A journey through Technology Transfer, Organizational Learning and the Search for Innovation

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To Andrew,

With immense love and gratitude for always being by my side and for being the most amazing, generous human being

– Tu ragioni troppo. Perché mai l'amore va ragionato?
– Per amarti di più. Ogni cosa, a farla ragionando, aumenta il suo potere.

Da "*Il barone rampante", Italo Calvino*

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Introduction

Motivation

A professor of mathematics at a prestigious university was also a talented inventor of new and useful devices, ranging from the fields of navigation to agriculture; he was employed by the university not to invent but rather to teach and supervise students who came from many distant places to sit in his classes. No objection, however, seems to have been made by the university to him spending time on his inventive activities; indeed, it is possible that both he and the university saw this as a normal consequence of his scholarly effort and he was allowed to keep all of the proceeds from his commercial activities. In the long run, however, the university which was that of Padua, received a huge value in terms of reputation from this professor, Galileo Galilei, considered the father of the modern science, who went on to make significant breakthroughs in astronomy and mathematics. It was the end of the 17th century and the university, at that point in time was considered to be a teaching and vocational institution. The first change of perspective about this outlook happened in the 18th century when universities became research institutions, places of free and open intellectual inquiry (Goldin, 2001). The second significant change, which represents the historical roots of this paper, happened in the last century, when the director of the Office of Scientific Research and Development (OSRD), Dr. Bush, presented to President Truman a policy report which is considered to be one of the most influential in the history of the United States, entitled "Science: the endless frontier" (1945, p.3). In this report he stated: *"Advances in science when put to practical use mean more jobs higher wages, shorter hours, more abundant crops, more leisure for recreation, for study for learning how to live without the deadening drudgery which has been the burden of the common man for ages past*.

advances in science will also bring higher standards of living, will lead to the prevention or cure of diseases, will promote the conservation of our limited natural resources and will ensure means of defense against aggression. But to achieve these objectives to secure a high level of employment, to maintain a position of world leadership, the flow of scientific knowledge must be both continuous and substantial."

Dr. Bush is credited as the first to formally talk about the importance of technology transfer from the universities to the marketplace and to state how beneficial this might have been for the entire society. Until the 1970s, much of university research was basic research that produced ideas and discoveries that were far from any possible commercial application. Nevertheless, the isolation of the Ivory tower was no longer economically sustainable (Etzkowitz et al., 2000) and universities started to look and to find a role for academic researchers in helping to boost national economies (Monotti & Ricketson, 2003).

I am fascinated by the history of academia and with the incredible scientists and inventors of the past and of the present who changed the history of us all. I am captivated with understanding more about the creation and application of new knowledge. How does this happen? What is the role of Academia? Who is paying for it? How do researchers transfer their new knowledge to the world? What are the consequences? I felt overwhelmed by a strong and irrepressible curiosity which probably every Ph.D. student has felt during his doctoral studies. The hardest part is to find how to channel this curiosity and make it work together with a theoretical background, econometrics and so many unpredictable constraints.

History of the three papers

I started studying management and economics for the doctorate. I have a bachelor's degree in Philosophy (focus on Language and Epistemology) as well as a master degree in Cognitive

Science and Decision Making. The first paper I worked on (which corresponds to the 3rd chapter of this thesis) together with Dr. Cinici and Professor Baglieri, is a study on the role of heuristics in designing business models and creating new technologies. It was my first year as a Ph.D. student, and even if it was too early for me to approach quantitative analysis, that paper represented an important step toward bridging my background in cognitive science and the new adventure with managerial studies. After one year and a half spent in my former university in Messina, I had the great opportunity to spend the remaining half of my Ph.D. (18 months), at the Wharton School of Business at the University of Pennsylvania. Taking a full course load during my time in the United States was the most enriching and challenging decision I made. Given my interests, I asked and had the honor to take Professor Levinthal's class for one semester. His class linked central questions in management with economic approaches but with a focus on behavioral perspectives. It was during this class that I started reading Herbert Simon and James March and learned about organizational learning and also discovered much more about heuristics within this context in the literature. This is how, at that time, I started thinking about my second paper (the 2nd chapter of this thesis) and about studying whether and how organizations learn from failure. I linked literature on R&D, heuristics, exploration and exploitation, organizational learning, with a special interest for learning from failure in situations in which the outcomes are ambiguous. I had to decide on which field I would test my hypotheses. It was one of the few cases during the three years of the doctoral program where I had no doubt and I chose the University Technology Transfer (UTT) field. There were several theoretical reasons why I found UTT to be an appropriate field to study organizational learning in face of ambiguity (I will specify them chapter 2) and as I stated above, I found it a highly relevant and contemporary topic. Moreover, I took classes in both Messina (with my supervisor Professor Baglieri and with Professor Cesaroni) and Philadelphia (with Professor Hsu) and at that time I strongly wished that I could explore it further. To be able to independently work on this second paper's analysis, on learning from experience, I took Professor Allison's courses on econometrics and in my last semester in the United States, I focused on longitudinal data analysis. While working on the second paper, I had to deepen how UTTOs work and some of their driving processes. This is how the idea of the third paper (which is the first chapter of this thesis) came to my mind. Scientific research generates an invaluable crucial asset for national economies, it is "the energy that fuels the technology transfer engine" (AUTM Survey, 2014 p.16) and its primary source of funding is the U.S government. It is the American government that supplies researchers and universities with the financial resources to start up scientific projects and discovery processes. Despite their value, in the last decade federal research funding has been starting to decrease in the last decade and stronger cuts will be happening in the coming years. There is ample evidence of these cuts in the first budget plan released by Trump's administration (Reardon et al., 2017). This disinvestment of public funding might lead to the slowing down of the progress in technology transfer that universities and industries have at worked to accomplish so far and as a reaction, universities have started to increase their relationships with industry (AUTM Survey, 2014). In light of these facts, it is important to have a clear picture of how public and private funding interact and I was surprised to discover that there were not many studies in the literature about this interaction. A plausible reason for this is that industrial funding has been increasing just in the last years but I believe that the increasing relevance of this topic will raise interest in the coming years. The aim of this last paper was to explore two different paths. In the first path I explored how the two main types of research funding, federal and industrial, affect three different research outputs: number invention disclosures, patents and licenses. In the second, and more insidious path, I explored if and how federal and industrial funding interaction affects the three research outputs.

The Common thread

The third chapter, which is the one about the heuristics, corresponds to my interest in understanding and disentangling how innovative ideas and technologies are created from a cognitive point of view (*micro-level*). The first chapter studies how the system of private and public funding supports this process (*macro-level*) and in the second chapter I explore how organizations involved in the technology transfer process learn from the past (*meso-level*). Each of the chapters corresponds to a different level of analysis.

This PhD thesis is built by using three complementary bodies of literature: technology transfer, organizational learning from failure, and literature on the search for innovation. It is to these three different literatures that I aim to contribute. The first and the second chapter are empirical works conducted using quantitative longitudinal analysis coming from the Association of University Technology (AUTM). I worked on them during my 18 months at the University of Pennsylvania. In order to build the research questions and the hypotheses, I had numerous informal meeting with the managers of the UTTO. This step has been crucial and has helped me in understanding and interpreting the heterogeneity, and sometimes ambiguity, of the dataset I was working with.

It is very important to underline that in the two empirical papers, I narrowed my studies to include only the U.S. environment and used data coming just from North America. UTTOs work differently in each continent (Monotti & Ricketson, 2003) and amongst the limitations of my studies there is the geographical constraints of the results. Two other important limitations that I would like to mention in this introduction concern the absence of qualitative data to integrate the quantitative analysis, and the several limitations of the author (myself). I hope to continue this journey into academic research and try to overcome some of the aforementioned limitations, and to continue working in the future on these beautifully relevant topics.

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Ph.D. DISSERTATION OVERVIEW

CHAPTER	*DATA*	*UNIT OF ANALYSIS*	*DEPENDENT VARIABLE*	*RESEARCH QUESTION*	*METHOD*
1. Are they getting along? Public and Private Funding in University Technology Transfer	AUTM dataset (longitudinal 1994- 2014), Carnegie Foundation dataset	Macro-Level	Research Outputs (Invention disclosures, patents, licenses)	Do public and private funding have the same effect on research outputs? Does their interaction have a positive or negative effect on research output? Do they get along and help each other in producing results or not?	Longitudinal analysis: negative binomial unconditional fixed effect model, Interaction effect
2. Do organizations learn from past falures? A longitudinal analysis of University Technology Transfer Offices	Interview to UTTO Managers, AUTM dataset (longitudinal 1994-2014), Carnegie Foundation dataset	Organization-Level	Likelihood of learning from past failures	Do university technology transfer offices learn from their past failures?	Longitu analysis: Logistic regression, with fixed effect
3. The Value of the Heuristic of Similarity in the Development and Understanding of Innovation	Survey Data	Individual-Level	Decision Processes	Which heuristics are used in the development of business models, and how do they function?	Survey, Content Analysis

1. Are they getting along? Public and Private Funding in University Technology Transfer

INTRODUCTION

In the summer of 2012, the University of Pennsylvania (Penn) and Novartis announced an exclusive global research and licensing agreement to further study and commercialize novel cellular immunotherapies. The agreement was worth 20 million dollars, and it followed a research team's 2011 publication of breakthrough results in a new personalized immunotherapy technique. Larry Jameson, dean of the Perelman School of the Medicine at the University of Pennsylvania stated "Penn's intellectual resources, combined with a pharmaceutical industry leader like Novartis, offer a powerful symbiotic relationship in our mutual goal of finding more effective treatments for cancer" (Thomas, 2012). That partnership broke new ground in the growing trend of academic institutions collaborating with pharmaceutical companies where both parties could benefit: pharmaceutical companies have access to the expertise of top researchers at universities and can use basic research advances to develop new therapies and procedures in exchange for funding their research. It seems to be a mutually beneficial situation. However, the Perelman School at UPenn has not just managed to make deals and getting funded by the private sector. Indeed, it is also consistently among the nation's top recipients of federal funding from the National Institutes of Health, with $392 million awarded in the 2013 fiscal year.

Federal funding has been the main source for scientific research in the United States since after the second world war (Monotti & Ricketson, 2003). This scientific research generates a substantial return on investment for both global and national economies, is a crucial source of development, and every year involves the investment of more than $60 Billion in the U.S. alone.

Federal funding coming from government agencies supplies faculty and research personnel with the necessary financial resources to begin discovery phases, innovation processes concerning all the disciplines, and facilitates the transfer of new technologies to all of the society.

Despite its important role, and despite the critical role of public science, federal funding has been decreasing over the last five years. More specifically, it declined 1,7% between 2014 and 2015, and since its highest peak, in 2011, it has fallen off nearly 13% (HERD Survey, 2015). The stasis in federal funding has led to increased worry that scientific research will suffer and that preliminary and risky activities will be no longer likely to be financed, turning the United States into a less innovative country and decelerating the pace of progress in science (Editorial, 2016). In the meantime, in this last decade, the research environment has become more competitive, and universities and research centers have started looking and relying on other sources of funding, which has become increasingly important over the years. Among these sources, there is the private funding coming from the industry. Do public and private funding have the same effect on research outputs? Does their interaction have a positive or negative effect on research output? Do they get along and help each other in producing results or not?

The aim of this work is to answer to these three research questions and to do it I will take examine three research outputs: the number of invention disclosures, the number of patents filed and the number of licenses options processed by the institutions' technology transfer office (TTO) in the United States. It is worth underlining that besides the research outputs I refer to (disclosures, patents, and licenses), there are many other research outputs which are objects of study in the technology transfer literature (which represents the main reference literature of this paper), but they will not be the subject of this article.

Disentangling the relationship existing between research funding inputs and its outputs is a formidable challenge. Research outputs are intended to produce knowledge, but the empirical measurement of science in the marketplace is laborious and complex (Heisey & Adelman, 2011). As a consequence of changes that have occurred over the past several decades, the character of universities' output has strongly changed, and they have become more commercially orientated (Monotti & Ricketson, 2003). Even if the commercialization of science has been a source of concern within universities (Bok 2003), rules and research agendas are changing in an increasing number of academic departments to boost the entrepreneurial mission (Baglieri & Lorenzoni, 2014).

Prior research on R&D has looked at the relationship between research inputs and research outputs. It is worth underlining, that despite the significant changes in universities and academia, academia still represents its own world. For this reason, it is not possible to simply take for granted the results coming from the firm R&D literature (Lavie & Rosenkopf, 2006; Lavie et al., 2011) and apply them to academia. Carlsson and Frid (2002) have looked at the relationship between research expenditure in academia, invention disclosures, and have found a positive impact of these two on university patenting and licensing while Heisey and Adelman (2011) found unclear evidence respect to the short-term impacts of research expenditures on licensing revenues. Many other scholars have estimated the effects of federal research funding on other research outputs. A different, widely used approach has been focused on the Bayh-Dole Act and its positive and negative consequences on the university technology transfer world. In a well-known paper appearing in the journal, *Science*, Thursby and Thursby (2003) stated that even if the evidence in the direction of the faculty research is limited, their results suggest that financial incentives coming from licensing activities have not changed the proportion of basic and applied research.

As shown in this sample of papers I just mentioned, the results have mixed findings and often look at the relationship between research input and output as if it were a linear one.

I explore how federal funding and industry funding interact and how they differently affect research outputs. If this interaction exists, to know if and how it affects the research outputs might provide valuable evidence for university administrators, private corporations, and federal agencies involved in financing research.

To test my hypotheses I combined longitudinal data coming from the Association of University Technology Managers (AUTM) Licensing Survey (years 1991–2014). The data come from more than 200 different North American institutions and 4.000 observations and cross-sectional data about the universities' ownership status (private or public) coming from the Carnegie Foundation for the Advancement of Teaching (CFAT). To analyze how federal and industrial funding have an effect on the research outputs, and to understand how they interact, I use negative binomials models with unconditional fixed effect specification. This kind of model, among other pros and cons, lets me take into account the high heterogeneity among the institutions of my sample. For each of my three dependent variables (disclosures, patents, licenses) I include the interaction effect between my two main independent variables of interest: federal and industrial funding. In this study, I ask three main questions:

1) Do different sources of funding (federal and industrial) have a different impact on research outputs?

2) Do these different sources of funding interact between each other?

3) Do private and public funding get along or not in affecting research outputs?

The structure of this paper is as follows. The next session introduces the theoretical background with the hypotheses development. This is followed by the methods section introducing the data, the variables I used in this study and the empirical strategy. In the third section, I present the results. The final section provides the theoretical and practical implications and the limitations of this work.

THEORETICAL FRAMEWORK AND HYPOTHESES

Bayh-Dole Act and University Technology Transfer

A central economic justification for the public funding of research is due to scientific knowledge being for the public good in nature. The economic, scientific, politic and legal environment in which universities operate has constantly been evolving, but the pace of change seems to have sped up since the early 1980s (Just & Huffman, 2006). In particular, changes in intellectual property right (IPR) policies and new scientific opportunities through rapid advances in biological and information sciences have created new, potential opportunities for universities (Forero-Pineda, 2006). But what happened in 1980?

