

We can now estimate this model using Maximum Likelihood Estimation beginning with the creation of a log likelihood function. This is done by defining an indicator variable Z_{ij}, which equals 1 if $y_i = j$ and 0 otherwise. The log likelihood function is simply:

$$\text{Ln}\, \boldsymbol{\mathcal{L}} = \sum_{i=1}^{n} \sum_{j=0}^{m} Z_{ij} \ln [\phi_{ij} - \phi_{i,j-1}] \qquad \text{where,}$$
$$\phi_{ij} = \phi(\mu_j - x_i\beta) \text{ and } \phi_{i,j-1} = \phi(\mu_{j-1} - x_i\beta)$$

For further intuition into the ordered probit model, please refer to Greene (2003).

3.9.1 Estimation Equations

Informal observations show that participants act in a 'more risky than normal' manner in an effort to compete with the other teams in the simulation. But before we explore team dynamics, we begin by first determining if any of the personal risk preferences and attitudes play a role in whether a team ultimately wins the simulation. To do so, we regress all pre-simulation demographic details and risk attitudes with the final finishing spot of the team. This model includes all responses from the control and treated groups and then only for our treated group.

Equation 1:

Pr (teamwin) =

$\beta_0 + \beta_1$(gender) + β_2(undergraduate degree) + β_3(undergraduate major) + β_4(race) + β_5(age) + β_6(on campus job) + β_7(percentage of education being self-funded) + β_8(entrepreneurship classes taken) + $\beta_{9\ldots14}$ (individual risk preferences) + ε_i

Our dependent variable *teamwin* is an ordered variable, ranking all teams from first place to fifth place in a specific industry. In addition to the standard demographic variables, the above equation has controls for family wealth and a predisposition towards taking entrepreneurship courses. Five variables designed to determine individual risk preferences are also included individually in *individual risk preferences*. They are represented here by a single *beta* coefficient for brevity purposes but used individually in the model. These risk variables are outlined in table 2 and their cumulative responses are detailed in table 5.

Equation 2:

Pr (teamwin) =

β_0 + β_1(influence on team) + β_2(attention paid to competitors) + β_3(strategy evolution) + β_4(competitor impact on strategy changes) + β_5(acting outside comfort zone) + β_6(team risk feel) + β_7(versus team) + β_8(win alone) + β_9(team conflict) + $\beta_{10\ldots15}$ (individual risk preferences) + ε_i

Equation 2 utilizes the entire response set from our treated group and includes all the individual risk preference variables outlined in equation 1. We also test results separately for first and last place teams to see what impacted their performance. Since the responses are collected after the simulation ended but before the teams know their final spot on the leaderboard, it incorporates several individual attitudinal variables as well. Each respondent answered these questions independently.

The *influence on team* variable reflects how respondents rated the influence they feel they, as individuals, had on the team's decisions. In the question related to the variable *Attention paid to competitors* individuals are asked to rate how much attention their team paid to possible competitor strategies when designing their own strategy, prior to round 1. During initial strategy formulation every team should have considered how to handle the event of an unexpected move by a competitor. *Strategy evolution* resulted from a question about how much the final strategy evolved as compared to the master strategy decided upon prior to round 1. The *competitor* *impact on strategy changes* is designed to gauge how much impact competitor moves had on a team changing its own strategy to compete more effectively. The next variable, *acting outside comfort zone*, relates to a question that asks respondents if their competitor's strategies forced them to act outside their comfort zone when making team decisions. Answers to the question on *Team risk feel* indicated how respondents rated the amount of risk their team took during decision-making. The question for the *versus team* variable asked if individuals would have adopted a more or less risky approach if they were making decisions alone, as opposed to what their team undertook. The *win alone* variable reflects whether an individual felt that they would have performed better if they were operating alone and *team conflict* measures the level of team conflict that may have existed during decision-making.

Equation 3:

Pr (strategy evolution) =

$$\beta_0 + \beta_1(\text{team risk feel}) + \beta_2(\text{competitor impact on strategy changes}) + \beta_3(\text{acting outside comfort zone}) + \beta_4(\text{versus team}) + \beta_5(\text{team conflict}) + \varepsilon_i$$

Equation 3 uses a subset of variables from equation 2 and is constructed to determine what factors each respondent felt were critical to their team evolving its strategies, as the simulation progressed. *Strategy evolution* measures how much the final strategy evolved as compared to the master strategy prior to the start of the simulation. This question was asked to individual team members to gain their perspective on what they personally felt about their team's decisions. Motivated by hypothesis 2, we also include the two individual attitude variables - *team risk feel* and *team conflict*. The regressions from equations 3 were also run separately for first and last place teams to determine how these teams may have behaved differently.

Equation 4:

Pr (acting outside comfort zone) =

$\beta_0 + \beta_1$(competitor impact on strategy changes) + β_2(lottery) + β_3(personal influence) + β_4(versus team) + β_5(team conflict) + ε_i

Our final equation uses many of the variables previously seen in equation 2 including a *lottery* variable that is used to estimate an individual's personal risk preference. The lottery question is a standard metric used in economics to measure risk averseness and is explained in table 2. This equation is designed to determine whether external factors and internal risk attitudes contributed to an individual acting outside his comfort zone while making business decisions. We hypothesize that individuals do act in a more 'risky than normal' manner because they are influenced by their competitors' actions and this equation should shed light on this issue. The regression was also determined separately for winning and losing teams.

3.10 Empirical Results – Hypothesis 1 and 2

Since our first two hypotheses involve participant behavior and balancing of personal and team risk preferences, it is reasonable to assume that individual behavior will impact the collective, team outcome. To investigate how individuals react when forced to make business choices while facing uncertain outcomes, we begin by investigating the six assumptions set forth in a previous section.

3.10.1 Assumption 1 - Exploring Changes In Individual Risk Attitudes

The lottery choice question was asked to both the treated and control group and it is important to see what deviation, if any, occurred post simulation. In the case of the control group, we measure this after 7 weeks. We find that 47% of the control group would pick the exact same lottery choice versus only 36% of the treated group.

When looking at what respondents personally found to be riskier, starting their own business or pursuing salaried employment, only 8% of the treated group selected the exact same answer choice post simulation. Comparatively, 28% of the control group selected the same answer choice for this question. We find that the majority of the treated group would not only pick a different lottery choice but also have a different perspective on the amount of risk involved with salaried employment.

It is important to balance these results against another question that is designed to determine risk profiles. Question 5, as outlined in table 13, is measured on a scale from extremely low risk to extremely high risk. We find that 50% of the treated group selected the same risk profile choice post simulation. Additionally, over 90% of this group selected a choice within one answer choice of their pre simulation profile, indicating only a modest change in thinking. For example, among the 90%, if a respondent had chosen a risk profile of 'very low' before the simulation, their post simulation choice was either 'extremely low' or 'low.' This consistency in risk profiles lends credibility to the argument that while individuals may act and make decisions divergent from their baseline risk profiles, the personal baseline itself does not change much over short periods of time.

To investigate if the simulation forces respondents to think more critically on the issue of uncertainty and risk due to competitive forces, we correlated two additional questions that were asked after every round of the simulation - how satisfied a respondent personally was after the results from the current simulation round and how much the team strategy changed when comparing it to their master strategy, set prior to round one. For the group, we find an overall negative relationship (-0.02) between these two variables for each round of the simulation. The more a team strategy changed each round, the less likely an individual was to be satisfied for that round. This relationship is showcased in figure 2.

These results are even more pronounced when we differentiate between first and last place teams. Winning team members have a tighter distribution between the two variables indicating that these participants tended to be more in sync with decision making and balancing risk. Teams finishing in last place have more wide-ranging correlation coefficients, indicating that these team members struggled aligning their personal risk preferences with the tough decisions that needed to be made to win the business simulation.

The overall negative correlation indicates that respondents understood that they had to change strategies (take risks) to be successful, but did not enjoy the process of doing so. The more a team strategy changed for each round, the less likely an individual was to be satisfied for that round.

3.10.2 Assumption 2: Individual versus Group Risk Attitudes

Each simulation participant was asked after each round to rate the amount of risk they felt their team took in arriving at their collective business decision. Additionally, we asked respondents to tell us how much risk they individually would have taken in the past round, operating alone, without team confines. Correlating these two questions we find that as a whole, the group starts off cautiously trying to align their personal risk preferences with the teams (r=32%), somewhat diverges in the middle rounds and then ultimately converges to a more cohesive number (r=41%). These results are outlined in table 17.

Table 17 Correlating perceptions of the amount of risk the team took, versus the amount of risk an individual would have taken if making decisions alone, after each round.

Round	Group	1st Place	2nd Place	3rd Place	4th Place	5th Place
1	32%	51%	24%	34%	36%	2%
2	36%	73%	56%	22%	48%	-53%
3	31%	5%	50%	67%	17%	7%
4	22%	18%	0%	34%	22%	44%
5	33%	54%	8%	17%	56%	4%
6	41%	67%	52%	42%	-7%	30%

While the above coefficients for the entire simulation give us a general indication of team behavior, viewing these numbers by 'winning' and 'losing' teams reveals a stark contrast in the results. First place teams start off with very strong round 1 and 2 correlation coefficients between team and individual risk attitudes, have some disagreements in the middle rounds and ultimately finish with strong team agreement (*r*=67%). Last place teams are all over the place. They not only begin with considerable disagreement in how decisions are made but also cannot seem to get on track. They display the opposite behavior as compared to winning teams.

We also notice that deviations between individual and team risk attitudes are most pronounced in the middle rounds. As discussed earlier, round 3 is the earliest point at which the entire industry finds out if a competitor has chosen to introduce a new product line. It is common, at this point, for the leaderboard to get shuffled, and the previous "winners" often find themselves replaced by a new leader. The need to adapt to changing market dynamics often leads to strategy disagreements within teams and many pivot away from the master strategy set prior to round 1. As facilitators, we can attest to the fact that rounds 3 and 4 are typically when individuals are the most uncertain about their team's direction and declare "we took too much risk" or "we need to take more risk" in their post-round surveys. Table 6 reflects these variances in risk perceptions.

It can be argued here that since individuals complete their surveys after reviewing the current round results, survey responses may be biased by actual team performance. For example, a losing team member may display more disagreement with their team decision-making process if results are especially bad. Vice versa, a winning team respondent may suppress some disagreement because things are going well.

Anticipating this issue, we attempted to address this in two ways. First, several questions specifically ask individuals to share their personal beliefs on how the team acted, and how they would have acted from a risk taking perspective, irrespective of results. Since survey responses were not shared with other simulation participants, confidentiality was ensured and respondents could honestly air their grievances. Secondly, we ask the same questions at the end of the simulation and when respondents look back and reflect. This removes any immediate bias a specific round may have produced in our survey results.

3.10.3 Assumption 3: Personal Satisfaction and Team Conflict

Each individual respondent is asked after each round to rate his personal satisfaction with the teams' performance. They were also asked if they would have taken more or less risk as compared to their team, if they were making decisions alone. For first place teams, the correlation coefficients are 23% in round 1 and 52% in round 2. Teams finishing in fourth place or better are different, resulting in correlation coefficients 44% in round 1 and -26% (negative) for round 2.

The numbers indicate that on first placed teams, individual and team preferences are similar in nature. Last placed teams have internal disagreements between individual and team risk preferences with respondents not agreeing with many of the strategy choices. These diametrically opposite results along with previous results from table 6, paint a picture of last placed teams and how different they are from the winners from the earliest rounds of the competition. We postulate that just these two metrics show us how easily the "losers" can be identified and this finding prompted us to investigate these relationships later in the paper.

We asked all teams in their final survey to rate how much conflict the team had while making business decisions. We find that amongst first place teams, 50% of the respondents claimed that their team decisions involved conflict and required some consensus building. Very surprisingly, only 7% of the respondents from last placed teams claimed to have any team conflict. This finding not only contradicts our assumption that losing teams have more conflict and raises further questions on how the last place teams are reacting as they watch other teams perform better in the simulation.

In their post-simulation debrief, losing teams openly admitting that they could not all completely agree on their team inputs for each round but preferred to remain quiet in order to avoid conflict. Teams admitted that they felt "out of sync," a feeling that was amplified by the absence of open conversations. By contrast, first placed teams did admit to team conflicts and verifying that they felt comfortable speaking up in during disagreements. As a side note, we did not specifically assign leadership roles within teams but did provide a "best practices" framework to all teams to help them think through their decision-making process.

To explore exactly how "out of sync" last place teams are in their decision-making, we looked at responses to the question "comparing your actual results to the projections you made for the previous round, are your actual results in line with your projections?" This question was asked after each round and also allowed participants to reply via an open-ended response. After just the first two rounds, the difference between first and last place team attitudes is striking.

A majority of respondents on last place teams stated that their pre-round projections were very different from post-round actual results but that is expected as these teams are struggling to do well in the simulation. What is fascinating though is that many of these respondents stated that they were "close to turning things around" and that they had full confidence things would "look different soon." This picture of risk perception suggests that there is a sense of reassurance amongst these respondents that they have done all that they can and similar to Smallman and Smith (2003), these respondents do not fully comprehend external, competitive risks.

On first place teams, 70% of the respondents stated that their projections and actual results matched very well and that they would stick to their master strategy moving forward. These respondents credited the strong start and vigorous team discussions (that resulted due to differences in risk attitudes) as helpful in reaching a final team decision. It must be noted that while some respondents stated that they personally would have adopted a different risk strategy if they were operating alone, they were satisfied by their team's performance. A strong start helped cement the master strategy and provided confidence moving forward.

3.10.4 Assumption 4: Impact of Strategy Deviations to Success

Since the simulation involves dynamic decision making, with each round presenting a different view of the industry, teams are expected to adjust their strategies after each round to stay relevant and competitive. But how much should teams deviate from their original strategy set prior to round 1? Should teams chase the market or generally stay the course to see the long-term benefits of their master strategy?

This exact question was asked to each respondent after each round to determine how much deviation (if any) occurred during the simulation. Table 18 tabulates these responses. What we immediately notice is that first place teams tend to stay the course but tweak their operational strategies as needed. Last place teams on the other hand, showcase more of a "yo-yo" approach and overreact to every market change. We suggest that one reason individual members on losing teams might have such varied perceptions on risk and performance is that there is a lack of clarity in overall team direction and strategy.