In 1980 the U.S. Congress passed the Bayh-Dole Act (PL 96-517) which greatly bolstered privatization of research in the public sector. The key issues were these: a uniform patent policy was established for federally funded research, the university-industry collaboration was encouraged, universities and/or for-profit grants/contractors were permitted to retain title to inventions developed with the help of federal funding, and the federal government retained a non-exclusive license to utilize the invention throughout the world (Mowery et al., 2001). This legislation cleared up any uncertainty about title to inventions, and established a uniform intellectual property right standard for all federally funded research (Coffman, Lesser, and McCouch 2003). Moreover, Diamond v. Chakrabarty Appeals Court Decision expanded the set of discoveries that could be patented to microorganisms, and later in the 1980s patenting was extended to animals and plants (Just & Huffman, 2006).

With the Bayh-Dole Act, research that results in patents and basic research discoveries which can be protected as intellectual property have become a potential source of additional revenue for universities and as different types of productivity are rewarded, it should not be surprising to see a university's focus shift toward their most lucrative rewards (Just & Huffman, 2006). In addition, more patenting freedoms were given and the ambition to achieve economic benefits through licensing new technologies may have led to more institutions applying for patents and appropriately modifying their organisations (Cesaroni & Piccaluga, 2002). New or expanded Technology Transfer Offices have been created, with the explicit aim of promoting effective licensing of patented technologies, through appropriate internal disclosure and external marketing tools. Several research universities have specialized knowledge and scientific expertise which led them to commercial successes (Mowery et al., 2001): new technologies in the areas of biotechnology, computer science, materials science and many other innovations. The manipulation of genetic materials, DNA analysis, the mapping of genomes for farm animals and plants, and the techniques for successful interspecies gene transfers, are just some of the major developments that have occurred in science in the last decades. These technical leaps have been made possible by smaller, prior steps in basic science, taking place in University research labs which make discoveries which are incorporated in materials or processes that are patented and sold commercially by the private sector (Aghion et al., 2008). For example, in the United States, 72 percent of the papers cited in biotechnology patents have been written by authors who are exclusively based in public institutions (McMillan, Narin, and Deeds 2000). Another 12 percent of citations have at least one author from a public institution. These statistics suggest that without the successful transfer and dissemination of basic discoveries, the rate of technical advances would decrease greatly. Also, there is evidence of a growing connection between U.S. technology and public science policy (Narin, Hamilton, and Olivastro 1997).

Colyvas et al. (2002) studied eleven particular cases of patenting and licensing at two universities, Columbia and Stanford. They concluded that in none of the cases the expectation of financial returns for the university or for the scientists themselves did play a significant role in research motivation, even though in some cases the research was funded by the industry. The importance of patenting, licensing, and the university technology transfer office (TTO) in affecting technology transfer changed from case to case. Intellectual property (IP) was found to be most helpful for embryonic, novel inventions, and unimportant for ‘‘off the shelf’’ technologies and TTO marketing activities were most important when university-industry links were less strong. To conclude, the Bayh-Dole Act has been having an important role in changing the university technology transfer environment (Table 1).

Table 1: selected papers on University Technology Transfer Offices: empirical studies of performance of TTOs with respect to licensing and patenting

Authors(s)	**Data Sets**	**Methodology**	**Key results**
Foltz, Barham and Kim (2000)	AUTM, NSF	Linear regression	Faculty quality, federal research funding, and number of TTO staff have a positive impact on university patenting
Rogers, Yin and Hoffman (2000)	AUTM, NSF, NRC	Correlation analysis of composite technology transfer score	Positive correlations between faculty quality, Age of TTO, and number of TTO staff, and higher levels of performance in technology transfer
Bercovitz et al. (2001)	Case studies interview, AUTM	Qualitative and Quantitative Analysys	Analysis of different organization structures for technology transfer at Duke, John Hopkins, and Penn State; Differences in structure may be related to technology transfer performance

Authors(s)	Data Sets	Methodology	Key results
Thursby, Jenses and Thursby (2001)	Author Survey, AUTM	Descriptive analysis of authors survey/ regression analysis	Inventions tend to disclosed at an early stage of development; elasticities of licenses and royalties with respect to invention disclosures are both less than one; faculty members are increasingly likely to disclose inventions
Friedman and Silberman (2002)	Milken Institute “Tech-Pole”Data, AUTM,NSF,NRC	Regression Analysis-Systems, Equations Estimation	Higher royalty shares for faculty members are associated with greater licensing income
Thursby and Kemp (2002)	AUTM	Data envelopment, analysis and logic regressions on efficiency scores	Faculty Quality and number of TTO Staff has a positive impact on Various TT outputs; Private Universities appear to be more efficient than public universities; Universities with medical school are less efficient
Thursby and Thursby (2002)	Authors’ own survey, AUTM	Data envelopment analysis	Growth in University licensing and patenting can be attributed to an increase in the willingness of professors to patent and license, as well as outsourcing of R&D by firms; Not to a shift toward more applied research
Carlsson and Fridh (2002)	AUTM	Linear regression	Research Expenditure, invention disclosures, and age of TTO have a positive impact on university patenting and licensing
Siegel, Waldman and Link (2003)	AUTM, NSF, and U.S. Census Data, Interviews	TFP of University Licensing-Stochastic Frontier Analysis and Field Interviews	TTOs Exhibit constant returns to scale with respect to the number of licensing; Increasing returns to scale with respect to licensing revenue: Organizational and environmental factors have considerable explanatory power
Lach and Schankerman (2004)	AUTM, NSF, NRC	Regression Analysis	Higher royalty shares for faculty members are associated with greater licensing income
Link and Siegel (2005)	AUTM, NSF, and U.S. Census Data, Interviews	TFP of University Licensing-Stochastic Frontier Analysis	Land grant universities are more efficient in technology transfer; higher royalty shares for faculty members are associated with greater licensing income

Authors(s)	Data Sets	Methodology	Key results
Chapple, Lockett, Siegel, and Wright (2005)	U.K- NUBS/UNICO Survey-ONS	Data envelopment analysis and stochastic frontier analysis	U.K. TTOs exhibit decreasing returns to scale and low levels of absolute efficiency: Organizational and environmental factors have considerable explanatory power

The next important puzzle piece to understanding is this: who is funding scientific research and what are some of its outputs?

University funding: inputs and outputs

As I stated in the introduction of this paper, the United States government has provided the greater part of all funds devoted to basic research since the second world war. It has been widely studied how scientific research taking place in universities has been generating positive effects on both the social and industrial level (Bozeman 2000; Cohen et al. 2002). According to the ‘‘Triple Helix’’ approach, university research is a crucial support for industrial competitiveness (Etzkowitz and Leydesdorff 2000), and this is why a stronger university–industry–government collaboration has been established.

Despite the important and undisputed role of public funding in American history, universities and research centers have started looking and also relying on private funding, which has over the years become increasingly important. The private funding I will refer to in this paper is coming from industry. It is important to specify because there is also a large amount of private funding coming from private foundations. Even if they are involved in several scientific challenges, they will not be included in the expression ‘private funding' which for the sake of this paper will just represent funding coming from private companies. A good example of how certain universities started relying on private funding is Harvard, where university data demonstrates an evident conversion toward private funding: 75% of research is still funded by the government, but corporate research funding has tripled, to $41 million, from 2006 to 2013 (Jahnke, 2015). There has been a considerable accordance in the economic literature about the importance of university-industry collaboration (Cesaroni & Piccaluga, 2015) and about how governments should carry forward all the measures to ease the path of academic research to the market (Muscio et al., 2012). The new academic funding logic and its new dynamics have raised several issues: what are the advantages and what the disadvantages of this new collaboration happening between university and industry? What does this shift imply on the way university technology transfer happens?

There has been a considerable stream of literature focusing on these questions. Several authors indicated the potentially negative effects of academic research going toward industry funding (Perkmann et al., 2013) while others pointed that university–industry collaboration has little negative impact on academic research activities (Thursby and Thursby, 2011). Finally, many showed that universities and corporations might instead take advantage of this collaboration (Gulbrandsen and Smeby, 2005).

In this research, I call *research input* the funding, public and private, used to conduct scientific inquiry and producing research outputs. Among many other research outputs, patenting and licensing of inventions have received a great deal of attention from the technology transfer literature and in the policy community (Phan and Siegel, 2006; Rothaermel et al., 2007). There are several other different and important research outputs which have been studied though, such as publications, citations, consulting, recruiting/hiring, conferences, and research collaborations (Agrawal & Anderson, 2002; Agrawal, 2001), start-ups formation (Pries & Guild, 2007), spin-offs (Lockett et al., 2005) and commercial spillover (Acs et al., 1992).

None of these latter research outputs will be the object of this paper, and I will instead focus just on patents, licenses, and invention disclosures. The invention disclosure is usually the first action taken to start the technology transfer process, and it happens when the academic researcher discovers something new and go to the TTO to officially communicate and register his scientific discovery/invention. After the disclosure, the collaboration between the inventors and the technology transfer office starts and the technology transfer office decides whether it is worth it or not to transfer the commercialization and hand over the protection of the intellectual property. In a certain way, therefore “a disclosure is the raw material needed to generate patents, products, and economic benefits” (Survey AUTM, 2014 p. 19). Not all the inventions which have been disclosed have a commercial value, and the TTO usually helps the scientist to find out how to exploit the discovery and if it is the case, to start the process to obtain the patent on that technology. TTOs might also contribute to promote the inventions to potential licensees and to negotiate the right accord of licensing. A License is a legal document that grants commercial rights to for-profit entities for the intellectual property owned by the academic institutions (Survey AUTM, 2014).

To understand the upcoming hypotheses, it is important to stress these concepts: invention disclosures represent the first step of the process and will not necessarily end up in a patent or in any kind of commercialization and exploitation. Patenting represents a preliminary step too, but it has a cost, and it already signals a propensity from the University towards some kind of exploitation (Perkman et al. 2013).

For me to build this paper’s hypotheses, it has been important to understand the expectations of both the faculty and industry when they work together. From a faculty perspective, a research collaboration between universities and industry means an industry-oriented project supported either entirely or partly by sponsoring firms (Lee, 2000).

As mentioned, again, by Lee (2000), the literature often alludes to university-industry collaboration as though it is an investment by both parties. This logic has been inciting some to use the expression of ‘‘return on investment’’ while analyzing the relationship between the resources invested (input) and the returns derived (output). There is more than one problem with precise delineation, especially in university-industry collaborations, because costs and benefits, cannot be reduced to commonly agreeable economic measures and the costs and benefits are not closely related in time and space. Moreover, while collaborating with a firm on a specific project, the university research group may serendipitously gain valuable insight which would be useful to boost a different project.

As a matter of fact, fundamental scientific breakthroughs often occur while dealing with very applied or practical problems (Rosenberg, 1989) and vice versa. Some of the most important discoveries in the history of science have come from people like Pasteur, who thought he was doing very applied research. He would not have said if asked at the time, that he was doing basic research. He was, in fact, trying to solve some very practical issues, linked to fermentation and putrefaction in the wine industry. However, behind solving those practical problems he ended up inventing the modern science of bacteriology.

This inherent ambiguity correlated to the delineation of applied and basic research could lead to an unclear view of how private and public funding influence research outputs. But even if it is hard to predict from which direction new discoveries will spring and to map the route which connects scientific discovery to applied science, it is possible to say that private companies strongly count on publicly funded research (Narin et al., 1997; Salter Martin 2001), and public funding enlarge scientific knowledge which firms can then use to enhance technological activities (Blume-Kohout, 2009). The activities of patenting and licensing can accelerate the transfer of new scientific discoveries and help to bring them to commercial viability (Mowery et al., 2014) but a patent is a form of legal protection which does not always result in something being commercialized. Industry tends to finance commercially-oriented research more than federal funding does (Di Gregorio & Shane, 2003) and being the license one of the most remarkable outputs representing the commercialization of new technology, I expect industry funding to affect it more than industrial funding.

Hypothesis 1a: federal funding has a stronger positive effect on invention disclosures than industrial funding does
Hypothesis 2a: federal funding has a stronger effect on patents than industrial funding does
Hypothesis 3a: industrial funding has a stronger effect on patents than federal funding does

While I described some of the research that explored the university-industry collaborations and some of its consequences, there has been a crucial factor that may have been left out as noticed by Muscio et al. (2012): what is the relationship between federal and industry funding?
It is possible to find theoretical grounds for this relationship in the literature which analyzes the complementarity between public and private R&D, which was started by Arrow (1962) and have then mainly focused on the impact of R&D public funding on private investments made in R&D (David et al., 2000).
It has been shown by Jensen et al. (2010) that there is strategic complementarity between government and industry funding and they also show how under certain sufficient conditions, federal and industry funding behave as strategic complements for university research any time "an increase in either type of funding increases the marginal effect of the other on the probability that the researcher's university project will be successful" (p. 3).
In addition, this complementarity would also imply that universities need federal funding to increment the impact of collaborations and fundraising opportunities with industry (Jensen et al., 2010; Dechenaux et al., 2011; Muscio, 2012).

Drawing on this theoretical background, I test the hypothesis on the interaction between federal and industry funding for three research outputs and explore whether or not this interaction exists and how this affects the generation of these research outputs.

Hypothesis 1b: federal funding moderates the relationship of industrial funding on disclosures

Hypothesis 2b: federal funding moderates the relationship of industrial funding on patents.

Hypotheses 3b: federal funding moderates the relationship of industrial funding on licenses

METHODOLOGY

Data and Sample

The data set I use in my analysis combines two sources: the licensing data from the Association of University Technology Managers (AUTM) Licensing Survey (years 1991–2014), data on University characteristics collected by the Carnegie Foundation for the Advancement of Teaching (CFAT). In order to become more confident with the data and to understand the dynamics happening in the university technology transfer field, I conducted seven unstructured informative interviews with two different managers of the Technology Transfer office of the University of Pennsylvania. During the interviews, the managers were asked to tell me how the funding process works from their perspective and how the technology transfer functions in the university. The AUTM dataset contains information related to some of the main research outputs and coming from 262 North American institutions. These 277 institutions are of two different types: Universities (public and private) and Research Centers. Due to its panel structure (22 years of observations) the AUTM dataset permits one to control for unobservable institution effects that may be correlated with the predictor variables and allowing one to use the fixed effect models and to accomplish simultaneous estimation of models with lagged predictors. The CFAT dataset instead, has a cross-sectional nature and I used it to collect time-invariant information on the institutions in my sample, for example on the private or public nature of the institutions. Overall, 189 institutions have more than 10 years of observations, 62 have between 2 and 9 observations, and eleven of them have just one year of observations. Considering my lag models, I had to drop the 11 institutions with just one year of observations because I could not use them with the fixed effect model. Fifty-three percent of institutions have a medical school and fifty-nine percent are public.

The variables present in the dataset are described in the following table

Table 2: Variables and Definitions

VARIABLE	DEFINITION
Research Inputs	
Federal Expenditures	Include expenditures made in by the institution in support of its research activities that are funded by federal government. Expenditures by State and Local Government should be excluded Amount of money coming from federal grants. These grants are assigned through a competitive process and judged based on the quality and potential impact in a certain area.
Industrial Expenditures	Include expenditures made by the institution in support of its research activities that are funded by for-profit corporations, but not expenditures supported by other sources such as foundations and other non profit organizations.
Other Funding	Include expenditures made by the instutition in support of its research coming from the University and from private foundations (No Profit).
Institutions Characteristic	
Type of Institution	Dummy variable equal to 1 if the institution is a University: 0 if it is US Hospital/ Research Institutes
Public Institution	Dummy variable equal to 1 if the institution is public; 0 otherwise
Medical School	Dummy variable equal to 1 if there is a medical school in the organization; 0 otherwise
TTO Characteristics	
Full time employees	Count of numbers of full time employees working in the Technology transfer office. Person(s) employed in the TECHNOLOGY TRANSFER OFFICE whose duties are specifically involved with the licensing and patenting processes as either full or fractional FTE allocations. Licensing examples include licensee solicitation, technology valuation, marketing of technology, license agreement drafting and negotiation, and start-up activity.

VARIABLE	DEFINITION
Start date TTO	Year in which the institution dedicated at least one full time employee at the technology transfer activities
Research Outputs	
Disclosures	Include the number of disclosures, no matter how comprehensive, that are submitted during the survey year requested and are counted as received by the institution
Patents filed	Count of the numbers of patents filed in the year
Patents newly filed	New patent application filed is the first filing of the patentable subject matter. NEW PATENT APPLICATIONS FILED does not include continuations, divisionals, or reissues, and typically do not include CIPs. A U.S. PROVISIONAL APPLICATION filed in fiscal year 2013 will be counted as new unless it is a refilling of an expiring U.S. PROVISIONAL APPLICATION. If a U.S. PROVISIONAL APPLICATION is converted in to a U.S. UTILITY APPLICATION, then that corresponding U.S. UTILITY APPLICATION filed in should not be counted as new.
License	Count the number of LICENSE or OPTION AGREEMENTS that were executed in the year indicated for all technologies. Each agreement, exclusive or non-exclusive, should be counted separately. Licenses to software or biological material end-users of $1,000 or more may be counted per license, or as 1 license, or 1/each for each major software or biological material product (at manager's discretion) if the total number of end-user licenses would unreasonably skew the institution's data. Licenses for technology protected under U.S. plant patents (US PP) or plant variety protection certificates (U.S. PVPC) may be counted in a similar manner to software or biological material products as described above, at manager's discretion. Material Transfer Agreements are not to be counted as Licenses/Options in this Survey.
License Income received	It includes: license issue fees, payments under options, annual minimums, running royalties, termination payments, the amount of equity received when cashed-in, and software and biological material end-user license fees equal to $1,000 or more, but not research funding, patent expense reimbursement, a valuation of equity not cashed-in, software and biological material end-user license fees less than $1,000, or trademark licensing royalties from university insignia. License Income also does not include income received in support of the cost to make and transfer materials under Material Transfer Agreements.
Startups formed	Startup companies formed during fiscal year that were dependent upon the licensing of institution's technology

Analysis

The dependent variables used in this paper are all counts of something: counts of disclosures, counts of papers, counts of licenses. Such variables are discrete, non-negative and typically highly skewed and it is for these reasons that conventional linear models are not appropriate (Allison, 2011). In order to analyze count data, it is more appropriate to use count models such as Negative binomial models. The negative binomial models assume that the distribution of y_{it} is negative binomial rather than Poisson and it is a generalization of the Poisson, with an over-dispersion parameter.

The model can be derived as follows. Assume y_{it} has a Poisson distribution with expected value λ_{it}, conditional on a random disturbance εit. That is:

$$\Pr(y_{it} = r \mid \varepsilon_{it}) = \frac{\lambda_{it}^{r} e^{-\lambda_{it}}}{r!}, \qquad r = 0, 1, 2, \ldots$$

Assume also that:

$$\log \lambda_{it} = \mu_t + \beta x_{it} + \gamma z_i + \varepsilon_{it}$$

where x_{it} are the time-varying predictor variables and z_i are the time-invariant predictors. This "log-linear" specification ensures that λ will be greater than 0, regardless of what's on the right-hand side. ε_{it} has a log-gamma distribution and is independent of *x* and *z*. Then the unconditional distribution of y_{it} is negative binomial. The overdispersion parameter controls the variance of ε. I can turn the negative binomial model into a random or fixed effect model by specifying another term, *alpha*. Both random and fixed effect models follow the same equation:

$$\log \lambda_{it} = \mu_t + \beta x_{it} + \gamma z_i + \varepsilon_{it} + \alpha_i$$

But in the fixed effect models, the alphas are treated as a set of fixed coefficients (one for each individual) rather than as random variables. This allows for any correlations between alfa and x and fixed effect methods only use variation within individuals in the sample to estimate the coefficients. Random effect models are considered to be more efficient, but given the nature of my data and in order to be able to control for all the unchanging characteristics of the institutions in my sample, whether observed or unobserved, I chose to use the unconditional estimation of fixed effect models.

A negative consequence is that standard errors tend to be larger for fixed effect rather than for random effect models but as a reward for this issue, there is that each institution serves as its own control (Allison, 2011). There are two approaches to maximum likelihood estimation: unconditional (using dummy variables to estimate the α_i) and conditional (where the α_i are conditioned out of the likelihood function). For the Poisson model, these two methods give identical results but conditional maximum likelihood is not possible for the negative binomial models (Allison & Waterman, 2002) and I will then use unconditional maximum likelihood including a dummy variable for each year and institution in my sample.

RESULTS

Hypotheses 1a and 1b. Dependent variable: number of invention disclosures

In **Table 1,** I present the results of the fixed-effect negative binomial models for disclosures by U.S. universities (from 1991 to 2014). Hence, this is the analysis of the first hypothesis(1a). The model 1 represents the primary model while in Models 2–8 I provide the robustness checks which I obtained changing the regression specification, by adding or removing control variables. These results provide considerable evidence that federal funding have a stronger effect on the number of invention disclosures than industrial funding has. Moreover, it is possible to see how the result remains stable over the eight different models and robustness checks. As I expected, the amount of federal funding received by each institution significantly predicts the number of disclosures. The model 1 shows, other things equal, that an increase in federal funding by one point means an increase of 23% (coefficient 0,23 highly significant with $p<0.01$) of invention disclosures. An increase in industrial funding by one point is instead associated with an increase of 2% (coefficient 0.02 significant with $p<0.05$). As a control (and time variant variable) which could act as a proxy for changes in the technology transfer offices, I used the number of their full-time employees. It is worth reminding the readers that because of the model I am using, I cannot use time-invariant variables.

***** Table 1*****

Table 2 presents the results of unconditional fixed-effect for disclosures by universities (from 1991 to 2014) this time with an interaction effect between federal and industrial funding. Does federal funding moderate the relationship of industrial funding on disclosures? According to my analysis, they do, and they have a positive effect on each other. In an interaction model, the "main effects" no longer have the meaning of being main effects. As a matter of fact, using this model means stipulating that there is no single effect of federal or industrial funding on the number of disclosures. Rather there is a different effect of federal funding (*logfedexp*) corresponding to each value of industrial funding *(logindexp*) and vice versa. How do I interpret the statistic that shows up in the output? The coefficient of *logfedexp* is the effect of *logfedexp* on disclosure conditional on *logindexp* being zero, and, again, vice versa. At any given value of *logindexp*, the effect of *logfedexp* is -0.156 + 0.0286*logindexp. The interaction term coefficient means that at larger values of federal funding, the value industrial funding of is also higher.

By contrast, in the hypothesis 1a where I use a non-interaction model, I am constraining the model to provide a single effect estimate for each variable *logfedexp* and *logindexp* that does not depend on the other.

*****Table 2*****

Hypotheses 2a and 2b. Dependent variable: number of patents filed

The second hypotheses are both rejected. **Table 3** shows the results of the fixed-effect negative binomial models with the count of filed patents (for each university, from 1991 to

2014). The model 1 provides the main model while in Models 2, 3 and 4, I executed the robustness checks by changing the regression specifications. Unlike the previous results, these lead me to reject the second hypothesis (2a) and provide evidence that federal funding do not have a stronger effect on the number of patents filed than industrial funding has. In fact, while the results in the first model show that federal funding have a more powerful positive effect on the number of patents filed, they do not remain significant over the three robustness checks.

*****Table 3*****

Does federal funding moderate the relationship of industrial funding on patents? **Table 4** shows the results to answer this question and the answer is negative. The interaction effect between federal and industrial funding does not have any effect on the number of patents filed each year. Both **Table 3 and 4** show, according to me, unexpected results and it is interesting to see how, according to the statistics, federal and industrial funding and their interaction effect have a strongly significant effect on the number of invention disclosures but not on the number of patents filed. Once I saw the results of this analysis, I went to the technology transfer office of the University of Pennsylvania, where I already had some informative conversations with one of its managers, and I asked him what he thought of the results and how he would have interpreted them. His help has been crucial to me since in many cases I did not find in scientific literature the information I was looking for. He told me that from his point of view, the results were not surprising and this was the ratio he shared with me: when a private organization invest a lot of money in research, it is generally to get one single relevant patent. To explore how industrial funding affects patent it is not easy: Novartis invested 200 million dollars at the University of Pennsylvania to get one single patent. This mechanism could be an issue to more deeply investigate further in another study.

*****Table 4*****

Hypotheses 3a and 3b. Dependent variable: number of license options executed

In the hypothesis 3a, I state that industrial funding has a stronger effect on the number of yearly licenses than federal funding does. In **Table 5**, I show the results that not just reject this hypothesis, but also state the opposite thesis. Industrial funding does not have a stronger effect on licenses than federal funding do, but the most surprising thing is that the coefficient of industrial funding is negative. What does it mean? It means that in the model 1, ceteris paribus, an increase in industrial funding by one point means a decrease of 5% (coefficient -0,053 highly significant with $p<0.01$) of license options. On the contrary, an increase in federal funding by one point means an increase of 20% (coefficient 0.198 highly significant with $p<0.01$). The results remain stable in the models 2, 3, 4, 5 where I did the robustness checks, and industrial funding holds a negative coefficient and remains highly significant.

*****Table 5*****

In **Table 6** I show the results about the last hypothesis. Does industrial funding moderate the relationship of federal funding on licenses? The answer is yes, and the hypothesis is accepted. How do these two different sources of financing research interact with each other? The coefficient of the interaction effect is negative (- 0.06 highly significant with $p<0.01$) , which means that they do not collaborate in helping the process of licensing. As I specified above, using this model means stipulating that there is no single effect of federal or industrial funding on disclosure and there is instead a different effect of federal funding (*logfedexp*) corresponding to each value of industrial funding (*logindexp*) and vice versa. The negative coefficient of the interaction term holds in all five models and passes all the robustness checks. What does its negativity mean? At larger values of federal funding, the value of industrial funding on licenses decreases, and vice versa, and even if the mechanism through which this happens is not entirely clear, we can infer that having more money is not generally good for any kind of research output and from where the money comes can be crucial.

*****Table 6*****

DISCUSSION AND LIMITATIONS

Scientific research generates an invaluable and crucial asset for national economies, it is "the energy that fuels the technology transfer engine" (AUTM Survey, 2014 p.16) and its primary source of funding is the U.S government. Several federal agencies in fact supply researchers and universities with the financial resources to start up scientific projects and discovery processes. Despite their importance, federal research funding have been starting to decrease in the last years. More frequent and stronger cuts will be happening in the next years, if we take as evidence the first budget plan released on March 16th by Trump's administration (Reardon et al., 2017). This disinvestment might lead to the slowing down of the progress in technology transfer that universities and industries have worked to accomplish so far. As a reaction, universities have started to increase their relationships with industry. In the light of these facts, it is important to have a clear picture of how public and private funding interact. The aim of this paper was to explore two different paths. In the first path I explored how the two main types of research funding, federal and industrial, affect three different research outputs: number invention disclosures, patents and licenses. In the second, and more insidious path, I explored if and how federal and industrial funding interaction affects the three research outputs.

What are the policy and managerial implications of this work? We contribute to the ongoing debate on the private and public funding of universities and with these empirical results this paper shows that a larger amount of funding does not always correspond to a larger amount of scientific output and in the production function of university research, federal and industrial funding do not always get along. In fact, they potentiate each other when it comes to generating disclosures, but not when it comes to generating licenses. In the first case, having more federal funding helps the industrial funding (and vice versa) to produce more disclosures, while in the second case, federal and industrial funding do not get along and their interaction is negative and highly significant: the more federal funding there is, the less the industrial funding helps in producing licenses and vice versa. Surprisingly, when I examined the case of patents, both with industrial and federal funding I did not find any measurable impact of federal or industry expenditures.

The mechanisms behind these effects are not entirely clear, but the technology transfer literature offers some explanations which it would be worth exploring further. Where do these conflicts between federal and industrial funding come from when it comes to generating licenses? Previous research has showed how many academics have established their own firms or have developed close relationships (often including relevant economic incentives) with private companies, bargaining their university research (Kenney & Patton, 2009). This mechanism contributes to create the emergence of a "gray market" for research outputs (Markman et al., 2008). More than 20% of the professors working in academia have started companies in their field of expertise without university licenses (Audretsch et al., 2006) and over 42% of the professors who applied for a patent bypassed the university technology transfer office (Markman et al., 2008).

Another possible mechanism to explain why funding coming from industry negatively affect the number of licenses, emerged from a conversation with another one of the University of

Pennsylvania TTO's managers. I asked him what he thought of these results and he answered that the biggest investments coming from industry are generally converted into one big license. This answer, could explain why a larger amount of money coming from industry corresponds to a low number of licenses. This information came from an informal conversation but I would like to dig deeper in my future works.

There is a long list of limitations of this study that need to be mentioned. First of all, my data represents just the technology transfer situations in the United States and the empirical results are limited to the U.S. and can't be declined for the European situation. It might be interesting to discover whether or not this analysis produces the same results in Europe as well. Another issue concerns the estimation of the impact of research expenditures on research outputs. This can in fact take longer than expected and this is the reason why modeling the relationship between research inputs and outputs is so complex. A strong point of this study is the longitudinal structure of the data I used, and the sample size, which gave me enough statistical power and allowed me to analyze several lag structures, but still, the effect of federal and industry funding on licensing activities could be lagged in ways I am not able to predict. Integrating the quantitative analysis with qualitative data could have helped to better understand the results and the mechanisms behind them.