Table 18 Perception of strategy deviation after each round compared to master strategy set prior to round 1.
(Responses collected on a 7-point likert scale but condensed here for brevity)

	First Place Teams				**Last Place Teams**		
Rounds	Not much Deviation	Deviated about 50%	Major Deviation		Not much Deviation	Deviated about 50%	Major Deviation
2	86%	0%	14%		41%	17%	42%
3	60%	4%	36%		66%	17%	17%
4	72%	4%	24%		38%	38%	24%
5	36%	11%	53%		46%	23%	31%
6	43%	17%	40%		18%	27%	55%
Overall Deviation Post-Sim	**53%**	**28%**	**19%**		**36%**	**14%**	**50%**

Once we find a lack of clarity in team strategy, it is natural to inquire if there is a connection between master strategies set prior to round 1 and strategy deviations after each round. To accomplish this, we begin by correlating strategy deviations from round 2 (the first opportunity to change strategy) with round 3, and then subsequently for each round thereafter.

For first place teams, there is a 23% correlation between the first two rounds, indicating that winning teams did not deviate much. For teams finishing in last place, the correlation is almost 3 times higher at 56%. This indicates that as early as round two, last place teams are implementing huge strategy changes and have little confidence in their initial strategy.

Calculating this correlation over a longer period of time further strengthens this finding. Correlating strategy deviations from round 2 with deviations in strategy from round 6 is very telling. First place teams have only a 2% correlation between these two rounds indicating that they do not deviate much. Last place teams have a 35% correlation indicating that even up to final round of the simulation, losing teams are still trying different avenues hoping to find something that works.

This finding was also anecdotally confirmed during the post simulation debrief when losing teams openly stated that they tried different strategic moves out of desperation as they found their pre-simulation strategy to be inadequate. This finding along with team comments confirms the importance of having a coherent strategy at the start of the simulation and creating a team dynamic that encourages debate. Having a well thought out master strategy underscores the importance of starting strong and tweaking directions versus starting off poorly and then trying to recover.

A possible shortcoming of asking the participants to evaluate the degree of deviation after each round is that respondents are engrossed in the simulation and may not have a long-term reflective approach to their answers. It is possible that respondent's over/under react to market results due to time and competitive pressures. To combat this possible issue, the same question was also asked in the post simulation survey but was phrased to be more reflective. We specifically asked respondents to view their initial strategy proposal and then tell us how much the team strategy ultimately evolved, compared to their initial strategic plan. The last row in table 18 tabulates the result of this question.

When asked to answer this question reflectively, 50% of the last place teams responded that they had major deviations in their strategy as compared to their initial outline. Only 19% of the respondents on winning teams felt that they had major deviations from their proposed strategy set prior to round 1. While this result by itself may convey limited information, taken in conjunction with results from table 17 (correlating perceptions of the amount of risk the team took, versus the amount of risk an individual would have taken if making decisions alone, after each round), it tells us that winning teams get in-sync quicker, have robust discussions and disagreements and ultimately devise a strategic plan that requires minor tweaks.

Losing teams behave differently. They struggle aligning individual and team risk preferences, cannot get in-sync quickly, choose to avoid having team disagreements and do not have a clear operational strategy prior to the start of the simulation. Thus, misaligned teams who avoid dialogue can be viewed as having effectively lost the simulation by the end of round 1, without much hope of catching up.

3.10.5 Assumption 5: Individual Satisfaction With Results

Based on the above findings, it appears that last placed teams are dysfunctional and should be dissatisfied with their performance. Conversely, top placed teams should be more satisfied with their performance as the simulation progresses. To find out if this holds true, we looked at responses to our question that specifically inquired about this issue and outline these results in table 19.

Table 19 Satisfaction with team performance measured after each round
(Responses collected on a 7-point likert scale but condensed here for brevity)

	First Place Teams				Last Place Teams		
Rounds	Not satisfied at all	Neutral	Totally satisfied		Not satisfied at all	Neutral	Totally satisfied
1	0%	3%	97%		30%	15%	55%
2	0%	4%	96%		15%	15%	70%
3	10%	7%	83%		26%	17%	57%
4	10%	10%	80%		10%	13%	77%
5	0%	4%	96%		30%	30%	40%
6	0%	11%	89%		9%	18%	71%

While we find our assumptions to generally hold for first place teams, the attitudes of last placed teams are truly confusing. These last place teams tend to have high levels of satisfaction with their performance and relatively low levels of dissatisfaction. This result is counterintuitive, as actual team performance is displayed to the entire industry after each round and it is very clear who the top and bottom teams are. Why do these last place teams have split perceptions?

One possible explanation could be that once a team discovers early in the simulation that it has insurmountable odds and cannot recover to win the industry, the team decides to accept its poor performance and is thus satisfied with its performance. But is this really true? To investigate this issue, we correlated two additional variables - satisfaction with current round results and confidence in projections for the next round. Table 20 outlines these findings.

Table 20 Correlating satisfaction with results for the current round with confidence in projections for the next round.

Rounds	First Place Teams	Last Place Teams
1	61%	40%
2	49%	76%
3	16%	65%
4	39%	50%
5	30%	75%
6	62%	63%

Once again there is a surprising result. After the first round, last place teams are more satisfied with their performance and have more confidence that their business decisions are 'right.' Another good place to focus on is round 3 as this is when many teams may be tempted to make changes in strategy because of the outcomes of the competitive positioning. If we focus on responses collected after round 3, we find that first place teams indicate that they are not very confident in their projections for the next round (r=16%). In open-ended responses, first place teams state that they are worried about what their competitors might do moving forward. Somewhat surprisingly, last place teams remain confident (r=65%) in their initial strategy and do not seem to be overly concerned with what their competitors are doing.

But since these teams are losing and the leaderboard is displayed after each round, are the last place teams accepting poor performance or are they setting lower, more attainable goals? This behavior was seen in Slattery and Ganster (2002), where it was found that decision makers who had failed to reach their goals set lower, less risky goals in subsequent decisions. We may be witnessing similar behavior.

A natural follow up question is whether or not participants simply enjoy the process of continually tweaking strategies to effectively compete in the simulation. Correlating two variables measured after each round - personal satisfaction with results and strategy deviations, gives us an answer. For all teams, we find negative correlation coefficients between the two variables, indicating that while respondents actively argued for strategy pivots, they did not enjoy personally the process of doing so. Last place teams tended to have less conflict but combining responses over all simulation rounds results in a final negative coefficient (r = -5%) indicating that our assumption holds across all teams. Thus, both first and last place teams indicated that despite differing performance outcomes, they did not enjoy the process of continually making risky decisions involving uncertain outcomes.

3.10.6 Assumption 6: Losing And The Dominance of Risk Aversion

Following the final round of the simulation, all respondents were asked about the amount of influence they as individuals, had on the team's decisions. Answer choices ranged on a 7-point likert scale from 'no influence' to 'team adopted all my decisions.' If we correlate this response with question 3 from table 2 (choice of job security and its relation to compensation), we find some surprising results. First place teams have a positive correlation coefficient (r=14%) indicating that on winning teams, the amount of influence a respondent had was positively correlated with their preferred employment structure – more influence is correlated with preference for a less stable job if it offered higher pay increases. This indicates that on winning teams, the individuals that have more influence are those that have a higher tolerance for personal risk.

Last place teams on the other hand, have a negative correlation coefficient between the influence and personal risk variables (r=-50%). This indicates that on losing teams, the individuals who had more influence on team decision-making are those with a lower tolerance for personal risk. In the case of last place teams, risk-averse teammates had a disproportionately higher influence on team decisions, perhaps holding the team back from pursuing bolder choices.