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TABLE OF RESULTS 1

Results of Unconditional Fixed- Effect Models for disclosures in university (1991-2014)

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Federal Fund. (t-1)(log)	0.234***	0.223***	0.216***	0.217***				
	(0.0215)	(0.0223)	(0.0225)	(0.0238)				
Industrial Fund. (t-1)(log)	0.0210**	0.0113	0.0131	0.0222**				
	(0.0102)	(0.0109)	(0.0110)	(0.0111)				
Full Time Empoyees TTO	0.0110***	0.0109***	0.00964***	0.00718***	0.0112***	0.0102***	0.00694***	0.00734***
	(0.00204)	(0.00204)	(0.00203)	(0.00195)	(0.00209)	(0.00208)	(0.00206)	(0.00199)
Year	0.0312***	0.0312***	0.0280***	0.0149***	0.0348***	0.0342***	0.0314***	0.0195***
	(0.00174)	(0.00184)	(0.00189)	(0.00204)	(0.00181)	(0.00191)	(0.00193)	(0.00209)
	(0.370)	(0.466)			(0.477)	(0.545)	(0.537)	
Other Fund. (t-1)(log)		0.0120*	0.00932	0.00492				
		(0.00697)	(0.00699)	(0.00684)				
License_income (log)			0.0396***					
			(0.00642)					
License_income (log)				0.0180***				
				(0.00650)				
Legal fee (log)				0.173***				0.183***
				(0.0128)				(0.0134)
Industrial Fund. (t-2)(log)					0.161***	0.152***	0.144***	0.119***
					(0.0213)	(0.0219)	(0.0219)	(0.0222)
Industrial Fund. (t-2)(log)					0.0144	0.0182*	0.0195*	0.0161
					(0.0102)	(0.0110)	(0.0111)	(0.0110)
Other Fund. (t-2)(log)						0.0172**	0.0178***	0.00787
						(0.00683)	(0.00682)	(0.00681)
license_option (t-1)							0.00230***	
							(0.000296)	
License_income (t-2)								0.0157**
								(0.00672)
Constant	-63.58***	-63.34***	-57.42***	-32.38***	-69.21***	-67.79***	-61.96***	-39.77***
	(3.187)	(3.409)	(3.504)	(3.729)	(3.334)	(3.553)	(3.594)	(3.863)
Log likelihood	-13835.35	-12854.546	-12661.081	-11932.659	-12905.384	-11991.739	-11595.754	-11434.272
Pseudo r2	0.2366	0.2365	0.2347	0.2439	0.2374	0.2374	0.2414	0.2409
Observations	3,245	3,011	2,950	2,802	3,010	2,795	2,710	2,663

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE OF RESULTS 2

Results of Unconditional Fixed- Effect Models for disclosures in university (1991-2014) with interaction between Federal and Industrial Funding

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
L.logfedexp	-0.156***	-0.192***	-0.214***	-0.0757				
	(0.0603)	(0.0623)	(0.0632)	(0.0768)				
L.logindexp	-0.493***	-0.538***	-0.559***	-0.349***				
	(0.0766)	(0.0794)	(0.0808)	(0.0949)				
cL.logfedexp#cL.logindexp	0.0286***	0.0307***	0.0319***	0.0204***				
	(0.00425)	(0.00442)	(0.00448)	(0.00519)				
licftes	0.00655***	0.00619***	0.00482**	0.00458**	0.00756***	0.00655***	0.00338	0.00386*
	(0.00212)	(0.00211)	(0.00210)	(0.00204)	(0.00215)	(0.00215)	(0.00211)	(0.00205)
year	0.0267***	0.0258***	0.0223***	0.0127***	0.0307***	0.0297***	0.0268***	0.0151***
	(0.00183)	(0.00196)	(0.00203)	(0.00210)	(0.00192)	(0.00205)	(0.00206)	(0.00222)
	(0.371)	(0.466)			(0.477)	(0.544)	(0.537)	
L.logotherfund		0.0161**	0.0134*	0.00680				
		(0.00693)	(0.00694)	(0.00684)				
log_license_income			0.0399***					
			(0.00639)					
L.log_license_income				0.0198***				
				(0.00651)				
loglegfee				0.169***				0.177***
				(0.0128)				(0.0133)
L2.logfedexp					-0.192***	-0.208***	-0.232***	-0.244***
					(0.0649)	(0.0674)	(0.0673)	(0.0690)
L2.logindexp					-0.447***	-0.453***	-0.473***	-0.462***
					(0.0816)	(0.0849)	(0.0852)	(0.0877)
cL2.logfedexp#cL2.logindexp					0.0256***	0.0263***	0.0274***	0.0264***
					(0.00451)	(0.00471)	(0.00471)	(0.00482)
L2.logotherfund						0.0207***	0.0218***	0.0117*
						(0.00681)	(0.00680)	(0.00678)
L.license_option							0.00217***	
							(0.000294)	
L2.log_license_income								0.0184***
								(0.00671)
Constant	-47.44***	-45.02***	-38.13***	-22.53***	-54.65***	-52.19***	-45.92***	-24.42***
	(3.983)	(4.294)	(4.412)	(4.513)	(4.187)	(4.504)	(4.516)	(4.760)
Log likelihood	-13813.723	-12831.558	-12636.731	-11925.367	-12889.615	-11976.651	-11579.421	-11419.681
Pseudo r2	0.2378	0.2379	0.2361	0.2444	0.2383	0.2383	0.2425	0.2418
Observations	3,245	3,011	2,950	2,802	3,010	2,795	2,710	2,663

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE OF RESULTS 3

Results of Unconditional Fixed- Effect Models for patents filed in university (1991-2014)

VARIABLES	Model 1	Model 2	Model 3	Model 3
L3.logfedexp	0.0722***	0.0715**	0.00544	-0.00351
	(0.0280)	(0.0290)	(0.0274)	(0.0268)
L3.logindexp	0.0296**	0.0256*	0.0275**	0.0188
	(0.0138)	(0.0149)	(0.0140)	(0.0137)
disclosure	0.00179***	0.00187***		0.00155***
	(0.000163)	(0.000170)		(0.000148)
licftes	-0.00594**	-0.00670**	0.00302	-0.00919***
	(0.00285)	(0.00286)	(0.00246)	(0.00251)
year	0.0577***	0.0555***	0.0341***	0.0299***
	(0.00252)	(0.00267)	(0.00268)	(0.00264)
	(0.617)	(0.693)	(0.588)	(0.583)
L3.logotherfund		0.0154*	0.00531	0.00473
		(0.00863)	(0.00828)	(0.00812)
loglegfee			0.412***	0.399***
			(0.0177)	(0.0173)
Constant	-113.6***	-109.0***	-70.13***	-61.36***
	(4.699)	(5.006)	(4.940)	(4.891)
Log Likelihood	-11933,116	-11093,022	-10687,885	-10633,444
Pseudo r2	0,2196	0,2189	0,2313	0,2352
Observations	2,773	2,571	2,513	2,513

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE OF RESULTS 4				
Results of Unconditional Fixed- Effect Models for Patents filed from university (1991-2014) with interaction between Federal and Industrial Funding				
VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**
L3.logfedexp	0.165*	0.158	-0.120	0.166*
	(0.0987)	(0.105)	(0.0890)	(0.0956)
L3.logindexp	0.149	0.137	-0.136	0.239**
	(0.122)	(0.130)	(0.111)	(0.119)
Interaction between Federal and Industrial funding	-0.00664	-0.00624	0.00909	-0.0123*
	(0.00675)	(0.00719)	(0.00615)	(0.00658)
disclosure	0.00184***	0.00191***		0.00164***
	(0.000171)	(0.000179)		(0.000156)
licftes	-0.00562*	-0.00640**	0.00199	-0.00864***
	(0.00288)	(0.00288)	(0.00254)	(0.00253)
year	0.0585***	0.0564***	0.0326***	0.0316***
	(0.00267)	(0.00286)	(0.00286)	(0.00280)
L3.logotherfund		0.0145*	0.00671	0.00289
		(0.00870)	(0.00831)	(0.00819)
loglegfee			0.410***	0.400***
			(0.0177)	(0.0174)
Constant	-117.0***	-112.3***	-64.86***	-67.82***
	(5.812)	(6.277)	(6.087)	(5.977)
Log Likelihood	-11932,627	-11092,641	-10686,8	-10631,667
Pseudo r2	0,2196	0,219	0,2313	0,2353
Observations	2,773	2,571	2,513	2,513
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

TABLE OF RESULTS 5

Results of Unconditional Fixed- Effect Models for disclosures in university (1991-2014)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
L4.logfedexp	0.198***	0.184***	0.142***	0.143***	0.137***	0.139***
	(0.0420)	(0.0426)	(0.0431)	(0.0431)	(0.0431)	(0.0431)
L4.logindexp	-0.0534***	-0.0626***	-0.0775***	-0.0774***	-0.0795***	-0.0766***
	(0.0193)	(0.0195)	(0.0196)	(0.0196)	(0.0197)	(0.0196)
L.patent_filed	0.000415**	0.000323*	0.000393**	0.000420**	0.000411**	0.000419**
	(0.000182)	(0.000185)	(0.000179)	(0.000178)	(0.000179)	(0.000166)
licftes	0.00340	0.00228	0.00171	0.000604	0.00115	
	(0.00370)	(0.00369)	(0.00354)	(0.00354)	(0.00356)	
year	0.0312***	0.0238***	0.0231***	0.0211***	0.0213***	0.0214***
	(0.00372)	(0.00400)	(0.00405)	(0.00409)	(0.00420)	(0.00408)
loglegfee		0.127***	0.0776***	0.0642**	0.0730**	0.0672**
		(0.0265)	(0.0291)	(0.0294)	(0.0293)	(0.0294)
L.logreimb_legfee			0.0597***	0.0564***	0.0591***	0.0564***
			(0.0148)	(0.0148)	(0.0148)	(0.0148)
L.log_license_income				0.0373***		0.0376***
				(0.0130)		(0.0129)
L4.log_license_income					0.0206*	
					(0.0123)	
Constant	-62.85***	-48.42***	-46.04***	-42.34***	-42.50***	-43.02***
	(6.884)	(7.384)	(7.468)	(7.544)	(7.778)	(7.524)
Log likelihood	-8678,9901	-8503,6506	-7920,2351	-7895,4903	-7875,9064	-7913,9704
Pseudo r2	0,2161	0,2149	0,2142	0,2138	0,2135	0,2136
Observations	2,479	2,417	2,214	2.206	2,198	2.211

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

TABLE OF RESULTS 6
Results of Unconditional Fixed- Effect Models for licenses released from universities (1991-2014) with interaction between Federal and Industrial Funding

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
L4.logfedexp	1.130***	1.074***	0.821***	0.808***	0.795***
	(0.205)	(0.209)	(0.215)	(0.215)	(0.214)
L4.logindexp	1.057***	0.998***	0.732***	0.718***	0.707***
	(0.238)	(0.243)	(0.250)	(0.251)	(0.249)
Interaction between Federal and Industrial funding	-0.0608***	-0.0579***	-0.0440***	-0.0432***	-0.0425***
	(0.0130)	(0.0132)	(0.0136)	(0.0136)	(0.0135)
L.patent_filed	0.000792***	0.000690***	0.000655***	0.000676***	0.000699***
	(0.000198)	(0.000202)	(0.000195)	(0.000195)	(0.000187)
licftes	0.00573	0.00443	0.00318	0.00207	
	(0.00373)	(0.00372)	(0.00357)	(0.00357)	
year	0.0326***	0.0255***	0.0243***	0.0223***	0.0228***
	(0.00381)	(0.00408)	(0.00411)	(0.00414)	(0.00414)
loglegfee		0.120***	0.0730**	0.0601**	0.0636**
		(0.0264)	(0.0290)	(0.0293)	(0.0293)
L.logreimb_legfee			0.0616***	0.0582***	0.0581***
			(0.0147)	(0.0147)	(0.0147)
L.log_license_income				0.0364***	0.0372***
				(0.0129)	(0.0128)
Constant	-82.80***	-68.23***	-60.99***	-57.15***	-57.89***
	(8.132)	(8.665)	(8.769)	(8.861)	(8.872)
Log likelihood	-8668,0636	-8494,024	-7914,9573	-7890,4212	-7908,9783
Pseudo r2	0,217	0,2158	0,2147	0,2143	0,2141
Observations	2,479	2,417	2,214	2,206	2,211

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

2. Do Organizations learn from their Past Failures? A Longitudinal Analysis of University Technology Transfer Offices

INTRODUCTION

Akamai is a Hawaiian word which means “intelligent” or “witty,” and it is the name of the world's most distributed computing platform, responsible for serving between 15 and 30 percent of all web traffic. Over the years, their customers have included Apple, Facebook, Bing, Twitter, eBay, and healthcare.gov. Akamai was founded in 1998 by Daniel M. Lewin (then a graduate student at MIT), and MIT applied mathematics professor Tom Leighton.

Not so long before this, in 1976, the science business was in its infancy when Stanley Cohen (Stanford) and Herbert Boyer (UC San Francisco) discovered the technique of making recombinant DNA using gene-splicing. To exploit that technology, Boyer founded a company, Genentech. Genentech created a model for making a profit through the possession of the intellectual property and provided an advanced technology platform for a range of industries. It shaped the biotech industry and resulted in 2,442 new products sold and over US$35 billion in revenue. Over the duration of the patents’ lifespan (25 years, they expired in December 1997), their technology was licensed to 468 companies, and both Stanford and the University of California system accumulated US $255 million in licensing revenue (up to the end of 2001). A large amount of this money was subsequently invested in research and research infrastructures (Feldman & Colaianni, 2005).

Akamai and Genentech are two of the most notable successes of university knowledge created and successfully transferred to the market in the United States, and they both shaped the status quo of their respective sectors.

Creating and applying new knowledge is the primary factor that drives economic growth. Despite the difficulty of transferring the knowledge produced in academia, to the practitioners (Rynes et al., 2001), it is broadly accepted that universities are a major source of new knowledge and key actors in the growing market for the transaction of ideas. Within this market, it is crucial to understand what *Licensing* means: “it is the process of giving or getting permission to have, produce, or use something that another person or organization has created or owns,” such as intellectual property or patents (Cambridge Business English Dictionary). However, despite its potential value, growing anecdotal evidence suggests that the market for ideas is prone to failure (Agrawal, 2015) and scholars have claimed that “a staggering $1 trillion dollars in [ignored] intellectual property asset wealth” is foregone in the United States (Rivette and Klein, 2000).

The mission of the Technology Transfer Office (TTO) of every university is to translate academic research and get it out into the world, so that it can, in the best case scenario, provide industries and practitioners with the insights gleaned from the research so that they can improve and save peoples’ lives and provide new solutions to problems. Despite the important role of these organizations, 84% of Universities in the US lose money every year through technology transfer offices and fail to capitalize on the value and potential of the ideas and inventions in their portfolio, potentially robbing them of their power to affect change. Saying that universities lose money, I mean to say that most of them spend more money to maintain their TTOs open than this office brings into the school (Abrams, Leung, and Stevens, 2009). These numbers and examples raise some interesting points for management scholars. TTOs are organizations involved in the growing market for ideas. They are prone to failure for both, the nature of their job, which consists in transferring technology and knowledge, and for the market features (Roth, 2007, 2008). What does failure mean in this context? Behavioral learning theorists (Cyert & March, 1963; March & Simon, 1958) have been saying that aspiration levels are a benchmark to evaluate organizational performance and organizations usually based their aspiration levels on their previous performances (Haunschild & Miner, 1997). The organization succeeds when the performance encounters the aspiration level, and fails when this does not happen (Rerup, 2006).

Theorists of Organizational Learning retain that organizations mainly learn through processes of "problemistic search" that they activate only after experiencing failures (Cyert & March, 1963; March & Shapira, 1992). The aspirations of Organizational members have an important role in differentiating performance into success and failure; when a performance exceeds some relevant aspiration level, it is considered to be a success, and when a performance falls below the aspiration level, it is defined as failure (Cyert & March, 1963; March & Simon, 1958). Existing evidence that failure is more important than success for organizational learning has been mostly anecdotal (Cannon & Edmondson, 2001; Tax & Brown, 1998). Furthermore, the empirical works on the efficacy of organizational learning from success and failure led to highly variable results. Indeed, while much research has determined that organizations can often improve their performance by investigating and learning from failures (Baum & Dahlin, 2007; Haunschild & Sullivan, 2002; Madsen & Desai, 2010; Desai 2015), some work has found that organizations may either generate incorrect lessons or fail entirely to learn from this form of experience (Baumard & Starbuck, 2005). This high heterogeneity of the results is due to the complex diversity of every field in which the organizations are in. How in fact is one able to identify what qualifies as a failure? For example, in the aerospace industry, where Madsen and Desai (2010) showed that there is more learning from failure than from success when a plane goes down or a shuttle breaks up after launch, the failure is explicit and glaringly apparent. This act will surely send shockwaves through not only the organization but the industry as well, prompting the company in question as well as its competitors (vicarious learning) to determine what caused the failure and how to avoid making this same mistake going forward. Within another field, however, like the one we take into account, the University Technology Transfer in the United States, where a failure does not result in some concrete and drastic loss (jobs, lives, material, stock value), this failure will be less detectable, if at all. Organizational members might not be aware of it.

Conventional models of organizational learning have ignored how organizations learn from ambiguous outcomes. Why? James G. March suggested two reasons for the field's inattention to ambiguous outcomes. First, "*Organizations and humans seem to be programmed only to deal with success and failure. They are not programmed to notice or learn from ambiguous 'gray' areas*" (personal communication, December 19, 2003 in Rerup 2006). Second, "*when you observe the process of transforming ambiguous outcomes, and portray managers and other stakeholders as being actively involved in transforming the murky, ambiguous outcomes into successes and failures, most people, including managers, conclude that you are making a negative assessment of their behavior*" (March in Rerup 2006, p.3).

Drawing on organizational learning, technology transfer and market for ideas literature, my purpose is to explore if university technology transfer offices (TTOs) learn from their past failure experience. To determine what a failure experience is, I will use a logistic regression analysis to model the likelihood that a given organizational failure at time t-1, influences the organizational failure at the time t and I include organization-specific fixed effect. Within this complex empirical context, I try to determine if the common findings of improved organizational outcomes with increasing organizational experience are due to learning from failure, learning from success, or a combination of the two.

As a preliminary contribution, this article adds to our understanding of both, organizational learning, from an empirical point of view, and technology transfer, from an organizational perspective. It extends prior theory on learning from failure, and it tests this on a field in which underperforming has a broad impact on the economy and society. As a second contribution, we aim to add empirical evidence which could help to determine why some organizations learn more effectively through failure experience than other organizations and set new boundary conditions.

This last point may represent an important insight for practitioners, and it has been identified as a critical theoretical challenge within the learning literature (Madsen & Desai, 2010). Moreover, it could enhance our understanding of how and if organizations facing crises undertake substantial changes to their strategies, markets, and processes, as well as why some organizations are more successful than others at enacting these changes (Argote & Miron-Spektor, 2011; Greve, 2003; Madsen & Desai, 2010).

THEORETICAL BACKGROUND AND HYPOTHESES

To investigate if University Technology Transfer Offices (TTOs) learn or not from their bad performance, I build on three main literatures.

University Technology Transfer and Market for Ideas

With the expression *market for ideas,* the literature has been referring to a theoretical market in which innovations of broad nature are sold or licensed even if they do not consist of a tangible final product (Agrawal, 2006). . The innovation is still an idea, or intellectual property, a proof of concept, or a prototype.

As affirmed by Agrawal et al. (2015) this market plays an important and expanding role for both: knowledge diffusion and growth of the economy. As it is conceivable, in the last 20 years, transaction value has strongly increased (Arora and Gambardella, 2010) and University Technology Transfer is an essential part of this market. In fact, early-stage inventions represent the majority of university licenses, Jensen and Thursby (2001) found that inventions licensed from universities as generally embryonic, and over 75 percent of the inventions licensed by these universities were early stage (Agrawal, 2006). As affirmed by Agrawal et al. (2015) this market plays a crucial role for both: knowledge dissemination and economic growth. As it is imaginable, transaction value has strongly increased in the last twenty years (Arora and Gambardella, 2010) and University Technology Transfer is an essential part of this market.

In this context, I use the concept of university technology transfer to refer to an institutional activity that requires organizational structures and processes to move the research results into the marketplace such as patent and licensing or spin-offs (Tran, 2013).

Studying the university technology transfer can be challenging: there is no agreement on how university technology transfer effectiveness (TTE) should be defined and different scholars have stressed various points. This lack of agreement represents both, a critical point, and an important part of the ratio behind the hypotheses of this study. As it is hard for the scholars to define what effectiveness in this field means, I infer it is also hard defining what to consider as a failure in this field. If it is hard to infer what a failure is, how would it be possible to learn from it?

Roger (2003), defined technology transfer as the degree to which research-based information is moved successfully from one individual or organization to another, but in his review of the broad literature on technology transfer, Bozeman (2000) suggests that technology transfer effectiveness can have several meanings and that trying to define the correct and complete one proves to be daunting. Despite this difficulty, Rogers et al. (2000) designed a six step measurement of technology transfer effectiveness which I believe to be consistent with the theory and that I will use to answer my question.

So far in this section, I stated the importance of the market of ideas as a growing phenomenon, I explained why the UTT is considered an essential part of this market and I affirmed that there is not a wide agreement in the literature on what is considered as a university technology transfer effectiveness. Growing anecdotal evidence together with theory and numbers of failed transactions suggests that the market for ideas is prone to failure (Agrawal, 2015) and numbers related to the UTT activities show the same (Abrams, Leung, and Stevens, 2009).

Organizational learning through failure and simple heuristics

Organizational learning refers to the modification and evolution of collective knowledge as a result of the organization's experience (Cyert and March, 1963; Levitt and March, 1988).

This literature states that organizations learn processes from experience (Argote, 1996) and that repeated engagement allows their members to draw inferences, gain insights from the outcomes of their actions and learn about heuristics (Bingham & Eisenhardt, 2011). This last statement means that when organizations accumulate experience through particular activities, they can to modify procedures in ways that are believed to improve those and similar events' outcomes in the future (Ingram and Simons, 2002).

In fact, from an empirical point of view, positive returns to the accumulation of operating experience represent one of the most robust findings in organizational learning (Argote, 1996) and the learning curve — unit cost reductions as a function of cumulative output — rests firmly on the psychological theory of reinforcement learning through repetition. However, outside of operational settings, where individuals and businesses are performing in more novel or uncertain environments, the effects of experience on learning and outcomes have proven to be less clear (Desai, 2014). Complex, unstructured task environments — such as corporate-level administrative and strategic activities — (e.g. the one I am interested in: the Technology Transfer) do not engage as much in reinforcement learning, and the identification of relationships between current actions and observed outcomes is more obscure (Denrell, Fang, and Levinthal, 2004).

Recently, studies have been focusing on learning through experience with errors (Ramanujam and Goodman, 2003), accidents (Baum and Dahlin, 2007; Madsen & Desai, 2010), and other failure events (Arthur and Aiman-Smith, 2001). However, as I mentioned in the introduction, within our context, failure refers to the termination of an initiative to create organizational value that has fallen short of its goals (Hoang & Rothaermel, 2005; McGrath, 1999; Shepherd, Covin & Kuratko, 2009).

To clarify the relationship between failure and organizational learning some significant but heterogeneous points have been raised: some studies state that organizations can improve performance by investigating and learning from failures (Baum and Dahlin, 2007; Madsen, 2009; Madsen and Desai, 2010, Madsen, 2014). Other studies argued that learning through and from failures is hard if not impossible (Baumard and

Starbuck, 2005; Meyer and Zucker, 1989; Staw et al., 1981). Some studies attempted to address this divide, for instance, by exploring the role of failure characteristics (Sitkin, 1992), of the failure disclosure (Desai, 2014) or the failure distribution within the organization (Desai, 2015). Nevertheless, the crucial boundary conditions that influence learning through failure continue to be an unresolved point (Baum and Dahlin, 2007; Madsen, 2009).

Theory suggests that experiential learning processes differ for success and failure and that limited organizational resources (e.g. cognitive and financial) contribute to differences in learning processes because successes and failures stimulate distinct search processes (Cyert and March, 1963). On the one hand, success experience promotes 'satisficing' and refinement of existing routines, which economizes on scarce resources but stifles the search for new and superior solutions (Cyert and March, 1963). We can represent it as if there is a curvilinear relationship in the form of positive but diminishing returns to success experiences (Muehfeld et al., 2012).

On the other hand, failure experience induces 'problemistic search' for superior solutions (Cyert and March, 1963), it "upsets the status quo" (Chuang & Baum, 2003) and favors an increase of radical change. This means that facing a failure, could push an organization to explore a new path, to improve its performance like for example through the use of a new technological system (Gruber, MacMillan & Thompson). Success instead, activates what is called local search and is often referred to the exploitation of already known resources (March, 1991). Moreover, failure has been argued to contain richer cues to causality compared with success because it generates new, unexpected types of information (Baum and Dahlin, 2007).

Organizations turn not-discrete measures of performance into the dichotomy of failure/success and in this way they learn from experience (Rerup, 2006). In fact, thanks to this mechanism, organizations can use a simple heuristic (Gigerenzer & Todd, 1999) for prescribing behavior: are you succeeding? Persist. Are you failing? Change (Greve, 2002).

Many studies have explored which mechanisms drive organizations to learn from their failures and success: trial-and-error (Levitt and March, 1988), experimentation (Brown and Eisenhardt, 1997) analogical reasoning (Gavetti, Levinthal, and Rivkin, 2005), forward looking (Gavetti and Levinthal, 2000), vicarious learning (Baum, Li and Usher, 2000; Madsen & Desai, 2010) are just some of the options. But how do organizations learn when they deal with ambiguous outcomes? This option has been less explored in literature, but it recently started to draw more attention (Rerup, 2005; Rerup, 2006; Levinthal & Rerup, 2006) and it is an important step to understand the ratio behind the hypothesis. A key point for this study is that learning from failure is particularly difficult when dealing with complex tasks in which repetitions are heterogeneous and characterized by causal ambiguity, temporal delays, and nonlinearities (Lomi, Larsen, and Ginsberg, 1997). These three last mentioned obstacles to learning from failure, are part and parcel of the TTOs environment. This lack and difficulty in interpreting outputs and even more, the difficulty in interpreting the relationship between input and outputs could result in a low failure mindfulness. Within the organizations and as a consequence, they will not be able to learn from it. Knowing this, I consider TTO organizations as part of a challenging, interesting and relevant setting in which to test organizational learning theory.

Hypothesis: Prior organizational failure experience does not reduce the likelihood of future organizational failure more than does prior organizational success experience.

METHODOLOGY

Sample and Data

To test my hypotheses and understand if University Technology Transfer Organizations (TTOs) learn from failure or not, I need to analyze longitudinal data organized as repeated observations of the same variables over long periods of time. For this purpose, I will use panel data coming from 277 University Technology Transfer offices between 1991 and 2014. The data will be derived from the AUTM (Association of University Technology Managers) Licensing Activity Survey and Tech Transfer database (STATT), which has been collected annually since 1991. The AUTM dataset contains information related to some of the main research outputs and coming from 262 North American institutions. These 277 institutions are of two different types: universities (public and private) and research centers.

Dependent Variable: how do I measure failure in learning?

I build upon previous literature on Organizational Learning from failure (Muehfeld et al., 2012; Madsen & Desai, 2010) and have dichotomous dummy variable coded 1 for *failure* in learning at time t from previous bad performances, and 0 when there is *success* in learning. It is important to stress that within our context, and in accordance with behavioral learning theorists ((Cyert & March, 1963; Haunschild & Miner, 1997; March & Simon, 1958;) I deem failure to be when organizations do not learn from their previous poor performances. Failure refers to the termination of an initiative to create organizational value that has fallen short of its goals (Hoang & Rothaermel, 2005; McGrath, 1999; Shepherd, Covin & Kuratko, 2009).

How do I decide what to classify as a failure and what not? As I stated in the introduction, this is a crucial point and the most challenging one: the university technology transfer is a field where there is a high heterogeneity of outputs, and there is not a broad, accepted agreement on what is considered to be a failure. For this goal, I will use the six-item scale that Rogers et al. (2000) developed to measure *technology transfer effectiveness* defined as the degree to which research-based information is moved successfully from one organization to another. The measures used in the scale are: (1) the number of invention disclosures received, (2) the number of U.S. patents filed, (3) the number of licenses/options executed, (4) the number of start-up companies, and (6) the gross licensing income received. All of these six variables can be derived from the AUTM database. The composite measure of university technology transfer effectiveness is obtained by averaging each university's z-scores for the six variables. While the goal of Rogers et al. (2000) was to assign rank scores to universities, the use of measure I do in this paper is different. Indeed, what do matter in my model is to compare how the same UTTO perform over the years and to understand if poor performances are significative and if they lead to perform better in the future. The dependent variable corresponds to 1 (failure) if

$$Y_t - Y_{t-1} < \text{ or } = 0$$

Where Yt represents a value measuring the last performance in time and Yt -1 is the value measuring the performance of the year before. I assume that an organizational improvement means a tangible and measurable improvement of the performance. Moreover, with this strategy, I use as a reference point the past performance of each TTO and should avoid any problem related to the heterogeneity of TTO in my sample.

Independent Variable

The main independent variable is a dummy variable which represents success and failure in learning from past performances at *t-1*. Building on Madsen and Desai (2010), I am asking my data if the prior organizational failure experience decreases the likelihood of future organizational failure more than prior organizational success experiences does.
Empirically, positive returns to the accumulation of operating experience are one of the most robust findings in organizational learning (Argote, 1999) and with this empirical analysis I will explore if learning from failure and learning from success are differently significative. Following prior studies, I will use a moving window of three years prior to the focal year to measure an organization's experience (Muehfeld et al., 2012; Haleblian & Finkelstein, 1999; Hayward, 2002; Laamanen & Keil, 2008). The choice of this time window is consistent with qualitative evidence coming from other fields, such as banking (Haleblian et al., 2006) and will help to understand how time is relevant for the organizational learning. Moreover, the technology transfer process often requires several years after a technology is patented and before the university earns royalties (income from product sales) from the technology (Rogers et al., 2000) and takes into account the aspect of time, might reveal some interesting issues.