To further investigate if this result holds, we correlate the influence variable with question 1 from table 13, which asks individuals to tell us what they find riskier on a 7-point likert scale: starting a business or pursuing salaried employment. Once again, we find a wide disparity between first and last placed teams. For first place teams, we have a positive correlation coefficient (*r*=30%), indicating that the more influence an individual had on team decisions, the more inclined they were to find salaried employment to be risky. The opposite was true for last placed teams. These teams have a negative relationship between the two variables (*r*=-22%), indicating that the more influence an individual had on team decisions, the more inclined they were to find starting a business to be risky. Taken in conjunction with the previous correlation result, it becomes evident that losing teams adopted a more risk-averse approach to decision making, truly believed that the risk-averse approach was the right one, and thus, stayed confident in their overall decisions.

We also measured level of confidence individual participants had in the wisdom of the team decisions. Each respondent was asked to specify whether their team would have performed better if they were able as an individual to make all the decisions, versus making decisions using team consensus. We find that for first placed teams, 32% of the respondents said that their team would have performed better if they had made decisions alone, 40% said no and 28% said that they were unsure. For last placed teams, only 7% of the respondents said that their team would have performed better if they had made decisions alone, while 43% said no and 50% said that they were unsure. Not surprisingly, self-confidence was low on last place teams.

3.11 Empirical Results For Hypothesis 3

Prior to determining the impacts of the simulation on individual risk preferences, a baseline regression (equation 1) was run with pre-simulation data to determine if any of the demographic, personal risk preference and proclivity towards entrepreneurship variables were significant in contributing towards a team winning the simulation. The results indicate that none of these variables are significant in predicting the final ranking of a team, thus clearing the way for us to determine the impact of the simulation on individual attitudes and team outcomes. Since none of the variables were significant, we have elected to omit the results from equation 1 in the interest of brevity.

3.11.1 Equation 2 Results

Equation 2 utilizes data collected at the end of the simulation to determine what factors contributed to the final finishing spots for teams and detailed results are outlined in table 21. Our dependent variable *teamwin* is an ordered variable ranking a teams' final finishing spot, from first to fifth place. For the entire respondent group, *teamriskfeel* is significant in predicting the final finishing order, though it has different signs and magnitudes for first and last place teams. A positive relationship indicates that the more risk an individual felt their team should have taken, the worse the team performed, a clear indication of differing risk preferences. Job security vis-à-vis pay increases *(jobsecur)* is also significant, indicating that individuals who are comfortable with less job security but wanting larger salary increases are positively linked to finishing first in the simulation.

The final overall significant variable *(versteam),* when positive*,* implies that the more risk an individual was willing to take operating alone, the higher the probability that his team would finish towards the top. This result is in line with our findings from hypothesis 1 and 2 where we deduce that the failure to align personal and team risk preferences leads to poor team performance and poor team dynamics.

Table 21 Results from Equation 2. Standard errors in brackets.
(* = 10%, ** = 5%)

Oprobit *(team winning)* **Variables**	**Coefficients** (std errors) *All Teams*	**Coefficients** (std errors) *First Place teams*	**Coefficients** (std errors) *Last Place Teams*
Compimpact	0.04 (0.09)	0.02 (0.12)	0.15 (0.13)
Outcomfzone	0.25 (0.21)	-0.35 (0.26)	0.19 (0.30)
Teamriskfeel	0.55** (0.13)	- 0.61** (0.16)	0.86** (0.20)
Versteam	0.55** (0.16)	0.52** (0.20)	- 0.83** (0.23)
Teamconflict	0.07 (0.06)	- 0.05 (0.07)	- 0.01 (0.08)
Riskbiz	0.13 (0.09)	- 0.28** (0.14)	0.22 (0.14)
Jobsecur	0.14** (0.06)	- 0.10 (0.08)	0.15 (0.09)
Overalinfl	- 0.21 (0.13)	0.24 (0.18)	- 0.13 (0.18)
Comptattn	- 0.20 (0.07)	- 0.00 (0.09)	0.01 (0.10)
Stratevol	0.02 (0.07)	0.01 (0.09)	0.03 (0.10)
Alonewin	0.14 (0.13)	0.13 (0.16)	0.11 (0.17)
Salarymix	- 0.03 (0.08)	0.08 (0.10)	- 0.04 (0.11)
Lottery	0.001 (0.08)	- 0.03 (0.11)	- 0.11 (0.12)
Riskprofile	- 0.12 (0.08)	0.14 (0.10)	- 0.12 (0.11)

The last two columns in table 21 display equation 2 results determined separately for first and last placed teams. The results are not surprising based on our previous findings. *Teamriskfeel* and *versteam* are significant for both first and last placed teams but with opposite signs. For top finishers, team members felt that the team took the right amount of risk and if they were making decisions alone, they would have taken slightly less risk than the level selected by the team. Overall, they found their personal risk preferences to be relatively well aligned to their team. Another significant variable *riskbiz* has a negative coefficient, indicating that the less an individual found self-employment to be a risky alternative, the more likely were they to perform well at the simulation.

Last placed team members felt that the team should have taken more risk as a team and they personally would have taken more risk as compared to their team's choices, if operating alone. Interestingly, *riskbiz* is not statistically significant for losing teams. This indicates that losing teams were made up of individuals that found safety in salaried employment and advocated for a more cautious or risk-averse approach. We know from our hypothesis 2 findings that risk-averse individuals tended to dominate the decision making in these last placed groups. Overall, for losing teams, there was no clear team agreement on how much risk the team should have taken while making business decisions. We argue that for losing teams, it is not the amount of risk that is a critical issue but instead, the constant strategy deviations that led to team disunity.

3.11.2 Equation 3 Results

Equation 3 is designed to determine what outside forces contributed to a team's strategy evolutions over the course of the simulation. As seen in table 22 under the equation 3 columns, three variables are significant for the entire cohort of respondents: 1) acting outside their comfort zone while making decisions, 2) the impact of competitors, and 3) the amount of risk an individual would have taken, versus what the team undertook.

Versteam is negatively related to how a team's strategy evolved, indicating that the more risk an individual was willing to take if he were operating alone, the lower the probability that his team would change strategies based on that individual's preferences. This is not too surprising, as the uncertain nature of what other teams might do is an unknown quantity and a team approach to decision making would probably leave team members at either ends of the risk spectrum dissatisfied.

When we look at results separately for first and last placed teams, we have more insight into how decisions were made in the team setting. First place teams focus on their competitors' moves and the more closely a team watched its competitors, the more likely they were to evolve strategies that allowed them to finish towards the top of the leaderboard. The *conflict* variable is significant, implying that the more conflict a team has, the less its strategy strays from the original plan. This clearly indicates that by allowing open debate and disagreement within the team, top placed teams arrived at better decisions.

For last placed teams, we find similar behaviors to those seen by some of the earlier correlation coefficients. These teams avoid conflict and perhaps more surprisingly, do not pay enough attention to their competitors as they change strategies. It appears that not only do last place teams have wild swings in the path of their strategy, these swings result from inclinations internal to the team, versus an analysis of competitor moves. Unlike first place teams, last place teams not only ignore what their competitors are doing, but also avoid active disagreements that can help their teams make better decisions.