Control Variables

Several control variables were also included to take into account different factors than previous organizational experience which could affect the probabilities of future University Technology Transfer poor performances. The first is the number of full-time employees working in the UTTOs, considered as a crucial variable in many studies. The second one measures a general trend in all the UTTOs so that I could control if there were any exogenous event affecting all the institutions of the sample during the same interval of time. The Third and fourth control variables are federal and industrial funding. Indeed, it is important to understand that any potential improvement of performance is not just given by the increase of different financial resources. As a fifth and sixth control variable, I created two proxy (Table 1) which represent the quality of invention disclosures received by the UTTOs and a measure of goodness in negotiating deals (Table 1).

Table 1: Description control variables

Name	Definitions
Quality of innovations	As a proxy for the quality I use the ratio between patents totally filed and patents newly filed, as suggested by the manager of the UTTO of the University of Pennsylvania during an interview
Patents newly filed	New patent application filed is the first filing of the patentable subject matter. NEW PATENT APPLICATIONS FILED does not include continuations, divisionals, or reissues, and typically do not include CIPs. A U.S. PROVISIONAL APPLICATION filed in fiscal year 2013 will be counted as new unless it is a refilling of an expiring U.S. PROVISIONAL APPLICATION. If a U.S. PROVISIONAL APPLICATION is converted in to a U.S. UTILITY APPLICATION, then that corresponding U.S. UTILITY APPLICATION filed in should not be counted as new.
Patents filed	Count of the numbers of patents filed in the year
Ability of the TTO in negotiating	This number corresponds at the ratio between expended legal fees and reimbursed legal fees
Legal fees expenditures	The amount spent by an institution in external legal fees for patents and/or copyrights. These costs include patent and copyright prosecution, maintenance, and interference costs, as well as minor litigation expenses that are included in everyday o ce expenditures (an example of a minor litigation expense might be the cost of an initial letter to a potential infringer written by counsel). Excluded from these fees is significant litigation expense, e.g., any individual litigation expense that exceeds 5% of total LEGAL FEES EXPENDITURES. They also do not include direct payment of any of these costs by licensees.
Legal fees reimbursement	The amount reimbursed by licensees to the institution for LEGAL FEES EXPENDITURES (see definition for LEGAL FEES EXPENDITURES). (Question 12) Include in this category both LEGAL FEES REIMBURSEMENTS paid via lump sum payments of costs incurred in prior years when a new license is signed AND regular reimbursements of new costs incurred after the license is signed. Do not include amounts deducted from LICENSE INCOME prior to internal distribution because LEGAL FEES EXPENDITURES have not been previously been reimbursed (e.g., technologies licensed non-exclusively).

Analysis

I will use a logistic regression analysis to model the likelihood that a given organizational failure at time t-1, influences the organizational failure at the time t and I include organization-specific fixed effect. Fixed effects models control for unobserved heterogeneity in the form of time-invariant variables (Allison, 1999). Moreover, after running both fixed and random effect models, I found the fixed effect to be equivalent or superior based on Hausman (1978) tests. The inclusion of organization fixed effects suggests that the reported models explain within-firm variation in performance over time rather than inter-firm variation in performance. The fixed-effects regression model takes this form:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right)=\mu_t+\beta x_{it}+\gamma z_i+\alpha_i$$

where p_{it} is the probability that the event happens to individual i at time t, α_i represents all differences between individuals that are stable over time and not otherwise accounted for by γ_{zi}.

RESULTS

The Hypotheses I stated in the hypotheses session above is accepted.

In the **Table of Results 1**, I report maximum-likelihood estimates for the fixed-effect logistic regression analysis of failures in learning from previous performances. In the models 1, 2 and 3 I consider the main independent variable, previous experience of failure, at t-1. In the model 4, 5 and 6 I lagged the variable of two years and tested how the experience of failure happened two years before(t-2) affects the failure at time t. Finally, in models 7, 8 and 9, I used the experience of failure at t-3.

***** Table of Results 1 *****

The interpretation of the results in Table of Results (1) is made complicated by two factors: we see as an output the coefficients instead of the odds ratios (OR), and this is a conditional fixed effects regression. In three different table of results (2, 3 and 4) I show the odds ratios for past failure lagged at t-1, t-2 and t-3.

***** Table 2, 3 and 4 *****

So, the first important thing to notice is that the coefficient for the lagged variable does not change much even as I change the other variables in the model. That does simplify the interpretation because it means I do not have to pay attention to all the control variables and can just pick one version and compare the different lags. Clearly, the odds ratio of 0.42 using t-1 is the most different from 1. The t-2 odds ratio of 0.87 is much closer to 1, and the T-3 odds ratio of 0.79 is in the same ballpark as the t-2 odds ratio. Given the purpose of the comparison, which is to identify which lag is most influential, I can affirm that t-1, is the most influential one. Moreover, the confidence interval around the 0.42 OR is 0.36 to 0.49 (Model lagged at T-1). The interval of confidence around the 0.87 OR (model lagged T-2) is 0.76 to 1.0. It is important to consider that 0.42 is not between 0.76 and 1.0; nor is 0.87 between 0.36 and 0.49. So if it is possible to think of intervals of confidence as values that show a range of imprecision around our estimates, I can affirm that neither of these ORs is within the range of uncertainty of the other. This last statement represents good news, and it means that the models do not provide only vague, dubious estimates of odds ratios that might not differ. The estimates are precise enough, and the difference between the estimates is markedly larger than the imprecision of the estimates. The same thing happens at lags T-1 and T-3: the contrast between the 0.42 OR estimate, T-1, and the 0.79 OR estimate from the T-3 model.

I used conditional logistic regression and the inferences are strictly within the grouping variable. So given a single institution, the odds of failure in learning from previous performances, for those who failed in the past (previous_learning =1) are estimated to be 0.42 times higher than the odds of failure for those who had a previous success (previous_learning = 0). It is important to note that with a conditional fixed effects model I cannot obtain any estimate of the actual odds in either condition, but only the odds ratio between the two conditions.

DISCUSSION AND LIMITATIONS

The general purpose of this paper was to test if organizations which deal with ambiguity learn or not from their failure. More specifically I wanted to test the organizational learning theories on the US University Technology Transfer world. The analysis confirmed the hypothesis and showed that these kind organizations do not learn from their previous poor performances, which in accordance with behavioral learning theorists ((Cyert & March, 1963; Haunschild & Miner, 1997; March & Simon, 1958;) I call failure.

This work represents a contribution to both theory and for managers, most of all to all who work in the University Technology Transfer institutions. Not having a clear benchmark of what a good or bad performance is in this field does not help in learning from their past poor performances. So when we as scholars ask whether or not organizations learn from failure, perhaps the more appropriate question we should ask is: how clear is the concept of failure within their field? Do they notice that there is a failure at all in the first place?

Through testing my hypothesis on a new empirical field, I hope to add a tiny piece of empirical evidence to the strategy research community’s endeavor to disentangle one of the obstacle that does not let organizations to learn from failure (e.g., Baumard and Starbuck 2005, Haunschild and Sullivan 2002, Tucker and Edmondson 2003). As a last contribution, I tried to better define the boundary conditions concerning the process of learning, as asked by Madsen and Desai (2010) in their inspiring paper.

Amongst the many limitations of this work, the absence of an integrated qualitative work made of structured interviews was one of the more difficult to deal with. Even If I had several meetings with the TTO of the University of Pennsylvania, I used them just as an informative step. Doing more interviews in more universities could have bring a great benefit to the data and to the interpretation of results. But the silver-lining is that this might represent a good future extension of this work.

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TABLE OF RESULTS #1

Results of Logistic Regression Models of Likelihood for Failure Outcome, 1992 - 2014

	LAG 1				LAG 2				LAG 3			
VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Failure t-1 (dummy)	**-0.864*** **	**-0.863*** **	**-0.811*** **	**-0.809*** **								
	(0.0742)	(0.0761)	(0.0819)	(0.0819)								
Year Trend in UTTO (dummy)	0.216	0.275	-2.446***	-2.451***	-2.170***	-2.167***	-2.308***	-2.315***	-0.0722	-0.117	-0.0991	-0.112
	(0.289)	(0.297)	(0.488)	(0.488)	(0.402)	(0.409)	(0.484)	(0.485)	(0.309)	(0.318)	(0.340)	(0.340)
UTTO Employees	-0.00129	0.00669	0.00336	0.00436	0.000766	0.00599	0.00382	0.00468	0.00118	0.00681	0.00410	0.00489
	(0.0140)	(0.0167)	(0.0173)	(0.0173)	(0.0143)	(0.0168)	(0.0171)	(0.0171)	(0.0147)	(0.0171)	(0.0173)	(0.0173)
Federal Funding		-4.78e-10	-6.13e-10	-6.39e-10		-4.58e-10	-5.47e-10	-5.64e-10		-4.88e-10	-6.77e-10	-6.94e-10
		(5.50e-10)	(5.75e-10)	(5.75e-10)		(5.60e-10)	(5.74e-10)	(5.74e-10)		(5.73e-10)	(5.86e-10)	(5.86e-10)
Industrial Funding		8.65e-10	1.98e-09	1.88e-09		1.42e-09	2.55e-09	2.44e-09		1.37e-09	2.71e-09	2.62e-09
		(2.69e-09)	(2.82e-09)	(2.82e-09)		(2.73e-09)	(2.82e-09)	(2.82e-09)		(2.79e-09)	(2.88e-09)	(2.88e-09)
Quality of UTTOs Outputs			0.0693	0.483			-0.259	0.167			-0.0147	0.407
			(0.392)	(0.454)			(0.422)	(0.493)			(0.443)	(0.528)
Intuition				0.341*				0.312*				0.300
				(0.191)				(0.185)				(0.191)
previouslearnexp_2					**-0.137***	**-0.148** **	**-0.162** **	**-0.158** **				
					(0.0733)	(0.0751)	(0.0805)	(0.0805)				
previouslearnexp_3									**-0.235*** **	**-0.248*** **	**-0.233*** **	**-0.231*** **
									(0.0764)	(0.0782)	(0.0836)	(0.0837)
Log Likelihood	-1902,7657	-1810,0711	-1506,6236	-1504,8741	-1825,4725	-1737,3298	-1497,343	-1495,8267	-1700,1864	-1618,6837	-1415,0152	-1413,6928
Observations	3,512	3,355	2,822	2,822	3,282	3,142	2,733	2,733	3,042	2,915	2,574	2,574
Number of institutions	227	223	200	200	223	221	199	199	214	212	195	195

Standard errors in parentheses

***** p<0.01, ** p<0.05, * p<0.1**

TABLE OF RESULTS 2: MODELS WITH PREVIOUS LEARN EXPERIENCE T-1 AND ODDS RATIO

MODEL 1 (ODDS RATIO)

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp	.4219414	.0321207	-11.34	0.000	.3634576	.4898359
dumyeartrend	1.317067	.3917669	0.93	0.355	.7352157	2.359398
licftes	1.006711	.0168376	0.40	0.689	.9742447	1.040259
federal_exp	1	5.50e-10	-0.87	0.384	1	1
industry_exp	1	2.69e-09	0.32	0.748	1	1

MODEL 2 (ODDS RATIO)

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp	.44449	.036392	-9.90	0.000	.3785916	.5218588
dumyeartrend	.0866579	.0422936	-5.01	0.000	.0332949	.2255479
licftes	1.003369	.0173641	0.19	0.846	.9699067	1.037986
federal_exp	1	5.75e-10	-1.07	0.286	1	1
industry_exp	1	2.82e-09	0.70	0.483	1	1
ratio_legal	1.071757	.4199868	0.18	0.860	.4972082	2.310227

MODEL 3 (ODDS RATIO)

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp	.4451388	.0364658	-9.88	0.000	.3791098	.5226681
dumyeartrend	.0861813	.0420742	-5.02	0.000	.0331018	.2243751
licftes	1.004372	.0173811	0.25	0.801	.9708767	1.039022
federal_exp	1	5.75e-10	-1.11	0.267	1	1
industry_exp	1	2.82e-09	0.67	0.505	1	1
ratio_legal	1.621362	.7368389	1.06	0.288	.6653429	3.951066
intuition	1.405692	.2688358	1.78	0.075	.9662727	2.044941

TABLE OF RESULTS 3: MODELS WITH PREVIOUS LEARN EXPERIENCE T-2 AND ODDS RATIO

MODEL 4

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp_2	.8719314	.0639495	-1.87	0.062	.7551848	1.006726
dumyeartrend	.114155	.0458631	-5.40	0.000	.0519415	.2508854
licftes	1.000767	.014358	0.05	0.957	.9730176	1.029307

MODEL 5

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp_2	.8628319	.0648239	-1.96	0.050	.7446911	.9997152
dumyeartrend	.1144713	.0468173	-5.30	0.000	.0513531	.2551685
licftes	1.006008	.0169237	0.36	0.722	.9733794	1.039731
federal_exp	1	5.60e-10	-0.82	0.414	1	1
industry_exp	1	2.73e-09	0.52	0.602	1	1

MODEL 6

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp_2	.8508654	.0684574	-2.01	0.045	.7267355	.9961973
dumyeartrend	.0995076	.0481836	-4.77	0.000	.0385201	.2570544
licftes	1.003824	.0171668	0.22	0.823	.9707355	1.038041
federal_exp	1	5.74e-10	-0.95	0.341	1	1
industry_exp	1	2.82e-09	0.90	0.366	1	1
ratio_legal	.7721827	.3261501	-0.61	0.540	.3374383	1.767037

TABLE OF RESULTS 4: MODELS WITH PREVIOUS LEARN EXPERIENCE T-3 AND ODDS RATIO

MODEL 7

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp_3	.790926	.0604322	-3.07	0.002	.6809232	.9186996
dumyeartrend	.9303019	.2874609	-0.23	0.815	.5076973	1.70468
licftes	1.001178	.0147004	0.08	0.936	.9727761	1.030409

MODEL 8

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp_3	.7806092	.0610474	-3.17	0.002	.6696774	.9099169
dumyeartrend	.8896602	.2826083	-0.37	0.713	.4773452	1.658119
licftes	1.006835	.0171998	0.40	0.690	.9736818	1.041117
federal_exp	1	5.73e-10	-0.85	0.395	1	1
industry_exp	1	2.79e-09	0.49	0.624	1	1

MODEL 9

learnexp	OR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
previouslearnexp_3	.7923448	.066264	-2.78	0.005	.6725552	.9334702
dumyeartrend	.9056347	.3081249	-0.29	0.771	.4648877	1.764242
licftes	1.004109	.0173908	0.24	0.813	.9705953	1.038779
federal_exp	1	5.86e-10	-1.16	0.248	1	1
industry_exp	1	2.88e-09	0.94	0.346	1	1
ratio_legal	.9854336	.4364595	-0.03	0.974	.4136383	2.347654

3. The Value of the Heuristic of Similarity in the Development and Understanding of innovation

ABSTRACT

Building on cognitive theories and business model literature, the object of this paper is to analyze to what extent entrepreneurs rely on heuristics, and in particular on the heuristic of similarity, to develop business models and technology. In fact, while recent research has referred to a cognitive view on 'business modeling', it is still unclear how the cognitive foundations of such modeling happens. This paper proposes building on heuristics as models of individual cognition and decision making, which have been proven effective foundations of adaptive individual and entrepreneurial behaviors. By also drawing on the building block rules used in cognitive science to analyze the heuristical mechanism, we propose business modeling as an entrepreneurial cognitive process of configuring these rules. Despite the constraining effects that traditionally management and entrepreneurship literature has attributed to these cognitive tools, we argue that in making sense of uncertainty, "fast and frugal" heuristics provides entrepreneurs with robust strategies to connect the dots that give rise to business models.

The paper makes two main contributions . First, we introduce the heuristic of similarity to the business modeling literature, and so provide an established theory of adaptive individual behavior that strengthens the cognitive foundations of business modeling. Second, through the results of a qualitative survey, we conceptualize and theorize on the cognitive activity of business modeling, presenting it as an iterative process of configuring heuristics. In this way, we contribute to the micro-foundations of the cognitive processes underlying

business modeling and thus to broader accounts of entrepreneurial behaviors.

INTRODUCTION

Interest in business models has grown exponentially in the past few years especially after the ecommerce boom in the late 1990s (Amit and Zott, 2001; Markides, 2013). Since then, the concept has been applied to different domains. It has been adopted by strategy scholars to discuss value creation and sustainable competitive advantage (Christensen, 2001; Teece, 2010), as well as by technology and innovation management scholars as a conceptual means for relating a firm's technological and market domains (Calia et al., 2007; Björkdahl, 2009). Nowadays, while many different definitions of business models have emerged (Zott et al., 2011) and have assumed multiple roles, there is an emerging consensus that the concept needs to be further treated from a cognitive perspective (Baden-Fuller and Mangematin, 2013; Demil et al., 2015). It is our intention to address this call and explore more fully the idea of looking at business model as a cognitive device (Chesbrough and Rosenbloom, 2002; Baden-Fuller and Morgan, 2010) used to process and structural information, in addition to representing business environments.

In fact, while the application of a cognitive lens has been identified and articulated as a promising avenue to enrich our current understanding of business modeling, this relationship has only so far been explored on a rhetorical level. As a consequence, the distinct underlying mechanisms and cognitive processes have largely remained within a 'black box.' In the cognitive view that currently prevails, the fundamental question about the micro-foundations of business modeling - 'How does business modeling happen?' - has remained unanswered. On the one hand, we need to shed further light on the very nature of entrepreneurial cognition in the context of business modeling by drawing on literature from other disciplines, such as the cognitive science. On the other - building on Morgan's (2012) view that modeling gives form to ideas and makes them formally rule-bound - we currently lack theory about how the processes of form-giving and rule-bounding can be conceptualized for business modeling (Loock and Hacklin, 2015). One the cognitively challenging aspects of defining the business model for entrepreneurs is that it requires connecting the dots in the face of great technical and market uncertainty (Chesbrough and Rosembloom, 2002). Dealing with uncertainty requires knowledge without an exhaustive use of information. In other words, dealing with uncertainty and eventually connecting the dots to develop a firm business model requires heuristics that deliberately and efficiently ignores information (Mousavi and Gigerenzer, 2014).

Given the diversity of cognition as a field, and the potential roles of models in considerations of individual cognition, business modeling could potentially build on a variety of models of cognition. Specifically, this paper offers a conceptualization of the cognitive processes that entrepreneurs employ when performing business modeling by drawing on the stream of research based on heuristics. Heuristics are rules of thumb for reasoning, a simplification, or educated guess that reduces or limits the search for solutions in domains that are difficult and poorly understood (Simon, 1976; Kunda, 1999). Actually, even if strategy scholars have shown a growing interest in the cognitive side of business models (Doz and Kosonen, 2010; Martins et al., 2015), specific cognitive tools, such as heuristics, used in the formation of a business model remains unexplored. In order to fulfil this theoretical gap, we aim to give an answer to the following research question: *which heuristics are used in the development of business models, and how do they function?*

We argue that entrepreneurs use both business models and heuristics as strategies to deal with business environments. This idea is rooted in the cognitive perspective in the business model research (Baden-Fuller and Mangematin, 2013; Doz and Kosonen, 2010; Martins et al., 2015) and research on ecological rationality in cognitive science (Todd and

Gigerenzer, 2012).

According to these views business environments are usually characterized by high levels of uncertainty about the markets entrepreneurs enter or create, the outcomes of technological developments they pursue, and their competencies to successfully run a venture (Shepherd et al., 2015).

Complex problems often call for simple robust solutions and heuristic strategies solve complex uncertain situations exactly because of their simplicity and not despite it (Gigerenzer et al., 1999): trying to calculate everything, spending more time, and processing more information does not necessarily provide a better, more accurate result. Especially in the field of business decision-making, plenty of information is often available, but one crucial point is that entrepreneurs can generate profit in the market precisely because they intelligently deal with immeasurable, irreducible uncertainty. Then, we agree that business models might result less from a carefully calculated choice from a diverse menu of well-understood alternatives, and more from a process of sequential adaptation to new information and possibilities (Davenport, Leibold, & Voelpel, 2007).

The cognitive view of business modeling is embedded in broader accounts of cognition in management (Eggers & Kaplan, 2013; Gavetti, Greve, Levinthal, & Ocasio, 2012; Gavetti, Levinthal & Ocasio, 2007), but at the same time also distinguishes itself from this stream, as business models do not focus on single managerial problems but have a more holistic perspective. Nevertheless, the extant literature provides only limited insights into the cognitive foundations of business modeling.

This research provides several contributions and the first consists in filling this gap by outlining a theory of business modeling as a cognitive process of configuring specific heuristics. The second contribution consists in opening up the cognitive toolbox that potential entrepreneurs use to recognize market opportunities and customer needs as well as the direction of technology evolution. Our study of heuristics and cognitive system provides a framework to model how entrepreneurs deal with the uncertainty linked to the decision making and to the process of innovating (i.e. a new business, a new venture, a new product) and provides empirical evidence on which specific heuristics entrepreneurs use when developing business models and new technologies.

THEORETICAL FRAMEWORK

The cognitive side of business models and the value of entrepreneurial heuristics

Business Model

Business model researchers increasingly converge on a definition of business models as systems of 'interdependent organizational activities centered on a focal firm' (Zott and Amit, 2010: 217) that are 'made up of components, linkages between components, and dynamics' (Afuah and Tucci, 2001: 4). Recently, Martins et al (2015) have highlighted that this literature has unfolded following three directions. First, the rational positioning view treats business models as purposefully designed systems (Zott and Amit, 2010) that reflect rational managerial choices and their operating implications (Shafer, et al., 2005; Casadesus-Masanell and Ricart, 2010). Second, the evolutionary approach to understanding business models is based on a view that strategists engage in local search and response to specific problems or opportunities.This view emphasizes the role of routines, their relative inertia, and incremental strategic change driven 'more by trial than by forethought' (Gavetti and Rivkin, 2007: 424). Third and finally, in line with a cognitive view of business models several scholars have suggested that business models reflect entrepreneurial mental models.

More specifically, early literature has highlighted the constraining effect of cognition on business models arguing that their evolution interact with managerial cognition (Tikkanen et al., 2005). It has also emphasized that cognitive barriers might prevent companies to innovate business models (Chesbrough, 2010). Because cognition acts as filtering process, it is likely to preclude identification of models that differ substantially from the firm's current business model. Particularly, Chesbrough and Rosenbloom (2002) have advanced the idea that the process of constructing business models is closely related to Prahald and Bettis's (1989) notion of dominant logic, since that logic is intended to reduce ambiguity and make sense of complex choice faced by entrepreneurs. In their view, while this logic is useful and beneficial, it comes at a cost. The choices made in the creating of a business model constrains other options and filters out certain possibilities (Chesbrough, 2002).

More recently, scholars have attached a more proactive role to cognition. In fact, in line with the development of research on cognition in strategic management (Kaplan, 2011), they have suggested that business models stand "as cognitive structures providing a theory of how to set boundaries to the firm, of how to create value, and how to organize its internal structure and governance (Doz and Kosonen, 2010: 371); business models have been also conceived as schemas or "cognitive structures that consist of concepts and relations among them that organize managerial understandings" (Martins et al., 2015: 105). According to this view, business models reflect conscious managerial choice and strategic design.

Heuristics

The origin of the term heuristic is the Greek word for "serving to find out or discover." Heuristics are, above all, strategies to solve problems that logic and probability theory cannot handle (Groner et al., 2014; Polya, 1954). In this respect, a heuristic is a specific instantiation of a strategy that ignores part of the information available in the problem space. It is fast and frugal as it relies on "a minimum of time, knowledge, and computation to make adaptive choices" (Gigerenzer et al., 1999, p. 14).

The use of heuristics in management has been documented for a broad range of decisions. However, the specification of different heuristics varies greatly, with the most basic form reported being mere verbal statements of rules of thumb. A large collection of such verbal heuristics was documented by Manimala (1992) in a study on pioneering innovative ventures. These include, among others, “start small, grow big organically,” “Look for new (product) ideas among technological developments abroad especially among new, rare, or specialized products developed abroad”, “minimize initial investments,” “repeat successes to take full advantage of them,” and “sharing is the way to loyalty and prosperity. Give everyone his due.”

Decision	**Heuristics**
Rather than start the first venture with a full-fledged production unit, start the manufacture of selected production unit, start the manufacture of selected products on loan licenses in the premises of another company and slowly come to one’s own using internally accumulated resources	1 Test the outcome before venturing out 2 Minimize (initial) investments 3 Start small, and grow big organically

Table 1. Example of heuristic according to Manimala 1992.

Coleman, Maheswaran, and Pinder (2010), who have worked on narratives for decisions in corporate finance, listed a number of similar verbal heuristics, such as “focus on keeping it simple and understand what are the fundamental things you have got to get right.” Verbal approaches such as these can provide valuable insights into how heuristics are part of everyday managerial decision making. As noted by Simon (1990), and later acknowledged in theories on contingent decision behavior (Payne, Bettman, & Johnson, 1993), heuristics as foundations of adaptive human behavior address the decision maker’s individual cognitive capabilities and the environmental specifics in which the actual decision task is embedded, as well as (obviously) the decision-making task itself (Gigerenzer et al., 2011; Goldstein & Gigerenzer, 2002). The ecological rationality of heuristics emerges from different directions (Loock & Hinnen, 2015): and more specifically, scholars have found that heuristics:

- Collect the essential results of learning processes (Bingham & Eisenhardt, 2011; Bingham & Haleblian, 2012);
- Systematically exploit information coming from the environment (Goldstein & Gigerenzer, 2002);
- Provide beneficial "effort/accuracy trade-offs" (Payne et al., 1993) and save time or costs in decision making, or enable accurate decisions when such resources are scarce (Hauser, 2014; Hu & Wang, 2014; Pichert & Katsikopoulos, 2008);
- Only require little information to arrive at accurate decisions, which is especially beneficial in situations of low information availability or uncertain information reliability (DeMiguel, Garlappi, & Uppal, 2009);
- Avoid over-fitting decisions to historic data, and appear to be more accurate in predicting new data (Czerlinski, Gigerenzer, & Goldstein, 1999);
- Can be assumed to balance efficiency and flexibility, the two conventional foundations of organizational development which are often assumed to conflict (Eisenhardt, Furr, & Bingham, 2010).

However, these approaches share the problem of producing a large unstructured body of very specific heuristics without stating when and why they perform well (Artinger et al., 2014). Different attempts to systematize this knowledge have been made. Bingham and Eisenhardt (2011) distinguished between heuristics for exploiting business opportunities and heuristics that allow linking different business opportunities. Reijers and Liman Mansar

(2005) classified heuristics according to the specific nature of classic business processes. Guercini (2012) proposed sorting heuristics according to the degree of transferability between different contexts or how widespread the use of a particular heuristic is within a reference group.

Meanwhile, in psychology, considerable effort has been invested in specifying generalizable and testable descriptions of heuristic decision processes. Psychologists have systematized heuristics by studying, among others, common building blocks and in particular, we rely on Gigerenzer and Gaissmaier (2011) that defined three such building blocks which work in this order:

1) Search rules: state where to look for information;

2) Stopping rules: state when to stop searching;

3) Decision rules: state how to decide given the attained information.

Artinger et al. (2014) identified a number of well-specified managerial applications of heuristics that can be traced back to five basic classes of heuristics of which the respective building blocks have been specified:

1) satisfying;

2) tallying and 1/N;

3) lexicographic strategies;

4) recognition;

5) similarity.

In Simon's (1955) seminal article on bounded rationality, he highlighted satisfaction as an important strategy for decision making. Satisfaction refers to the realistic goal of finding a "good enough" solution. The tallying and 1/N strategy counts the number of cues favoring one alternative over another. Take the best, which order cues by decreasing validity, is a lexicographic strategy. Recognition-based decisions describe situations where “ the mere recognition of an object is a predictor of the target variable” (Gigerenzer & Goldstein, 1996, p. 653).   Finally, the similarity heuristic is an adaptive strategy. The goal of this last heuristic is maximizing productivity through favorable experience while not repeating unfavorable experiences. Decisions based on how favorable or unfavorable the present seems are based on how similar the past was to the current situation. Table 1 that follows offers a description of the building blocks of each of the above heuristics.).

Table 2. The building blocks of the heuristics.

Building blocks	**Satisfying**	**Tallying and 1/N**	**Lexicographic strategies**	**Recognition**	**Similarity**
Search rule	Set an aspiration level and search through objects	Search through cues in any order, add positive cues to the tally, and deduct negative cues from it	Order cues by their validity	Search for an object that you recognize.	Search for an object that is more similar to the target than objects drawn from a reference class
Stopping rule	Stop search when the first object meets the set aspiration level	Stop after n cues (where n can be any number up to the complete set of cues)	Stop on finding the first cue that discriminates between the alternatives	Stop as soon as one object is recognized	Stop as soon as a more similar object is found
Decision rule	Choose this object	Decide for the alternative with the higher tally. If after searching through all cues there is a draw, guess	Choose the alternative with the higher cue value.	Infer that the recognized object has the higher value with respect to the criterion.	Infer that the identified object has a higher criterion value than those from a reference class

It is finally important to say that all the above heuristics are not all-purpose tools but strategies that can perform well in particular environments. This is why an entrepreneur should have an adaptive toolbox of several heuristics, not just a single one.

How do we connect the dots? An heuristical explanation

The decisional processes which aim to build business models can be considered of pragmatic nature and we consider 'pragmatic' the culture that uses empirical facts as its building blocks (Katsikopoulos, 2014). Pragmatic models are defined as those in which a person's goal is to achieve a satisfactory outcome as opposed to attempt to optimize (Katsikopoulos, 2011) and the pragmatic culture is based on an approach that gathers empirical evidence on people's rationality different from that of the idealistic culture and indifferent to testing adherence to axioms. Indeed, this approach focuses on the impact of providing people with tools for boosting performance on tasks of practical importance as we consider in this paper the task of shaping a business idea.