Table 22 Results from Equation 3 and 4. Standard errors in brackets. (* = 10%, ** = 5%)

	Equation 3 Oprobit *(strategy evolution)*				**Equation 4** Oprobit *(outside comfort zone)*		
Variables	Coefficients (std errors) *All Teams*	Coefficients (std errors) *First Place*	Coefficients (std errors) *Last Place*		Coefficients (std errors) *All Teams*	Coefficients (std errors) *First Place*	Coefficients (std errors) *Last Place*
Compimpact	0.26** (0.08)	0.36** (0.18)	0.35 (0.44)		0.64** (0.11)	0.62** (0.23)	1.15** (0.46)
Versteam	- 0.29** (0.14)	0.10 (0.35)	- 0.19 (0.78)		0.04 (0.17)	- 0.25 (0.43)	0.78* (0.47)
Teamconflict	- 0.07 (0.05)	- 0.37** (0.14)	- 0.40 (0.38)		- 0.19** (0.06)	- 0.34** (0.15)	- 0.49 (0.42)
Outcomfzone	0.48** (0.20)	0.39 (0.42)	- 0.08 (0.96)				
Teamriskfeel	0.04 (0.12)	- 0.18 (0.28)	0.60 (0.65)				
Overalinfl					- 0.02 (0.15)	0.08 (0.38)	0.18 (0.25)
Lottery					- 0.20** (0.08)	- 0.18 (0.17)	- 0.99** (0.37)

3.11.3 Equation 4 Results

From equation 3 results it is clear that teams act outside their comfort zones while making strategy decisions, but what factors contribute to this phenomenon? Equation 4 investigates this issue and tests our hypothesis that it is the pressures of outside competition that forces teams to act in a manner different from their internal preferences. The results for the entire group and for first and last placed teams respectively are displayed in table 22 (under equation 4 columns), showing a variety of outcomes, some expected and some surprising.

For individuals, competitive pressures led them to act outside their comfort zone. The variable *competitor impact on strategy changes* is statistically significant, indicating that simulation participants had to make decisions that forced them to act outside their comfort levels in order to respond effectively to competition. Both *Team conflict* and *lottery* variables are negatively related to our independent variable, implying that the more conflict an individual experienced, the less likely they were to act outside their comfort zone. Phrased differently, the more discussions a team had on a business decision, the less likely an individual felt the need for an impulsive or completely different action. The significance of our *lottery* variable has similar implications. The lower the individuals risk preference, the more likely they were forced to act outside their comfort zone.

For winning teams, the *lottery* variable is not significant, indicating that on these first placed teams, risk averseness was not an issue when it came to making business decisions. These individuals relied on making decision by analyzing competitors and on allowing for team conflict, and were comfortable with the team making decisions that they normally may not have made, had they been operating solo.

For losing teams, we have some differing results. Competitive pressures did force these individuals to act outside their comfort zones and, similar to results from equation 3, *team conflict* is not statistically significant for these individuals. The *lottery* variable is significant (with a high coefficient), implying that these individuals tend to be more risk averse in their decision-making and thus only act outside their comfort zones when forced to do so by an outside stimulus. This result also is implied in the significance of the *versus team* variable, with individuals stating that compared to their team, they would have taken more risk in their decisions.

3.12 Results Summary

Our findings confirm our three hypotheses and demonstrate that participation in the business simulation leads individuals to behave in a manner inconsistent with their stated, baseline risk preferences. We found some changes in risk perceptions and attitudes towards employment and salary options, post simulation. Also, while the inability to align personal and team risk preferences leads to poor team performance and lower self-confidence, we found that contrary to our assumption, these factors do not lead to increased team conflict amongst poorly performing teams. Losing teams do make risk-averse decisions as a group but individuals on the team clamor for more risk if they were operating alone.

Summarizing our major findings from equations 1-4, there are distinct differences between how winning and losing teams behave and operate in a dynamic, competitive environment. Losing teams do not have much agreement on team strategy direction and tend to adopt a more risk-averse approach as a group. Individuals on losing teams have strategy disagreements but do not share their concerns with the entire team in an effort to avoid conflict. Not only do last placed teams avoid conflict, they change strategies based on internal inclinations versus external competitive indicators. These individuals also need a combination of competitive and internal team discontent to make the tough decisions that fall outside their usual comfort zones.

First placed teams behave in an opposite manner, thus giving us a blueprint on how teams should perform when operating in an ever-changing business environment. A key educational outcome from our simulation is that the losing teams were not oblivious to the difference in performance and attitudes. Upon reflecting on their performance during the feedback session following the end of the simulation, individuals in losing teams acknowledged that they should have adopted a more risk-seeking approach to decision making, including having more open discussions on team strategy. They also stated that if they were to partake in the simulation again, they would spend more time formulating a strong initial strategy and analyzing competitor moves. Somewhat sheepishly, losing teams also admitted that they were overconfident in their own abilities and underestimated the dynamic nature of the simulation. After falling to the back of the leaderboard early in the simulation, some lost hope for winning and redefined winning as not finishing in last place. This led them to try many different strategies to avoid being in last place, giving us the 'yo-yo' effect we find in our results.

3.12.1 Relevance To Entrepreneurship

These attitudinal differences are one of the critical findings of our research, because they may lead to a method for quickly pinpointing losing teams. Simply by looking at the first two rounds we can quickly identify teams that have poor decision-making processes based on the specific correlation coefficients from table 6. We see that the potential for being the losing teams is grounded in severe disagreement on individual versus team risk preferences. As the simulation progresses, these last placed teams find themselves struggling to recover (in 4^{th} or 5^{th} place), collectively get more polarized and the disagreements in team versus individual risk attitudes become more pronounced. Since all teams start off in the same place with the same financial metrics and no new products, we can confidently state that poor team performance is a direct result of poor interpersonal dynamics and team decision-making.

Conversely, when we look across the correlations, we notice that first place teams experience disagreements in risk preferences earlier in the simulation, which helps them openly debate, and agree upon a group risk attitude. This allows the top teams to move forward "in sync" better than their competitors. These results also hold true from the results for hypothesis 3 and highlight the importance of aligning individual and team risk attitudes in a business setting.

It is here that we can draw a parallel to entrepreneurship and startup teams. Most university startup teams tend to be small, results focused, and operate under severe pressures (time, funds etc.) and constraints. The one critical issue that these founders or their faculty advisors tend to ignore is individual risk preferences and whether the team can quickly align its risk preferences moving forward. Differences in operation strategy (for example), essentially arise from differing risk preferences and how much risk an individual is willing to take operating alone. We not only can simulate many of these pressures and get insights into team preferences, we can also allow the team to gauge how they performed under pressure. Politis & Gabrielsson (2009) found that business failure due to poor performance is a valuable source of learning and we contend that such an exercise can be a valuable resource for academic incubators. We validate that risk attitudes play a critical role in determining team success where one strategic error could prove fatal for a startup. Thus, the importance of aligning risk preferences and embracing conflict to enable better decision-making cannot be overstated.

3.13 Theoretical Implications

We now know that last place teams can be identified early, do not start with a clear plan, tend to have major strategy deviations as compared to first place teams, avoid conflict, and do not enjoy the process of making risky decisions. But, we have also seen that these last place teams claim to be more confident in their round-by-round projections and become more risk averse in their decision-making. Since team standings are shared with the entire class, shouldn't confidence levels of these potential last place teams decrease as the rounds progress? Also, if these teams have "nothing to lose" as they consistently are towards the bottom of the standings, why do they become more risk averse as the rounds progress? What about the notion of "go big or go home," a thought process often associated with taking risks and finishing on top? Why do risk averse individuals dominate decision making on last placed teams when risk taking behavior is required to succeed? Superficially, it is easy to dismiss losing teams as delusional, out of touch or as having lost interest in the simulation and thus, displaying odd behavior. We begin by first looking at the issue of overconfidence in losing teams and then introducing the concept of "losers dilemma" to explain the risk aversion tendencies in losing teams.

3.13.1 Overconfidence In Last Place Teams

Taylor and Brown (1988) showed that individuals generally tend to be overly optimistic when making decisions under uncertainty. DeBondt and Thaler (1995) also find that individuals exhibit overconfidence in judgment and overestimate their relative abilities. But perhaps what may best describe the behavior of losing teams we see in our simulation is the effect of "escalation commitment," as proposed by Staw (1976). Simply stated, this bias causes a decision maker to refuse to withdraw from a losing situation, or to continue to throw money, effort, time and other resources after bad investments, in an attempt to "turn things around." Gamblers often display this trait when losing and instead, keep looking for the next hand that will be a "guaranteed winner." In a competitive environment such as our simulation, it is easy to see how this concept can apply to all teams, not just last place teams.

From our data, we know that losing teams start the simulation without a concrete strategic plan as witnessed by their numerous strategy deviations throughout the simulation. This fact is additionally verified by reading the team's strategy statements submitted prior to round 1 and from their team debrief, post simulation. Poor performing teams tend to have vague and grandiose strategies, while winning teams tend to be focused and detail oriented.

Additionally, losing teams are also relatively quick to submit their round-by-round decisions as compared to the rest of the industry. Since decisions are timed and entered into a web portal, we can tell when a certain decision was submitted. While there is no clear pattern for some of the better performing teams, last place teams tended to submit decisions faster, on average, than the rest of their competitors. Since we know these teams have little conflict, arriving at a consensus quickly seems a logical outcome. Shipman and Mumford (2011) found that strategic plans are hurt by overconfidence as individuals fail to see deficiencies during idea development. It is this narrow aspect of overconfidence that is possibly displayed by the losing teams.

While some of the existing research can explain overconfidence in last place teams, the reasons why these teams become risk averse as the simulation progresses, is unclear and conflicting in current literature. Jensen & Meckling (1976) found a positive correlation between risk and returns and Knight et al. (2001) found that teams facing difficult goals chose riskier strategies. Based on these findings, losing teams should employ riskier strategies to deliver better returns in an attempt to win the simulation. This expectation of "riskier" behavior is also predicted by Gardner and Stenberg (2005) where they find that in groups, people tend to act more risky. But we do not see these behaviors in last placed teams and the next section explores this phenomenon.

3.13.2 Risk Aversion and Losers' Dilemma

Contrary to findings by Knight et. al., Slattery and Ganster (2002) found that people who failed to reach their goals set lower, less risky ones moving forward. While we find similar risk aversion behavior, we disagree that our last place teams are setting lower, less risky goals as the simulation progressed. Many members on these last placed teams stated that they would take more risks operating alone and disagree with the level of risk the team adopts, especially in the latter rounds. What is puzzling is that these last placed teams claim to want to take on more risk but aren't willing to take this risky approach in decision-making. It is this disagreement in stated versus acted risk preferences that leads us to propose a new concept to explain the in-team confusion facing losing teams – losers' dilemma.

Losers' dilemma is defined as the predicament facing losing teams as they struggle keeping pace with competitors and have to choose an operational strategy based on their individual risk preferences. These individuals have to decide between adopting a risk seeking strategy that has a higher variability in outcomes (risk and failure) or a safer, more risk averse choice that does not yield high rewards but more critically, offers a higher probability of not finishing in last place. In such situations, losing teams seek to minimize failure, refocus their efforts, and adopt strategies that they believe will lead to this more attainable outcome of "not finishing in last place." We contend that many of these last place teams redefine "winning" as not finishing in last place, and thus display behavior that may seem counter to the "nothing to lose" notion we expect to find in such situations.

In summation, we contend that the primary reason teams lose is because they have poor alignment of team and individual risk preferences, are poor at initial strategy development, avoid conflict, and grossly underestimate systematic risk, i.e. the abilities of their competitors. Once losing is imminent, the concept of losers' dilemma is witnessed and risk averse choices dominate team decision making.

3.14 Discussion

Taking these findings a step further it is worth exploring the larger implications. For example, are some aspects of the research reflective of the real (non-simulated) world? We know that the simulation begins with teams choosing a business strategy and as we have seen, winning teams tend to tweak their strategies based on market dynamics while losing teams adopt a more "yo-yo" approach. To draw a parallel, a good real world reflection of our simulation is Dell Computers.

Michael Dell started his company with a specific strategy and executed on it to become a global leader in the PC market. His operating strategy was simple - become a low cost leader to achieve scale and focus on customer service. Under Michael's leadership, Dell Computers became a publically traded, multi-billion dollar company that revolutionized the PC buying experience. In 1999, Dell Computers had a market capitalization of $122 Billion and a stock price of $50/share. But by 2010, the company was a shadow of its former self and had spread itself too thin by selling consumer laptops, enterprise hardware, cellphones, tablets, online storage and consulting services. Many analysts blamed Michael Dell for not understanding changing technology trends and for overreacting to competitor strategies with non-strategic acquisitions. In 2013, Dell's market capitalization had dropped to $17 Billion and its stock price was hovering around $9/share. Simply put, Dell Computers lost the focus that made it successful and in many ways, began reflecting the type of company our simulation features – an entity struggling to stay relevant and in desperate need for a management team that can turn things around.

Today, just as in the scenario presented our students, Michael Dell is attempting to turn things around. He has reemerged as part of the management team that is attempting to turn Dell Computers back into a private company and refocusing on profitable portions of the business and discontinuing non-core operations. As Chief Financial Officer Brian Gladden told *Reuters* *"ta*king Dell private will make it easier for the company to focus on the most successful part of its business, the strategy of becoming a one-stop-shop for enterprise customers." This pivot is reflective of what many teams in our simulation adopt, eliminating a product line they feel is not profitable and focusing on a segment that they believe will help overall profitability. In a recent interview, Michael Dell also stressed the importance of designing and executing on a specific strategy versus reacting to every move a competitor makes. In this instance, he sounded a lot like our students in the debrief session where they discuss their lessons learned and how staying true to a core vision is critical for success.

In an effort to relate our findings to startup success and failures, we reached out to industry contacts with relevant experiences that could help us draw parallels between our research and real world situations. Eric Young, co-founder of Canaan Partners and an early stage venture capitalist for over 20 years, not only agrees with our findings but was also impressed that our simulation picked up these behaviors. Based on his experience watching hundreds of startups, he has seen "winners and losers" act in this manner and he immediately identified what he sees as the key differentiator– team conflict. As an investor, he agrees that it is often hard for venture capitalists to predict what investment will become a bad team situation, but has found that employees and other non-involved parties often have a read on team dynamics and can pick up on impending trouble. This insight is reflected in our findings, where we knew certain individual and team risk preferences were not aligned, even before the team did. We were able to identify losing teams as early as round 2 just by asking a few questions around risk preferences.

During our conversations with Eric, he also highlighted the differences between task conflict and interpersonal conflict. According to him, task conflict is easily fixed but it is the interpersonal issues that can derail a startup. In startups, it is often critical for the founding team to change course quickly but this can only happen if all team members are aligned in their vision. It is this issue that we pick up using risk preferences as a proxy for team unity. Failed startups also tend to change course continually even though it eventually leads to failure, just as reflected in our findings. While "pivot" may be the hottest buzzword in Silicon Valley, it is crucial to remember that multiple pivots do not constitute a winning strategy.

Another conversation was held with Gabriel Corredor, founder of Artissano, a young startup that is currently building its core team. According to Gabriel, finding early employees who share the founder's strategic vision and appetite for risk is critical to success. He has already lost two employees who felt that the company was taking "too many risks" and while their departure was sudden, the employees never voiced their concerns during strategy development sessions or in private meetings. One employee even emailed his resignation to Gabriel and claimed that Artissano was structurally "too loose" and while the employee had not worked for any other startup, he was sure that other startups were more stable. Here, the employee was hinting at his discomfort with operational risk versus the better-known salary risk, often associated with startup pay structures.

Gabriel not only agrees with the importance of open discussions and conflict but also upon looking back, can see behavioral indicators in these employees that could have predicted this outcome. He was very interested in how we assessed risk differences within teams and stated that he could see the benefits of developing some type of psychometric testing for team formation. Hearing about our research findings also helped him narrow in on the behaviors of losing teams and he is now more aware of what to avoid as he pursues success. As he stated, "I just wish I could have my team undergo a simulation like this to learn how they think and feel compared to how I view things."

This comment from Gabriel raises an interesting question. Is it reasonable to expect a startup team to undergo a simulation of some sort to learn how the founding team reacts to market uncertainty and pressures to succeed? We could argue that it is feasible for early stage accelerators and incubators to administer a simulation like this to determine if the startup team has the right makeup. Since these entities spend prolonged periods with admitted teams, provide coaching and often make financial investments, a simulation could serve as an additional data point when deciding on which teams are worthy of investment and/or which teams need coaching on team decision-making processes. An on-campus incubator could adopt a similar approach and with the growth of campus-based startups, the competition for limited resources has intensified. This is a practical application of our methodology and can help institutions make more efficient decisions while juggling constrained resources.

As with any experiment or simulation, our methodology does have its limitations. The obvious question on our findings is if undergraduate students can truly serve as a proxy for business decision-makers. We contend that these students are not just a good proxy but with the trend of technology startups being run by 20-year olds, these students are the key demographic for such a simulation.

Other questions arise on the use of the simulation itself and what applicability it has in real world situations. There are also logistical limitations of designing, implementing and studying the simulation and the data generated. For example, it is unreasonable to assume that a venture capital firm will run simulations before investing in a prospective startup. The time frame of running the simulation itself is its biggest drawback and while possible to do in a classroom setting, it is very challenging to expect professionals to dedicate the time and effort to do so.

But despite these practical limitations, we can learn a lot about what can contribute to a team's success. Similar to the current situation with Dell Computers, a turnaround management team needs to have clear alignment of vision to formulate and execute its strategy without the "yo-yo" approach seen from some of our losing teams. And while we have focused on startups and risk preferences, Michael Troy, a 25-year Wall Street veteran, provided an alternative perspective to our findings. He observed that in corporate settings, functional teams are created around subject matter expertise and are actually designed to avoid conflict, which he feels reduces their effectiveness. In his opinion, teams would be better of if they were designed to maximize output rather than minimize client anxieties.

According to Michael, he can absolutely see the benefits of "conflict" as found in our results. He recommends conducting a simulation with attitudinally-diverse teams and to comparing their performance against a few baseline homogenous teams. His belief is that teams designed around some of our insights would outperform the other teams and this finding would be of great interest to a corporate client. From his corporate experience, risk preferences in team settings are never discussed and this often leads to counter productive work environments. Based on our findings, we have similar observations and believe that this fact could be another key outcome of this research and future iterations.

Our belief is that simulations are not limited to helping entrepreneurship programs give students a more realistic feel for venture creation and the importance of team formation, but can also be used to teach the importance of risk preferences in decision making. The simulation is a great learning tool for early stage teams that are still unsure of future growth and success. The impact of simulation-based training programs is under-investigated in economics literature and we contend that this study is a step that bridges the gap between how economics and psychology approach risk perceptions and incentive effects on decision-making.

3.14 References

Arrow, K.J.,(1965), "The theory of risk aversion," in Aspects of the Theory of Risk Bearing, by Yrjo Jahnssonin Saatio, Helsinki. Reprinted in: *Essays in the Theory of Risk Bearing*, Markham Publ. Co., Chicago, 1971, 90–109.

Barsky, R. B., T. F. Juster, M. S. Kimball, and M. D. Shapiro (1997): "Preference Parameters and Individual Heterogeneity: An Experimental Approach in the Health and Retirement Study," *Quarterly Journal of Economics*, 112(2), 537–579

Binswanger, H. P. (1981), `Attitudes toward risk: Theoretical implications of an experiment in rural India', *The Economic Journal* 91(364), 867{890.

Binswanger, Hans P. (1980), "Attitudes toward Risk: Experimental Measurement in Rural India", *American Journal of Agricultural Economics.* 62 (3).

DeBondt, WFM, & Thaler, RH. (1995). "Financial decision-making in markets and firms: a behavioral perspective", *Handbook in operations research and management science*, Vol. 9, Chap. 13 (pp. 385–410).

Dell Computers: http://www.channelinsider.com/c/a/Dell/Dells-Enterprise-Fail-10-Ways-Dell-Blew-It-221897/

Dohmen, Thomas J & Falk, Armin & Huffman, David & Schupp, Jürgen & Sunde, Uwe & Wagner, Gert Georg, (2005), "Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally Validated Survey," *CEPR Discussion Papers* 5517, C.E.P.R. Discussion Papers.

Donkers, B., B. Melenberg, and A. V. Soest (2001): "Estimating Risk Attitudes Using Lotteries: A Large Sample Approach," *Journal of Risk and Uncertainty*, 22(2), 165–195.

Durham, C. C., Knight, D., & Locke, E. A., (1997), "Effects of leader role, team-set goal difficulty, efficacy, and tactics on team effectiveness", *Organizational Behavior and Human Decision Processes*, 72: 203-231.

Durham, C. C., Locke, E. A., Poon, J. M. L., & McLeod, P. L., (2000), "Effects of group goals and time pressure on group efficacy, information-seeking strategy, and performance", *Human Performance*, 13: **115-138.**

Finucane, M., Holup, J. (2006). Risk as value: Combining affect and analysis in risk judgments. *Journal of Risk Research, 9*(2), 141-164.

Fischer, Gregory W., Mark S. Kamlet, Stephen E. Fienberg, and David Schkade (1986), **"**Risk Preferences for Gains and Losses in Multiple Objective Decision Making,**"** *Management Science*, 32 (September), 1065-1086.

Friedman, D. and S. Sunder (1994), *Experimental methods*, Cambridge: Cambridge University Press

Gardner M. and Steinburg L, (2005), "Peer Influence on Risk Taking, Risk Preference, and Risky Decision Making in Adolescence and Adulthood: An Experimental Study ", *Developmental Psychology*, 2005, Vol. 41, No. 4, 625–635.

Greene, William H., (2003), *Econometric Analysis* (5th edition), Prentice Hall, 736-740.

Guillemette, M., Finke, M.S. and Gilliam, J.E., (2012), “Risk Tolerance Questions to Best Determine Client Portfolio Allocation Preferences,” *Journal of Financial Planning*, 26, 5: 34-42

Guiso, Luigi & Paiella, Monica, 2001 (published 2008), "Risk Aversion, Wealth, and Background Risk," *Journal of the European Economic Association*, MIT Press, vol. 6(6), pages 1109-1150, December.

Hanna, S. & Chen, P.,(1997), “Subjective and objective risk tolerance: Implications for optimal portfolios”, *Financial Counseling and Planning*, 8(2), 17-25.

Hanna, S., & Suzanne L., (2004), “An Improved Measure of Risk Aversion.” *Financial Counseling and Planning* 15, 2: 27–38.

Hindle, K.G.,& Angehrn A., (1998), *“Crash Landing at Insead: Initiating a Grounded Theory of the Pedagogical Effectiveness of Simulation Games for Teaching Aspects of Entrepreneurship*”, Paper presented at the 8th Annual Global Entrepreneurship Research Conference, Fontainebleu

Holt, C. A. & Laury, S. K. (2002), `Risk aversion and incentive effects', *American Economic Review* 92(5).

Just, David R. & Peterson, Hanawa, (2010), “Is Expected Utility Theory Applicable? A Revealed Preference Test”, *American Journal of Agricultural Economics*, 92 (1): 16-27

Kachelmeier, S. J., and M. Shehata. (1992), "Examining Risk Preferences Under High Monetary Incentives: Experimental Evidence from the People's Republic of China". *American Economic Review.* 82 (5): 1120.

Kahneman, Daniel, and Tversky, Amos, "Prospect Theory: An Analysis of Decision Under Risk". *Econometrica*, XLVII (1979): 263-291.

Kahneman D. (2003), “A perspective on Judgement and Choice”, *American Psychologist*. *58*, 697-720.

Kahneman, Daniel. (2011), *Thinking, fast and slow*. New York: Farrar, Straus and Giroux.

Kapteyn Arie, and Teppa Frederica,(2011), “Subjective measures of risk aversion, fixed costs and portfolio choice”, *Journal of Economic Psychology*, vol. 32, no. 4, pp. 564-580, 2011

Knight D., Durham, C., Locke, E., (2001), “The Relationship of Team Goals, Incentives, and Efficacy to Strategic Risk, Tactical Implementation, and Performance”, *The Academy of Management Journal*, Vol. 44, No. 2

Kogler, C., Kühberger, A., (2007), “Dual process theories: A key for understanding the diversification bias?” *Journal of Risk and Uncertainty* 34, 145–154.

Lant, T, (1992),“ Simulation games as a research method for studying strategic decision making: The case of MARKSTRAT”, *Stanford Business Review.*

Luis Diaz-Serrano & Donal O'Neill, (2004), "An Empirical Note on the Relationship between Unemployment and Risk-Aversion," *Economics, Finance and Accounting Department Working Paper Series*, National University of Ireland - Maynooth.

Masclet, D., Colombier, N., Denant-Boemont, L & Loheac, Y, (2009), “Group and individual risk preferences: A lottery-choice experiment with self-employed and salaried workers”, *Journal of Economic Behavior & Organization*, Volume 70, Issue 3, Pages 470–484

Mukherjee K. (2010), “A dual system model of preferences under risk”, *Psychological Review, 117*(1), 243-55.

Ozdenoren, E., Salant, S.W., Silverman, D., (2012), “Willpower and the Optimal Control of Visceral Urges”, *Journal of the European Economic Association,* 10, 342–368.

Parish, L., (1975), “Business Simulations: Competition Or Learning”, *Business Games and Experiential Learning in Action*, Vol. 2.

Politis, D. & Gabrielsson, J. (2009), “Entrepreneurs’ attitudes towards failure – an experiential learning approach”, *International Journal of Entrepreneurial Behaviour and Research*, 15(4), 364–383.

Pratt, J. W., "Risk aversion in the small and in the large," *Econometrica* 32, January–April 1964, 122–136.

Rabin, M. (2000), “Risk aversion and expected-utility theory: A calibration theorem”, *Econometrica* 68(5), 1281-1292.

Rohrmann, B. (2005), “Perception of risk: Research, results, relevance”, In Gough, J. (Ed.), *Sharing the future*. Christchurch: CAE publications.

Sahlman, W., & Roberts, M. (1999), “Launching a high-risk business”, *Harvard Business School Publishing*, CD: Interactive Simulation Product Number: 9326.

Schechter, L. (2007), “Traditional trust measurement and the risk confound: An experiment in rural Paraguay”, *Journal of Economic Behavior and Organization*.

Schulze W., Wansink B. (2012), Toxics, toyotas, and terrorism: The behavioral economics of fear and stigma, *Risk Analysis: An Official Publication of the Society for Risk Analysis, 32*(4), 678-94.

Sharif, A., and Ranchhod, A., (2009), “Using the markstrat business simulation to develop strategic management behaviours”, *European and Mediterranean Conference on Information Systems,* 2009.

Shipman, Amanda S. & Mumford, Michael D., “When confidence is detrimental: Influence of overconfidence on leadership effectiveness”, *The Leadership Quarterly*, Vol 22 (4).

Slattery, P. & Ganster, D. (2002), ‘Determinants of Risk Taking in a Dynamic Uncertain Context’, *Journal of Management February 2002 vol. 28* no. 1 89-106

Smallman, C. & Smith, D. (2003), ‘Patterns of Managerial Risk Perceptions: Exploring the Dimensions of Managers' Accepted Risks’, *Risk Management* 5, 7–32

Sloman S.A. (1996) The empirical case for two systems of reasoning. *Psychological Bulletin*, *119*, 3-22.

Slovic, P. (1964): "Assessment of Risk Taking Behavior," *Psychological Bulletin*, 61(3), 220–233.

(1972a): "Information Procession, Situation Specificity, and the Generality of Risk-Taking Behavior," *Journal of Personality and Social Psychology*, 22, 128–134.

(1972b): "Psychological Study of Human Judgment: Implications for Investment Decision Making," *Journal of Finance*, 27, 777–799.

Slovic P. (1983). Perception of risk/behavioral perspective. *American Journal of Roentgenology, 140*(3), 601-2.

Slovic, P., Finucane, M. L., Peters, E., MacGregor, D. G. (2004). "Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality". *Risk Analysis, 24*(2), 311-322.

Staw, Barry (1976). "Knee-deep in the Big Muddy: A Study of Escalating Commitment to a Chosen Course of Action". *Organizational Behavior and Human Performance* 16(1):27-44.

Taylor, SE, & Brown, JD. (1988). "Illusion and well-being. A social psychological perspective on mental health", *Psychological Bulletin*, 103, 193–210.

Tecles, Patricia, and Resende Jose, (2011), *Brazilian Review of Econometrics*, v. 31, n2, pp. 201-229

Tjoa, S.; Jakoubi, S.; Goluch, G.; Kitzler, G.; Goluch, S.; Quirchmayr, G., (2011), "A Formal Approach Enabling Risk-Aware Business Process Modeling and Simulation," *Services Computing, IEEE Transactions on* , vol.4, no.2, pp.153,166.

Tobin, J. (1958), "Liquidity Preference as Behavior Towards Risk", *Review of Economic Studies,* 67, 65-86.

Weldon, E., Jehn, K. A., & Pradhan, P. (1991), "Processes that mediate the relationship between a group goal and improved group performance" *Journal of Personality and Social Psychology*, 61: 555-569.

Yao, R., Hanna, S. D., & Lindamood, S. (2004). Changes in financial risk tolerance, 1983-2001. *Financial Services Review*, 13 (4), in press.

Figure 1 Quick overview of simulation process