According to the ecological rationality approach (Todd and Gigerenzer, 2012) the accuracy of a decision-making strategy depends on the structure of the environment in which it is used. Ecological rationality formalizes statements about the relative success of different decision strategies for different environmental structures (Katsikopolous, 2014) . Success is measured by external criteria, such as speed, frugality, and predictive accuracy rather than by internal criteria, such as logical consistency. All decision strategies use cues to make inferences, but they tend to differ in how they consider and process these cues. Some models are computationally complex in the way they weight and add cues (linear regression) or make probabilistic computations (naïve Bayes), whereas other models, such as simple heuristics, may use only one cue (e. g., take-the-best) or add cues without weighing their values (e. g., tallying).

If, as we strongly believe, the business model can be considered as an heuristic (Chesbrough and Rosenbloom, 2002) and if any heuristic must have a referential formal structure such as the building blocks structure (Todd and Gigerenzer, 2012) , in this paper we want to find the structure of this business model heuristic.

According to us, business model results less from a carefully calculated choice from a diverse menu of well-understood alternatives, and more from a process of sequential adaptation to new information and possibilities.

The intuition behind this paper is that among the five classes of heuristics that we have treated above, there is one which fits the best to the business model environment and to the process of shaping an idea under uncertain coinditions: the similarity heuristic. Our idea is that the similarity heuristic is strongly linked to the analogical thinking which is already proven to be a powerful and empowering tool for product innovation and increasing performance.

Why the similarity heuristic?

From a cognitive psychology perspective, analogical thinking entails the transfer of knowledge from one domain that usually already exists in memory to the domain to be explained (Gick & Holyoak, 1983; Vosniadou & Ortony, 1989). Management scholars have argued that the use of analogies typically includes the transfer of knowledge (Majchrzak, Cooper & Neece, 2004), where knowledge acquired in one situation is applied to another (Argote & Ingram, 2000). The ability to combine different pieces of knowledge ('combinative capability') for product innovation is a strategically significant resource to a competitive organization (Kogut & Zander, 1992; Grant, 1996).
However, there is limited insight into how analogical thinking is enabled and applied at the level of the firm for product innovation.

Cognitive scientists commonly agree that innovation entails reassembling elements from existing knowledge bases in a novel fashion (Gagne & Shoben, 1997; Hampton, 1998). Thus, analogical thinking is a mechanism underlying creative tasks, in which people transfer information from a familiar setting and use it for the development of ideas in a new setting (Gentner, Rattermann & Forbus, 1993; Dahl & Moreau, 2002). Similarity of concepts (such as problems, situations, solutions) at any level of abstraction is argued to enable analogical thinking and is argued to be the process which leads to connecting the dots.

We explore the way our cognitive system process information when shaping a business idea and try to investigate which are the three building blocks of the similarity heuristic.

METHODOLOGY

In accordance with previous studies both in management and entrepreneurship, such as that Westphal and Stern (2007), and of Gupta et al. (2014), we adopted a qualitative survey methodology (Fowler, 2013). As our intent was to analyze how potential entrepreneurs use the similarity heuristic (and highlight the diversity among them), we chose to devise a questionnaire for students enrolled in management and/or entrepreneurship courses.

The survey contained questions on the adoption of the heuristic of similarity. It also asked respondents to describe the processes underlying the elaboration of their business model. Table 3 shows the technical datasheet of the survey.

Table 3. Technical datasheet of the survey.

Population	**Students**
Scope	Department of Economics of the University of Messina (Italy)
Sample size	130 students

Sample design	Stratified random sampling, taking into account degree course studies as stratification variable
Fieldwork period	April 2015/July 2015

Objective of the survey

The objective of this survey is to take a deeper look at the management students' use of the similarity heuristics when they are asked to elaborate and define their business models.

Definition of the population and creation of the sampling

The population for which the questionnaire was designed was comprised of students from the department of Economics of the University of Messina (Italy). The survey was carried out using stratified random sampling, taking the degree course followed by each student (management vs business economics) as stratification variables.

Characteristics of the sample

A total of 130 subjects participated in the survey. They were all undergraduate students who enrolled by responding to ads posted at the department website. The demographics of the subjects showed a good balance between male (46%) and female (54%). They were relatively young (22 years old on average) and had an average performance corresponding to a score of 25 out of 30. The 79% of the subjects had a background in management while the remaining 21% in business economics. The 16% of the subjects had a job and the 22% declared to aspire to become an entrepreneur.

Table 4 summarises the most relevant characteristics of the sample used for this study.

Table 4. Characteristics of the sample.

Sex (N=130)	
Male	46%
Female	54%
Total	100%
Age (N=130)	
Average	22
SD	1,4
Minimum	21
Maximum	27
Marks (N=130)	
Average	25,5
SD	1,8
Minimum	20
Maximum	29
Laurea Degree Course (N=130)	
Management	79%
Business Economics	21%
Total	100%
Employment rate (N=130)	
Workers	16%
No workers	84%
Total	100%

Writing the survey

The survey was prepared following extensive information and documentation gathering, which included consultation of previous studies by other authors, as well as those designed by official bodies devoted to carrying out similar surveys in a university context.

When designing the survey, particular attention was paid to ensuring that all text would be clear and understandable to all respondents, and also that the language used would be balanced with no hint of bias. All of the questions were followed by a space for answers, making the process of filling out the questionnaire easier for respondents.

Respondents provided personal data and general information (such as gender, age, title of degree course they were taking), as one of the objectives was to ascertain whether there were differences in the opinions of each of those groupings. However, no information was kept that would allow the people who participated in the study to be identified.

Data gathering

The Survey was conducted with paper and pencil at the Aula Magna of the Department of Economics of the University of Messina. Students received a sheet with instructions for taking the survey. After reading the instructions, they were asked to read the case study and answer to the questionnaire. They were not paid with money but received one more grade point to cumulate to the final mark of Strategic Management. The experiment lasted 30-35 minutes on average. Students had no time limit to make their choice in the survey.

Once questionnaires were completed, they were examined individually to ensure the quality of the data provided therein.

The number of participants at the Department of Economics allowed us to gather answers from a significant sample of students. All responses were anonymous, and were collected under the laws governing statistical secrecy and data protection. The responses were used on an aggregate basis, without individual references of any kind.

Data processing

Data was gathered from the completed questionnaires and stored in spreadsheet format, reflecting the answers to each item from respondents. The file was organized into rows and columns, with each row corresponding to one satisfactorily completed questionnaire (one interviewee per row), while the columns reflected the questions contained in the survey. A word-frequency statistics software was used to manage, analyse and codify answers.

RESULTS

The survey was in form of a case study followed by a questionnaire (a translation of both case study and questionnaire is available in the Appendix). A short case study was developed for the subjects to evaluate. Cases can capture the complexities of elaborating a business model and have been used in several studies that evaluated business venture decisions (Zacharakis and Shepherd, 2001). The case method allows the context to be specified so that the subjects are exposed to the same set of information (Finch, 1987; Hughes, 1998). Although long cases both contain rich information and are more typical to entrepreneurs, we kept the case to half a page long. Actually, the length is typical of cases as part of a survey (e.g., Hughes, 1998). We decided to give frugal information about the industry and we deliberately choose to use an attractive topic for our subjects, i.e., service for students, to increase their commitment through stimulating their empathy.

Immediately following the case study, two questions tackle with the key two aspects of our research questions:

1. The first question was a double choice question whose set of options aimed to test whether or not our potential entrepreneurs adopt the heuristic of similarity when approaching a business model under uncertainty;

2. The second question was open and was conceived to uncover the decision rules of the subjects

Similarity heuristics adoption

In the first part of the survey we asked the subjects to put themselves in the entrepreneur's shoes and choose between two options. These two options, gamma and delta, represent two strategies that are possible to adopt for shaping a business model. Specifically, gamma represents the similarity strategy and delta represents the opposite strategy.

As is possible to see in the case study reported in the appendix, we kept the language neutral and the two options were put horizontally on the survey's sheet, to avoid any subconscious suggestion through their position.

The findings of the first part of the survey widely confirmed our intuition. Seventy percent of the sample chose the option gamma, which has been confirmed to signify a more convenient and intuitive decision strategy to adopt. In this way subjects asserted that in approaching the development of a business model they would follow a similarity reasoning and in the second part of the survey they simulate how they would build it. To better understand the significance of this result it is important to consider that both of the options gamma and delta follow a ratio and both of them are meaningful. Nevertheless, the variance between the two percentages is clear.

Table 5. Percentage of similarity heuristic adoption.

Option Gamma (Similarity Heuristic)	**Option Delta (Avoiding external influence)**
70% (90/130)	30% (40/130)

The building blocks of similarity heuristics

A content analysis was conducted of the descriptions of the similarity heuristics adoption process that represent the 70% of answers in our sample in order to surface the key building blocks of the similarity heuristic mentioned in these answers, and to profile the decisions rules used in relation to each decisions rule.

Content analysis is defined as “a research technique for the objective, systematic and quantitative description of the manifest content of communication” (Berelson, 1952, p. 8), or “any technique for making inferences by objectively and systematically identifying specified characteristics of messages” (Holsti, 1969, p. 14). Various phenomena can be counted in a content analysis, including, for example, actors, words or themes. What we were counting were the words. Content analysis was selected as the most appropriate to codify and analyze textual answers as it “is an approach to the analysis of documents and texts ... that seeks to quantify content in terms of predetermined categories and in a systematic and replicable manner” (Bryman, 2001, p. 177). Descriptions of the process of similarity heuristic adoption are considered as sections of text, which are amenable to deconstruction into key words, which can be categorized and counted. However, from our search of the literature, there were no predetermined categories available. Therefore, we used a modified approach to content analysis, which enabled the construction of categories. This is similar to qualitative or ethnographic content analysis (Altheide, 1996; Bryman, 2001), where there is an emphasis on allowing categories to emerge out of the text. However, the categories emerged through transparent quantification (as demonstrated in the following) rather than the researchers simply generating these. In addition, care was taken with coding (to ensure discrete dimensions and mutually exclusive categories) and interpretation of meaning to ensure consistency, reliability and validity.To be more precise, the following steps have been taken in the content analysis:

(1) Cleaning the text in order to simplify the word frequency count process. For example, the word “model” has been used as two different concepts: model as a type of business; and, model as procedures or set of routines. To resolve this complication in the content analysis, “model” as a type of business remained the same but “model” as routine was changed to “procedure”. Another example is the words “university” and “academia”, both referring to the same type of client segment; they have been used interchangeably and hence occurrences of these two terms have been merged and the preferred term is “university”.

(2) Counting of word frequencies – The number of times words appeared in the students’ answers was counted using the word frequency query option of NVIVO11 software.

(3) Grouping of words with the same stem (e.g. implement, implementing, and implementation) in the word frequency results.

(4) Elimination of the words, which appeared only once or twice, or words, which are of no value, such as pronouns.

(5) Clustering of the words students use in connection with each words when they are asked to explain similarity heuristic as shown in Table 4.

(8) The proposal of the similarity heuristic building blocks

It should be noted in Table 4, the counts for some words exceed the total number of answers, for example “service” has been repeated 159 times where there are only 130 answers. This is due to the fact that the word “service” appeared in some answers more than once, for example. Additionally, we split the frequencies of those words that appear exclusively in one answers’ categories from those words that appear in two or three categories. For example, “service” is a common word and appears 85 times in “focus on strengths”, 49 in “overcome weaknesses” and 25 in “rely on successful services”.

Table 6 summarises the total number of occurrences of words in the database of answers, relative to the total number of answers in which that word appears.

Categories	**Frequency count of exclusive words**	**Frequency count of common words**	
Focus on strengths	Strengths, 45 Competition, 30 Differentiation/ Uniqueness, 38 Innovation, 39 Benefit, 20 Certainty, 15	Service, 122 Product, 37 Student, 52 Client, 43 Price/Monetization, 35 Market/Segmentation, 25 Business Model, 24 University, 23	Collaboration/ Network/Interaction, 30 Entrepreneur, 20 Capability, 10 Marketing/ Communication/ Brand, 14 Profit, 30 Web, 13
Overcome weaknesses	Weaknesses, 30 Need, 28 Satisfaction, 27 Improvement/ Development, 32 Problem, 10 Creation/Creativity, 15 Opportunity, 18 Feedback, 17 Efficiency, 28	Service, 59 Product, 26 Student, 30 Client, 37 Price/Monetization, 22 Market/Segmentation, 10 Business Model, 20 University, 17	Collaboration/ Network/Interaction, 9 Entrepreneur, 20 Cost, 10 Marketing/ Communication/ Brand, 16 Profit, 18 Web, 10
Rely on successful services	Success, 11 Fit/Adaptability, 15 Platform, 5 Uncertainty, 15	Service, 33 Product, 22 Students, 4 Price/Monetization, 20 Market/Segmentation, 5 Business Model, 106 Collaboration/Network, 12	University, 8 Entrepreneur, 9 Capability, 8 Cost, 11 Marketing/ Communication/ Brand, 5 Web, 7

Table 7. Words frequencies grouped by categories.

	Total nº of occurrences	**Nº of occurrences in distinct answers**
Service	189	130 (100%)

Product	85	60 (46%)
Students	84	80 (62%)
Clients	80	65 (50%)
Price/Monetization	77	59 (46%)
Market/Segmentation	56	55 (42%)
Collaboration/ Network	51	38 (29%)
Business Model	50	48 (38%)
Entrepreneur	49	37 (28%)
Profit	48	46 (35%)

On the ground of the above word analysis, it is possible to affirm that in the nearly 50% of the cases subjects tend to consider similar services with the specific intent to overcome the weaknesses of those services in their own business models.

“In order to develop my business model, I would analyze a similar service. This process would help me in understanding customer needs and which expectations this service is not able to satisfy”

“To develop my business, I would try to improve and solve weaknesses of similar services, focusing on negative feedbacks from customers”

Accordingly, the building blocks of this decision are as follows:

1. search rule: identify a similar service
2. stopping rule: detect its weaknesses
3. decision rule: overcome its weaknesses in my business model

In the 30% of the answers subjects considered similar services to transfer and improve the strengths of those services into their own business model .

“If already exists a similar service I’m pretty sure that my idea has the potentiality to be successful. That’s way I would try to detect its strengths and improve them in my project”.

“I choose the first option because I think that to consider a similar service is helpful to understand new elements to include in my business model and which feature are crucial for a successful service”

Accordingly, the building blocks of this decision are as follows:

1. search rule: identify a similar service
2. stopping rule: detect its strengths
3. decision rule: improve its strengths in my entrepreneurial venture

Finally, in the remaining 20% of the answers the choice of similarity is considered a parachute to avoid too high risks.

“I would start by considering a similar service to give a foothold to my idea”

“I choose the first option because I’m not a creative person. I’m rather rational and prefer to be inspired by an existing successful model. In this way I wouldn’t be wrong”

Accordingly, the building blocks of this decision are as follows:

1. search rule: identify a similar service
2. stopping rule: select a successful service
3. decision rule: bank on it to avoid risks

Table 8. The building blocks of the similarity heuristic in our sample.

Building blocks	Overcome weaknesses	Focusing on strengths	Rely on successful services
Search rule	Identify a similar service	identify a similar service	identify a similar service
Stopping rule	Detect its weaknesses	detect its strengths	select a successful service
Decision rule	Overcome its weaknesses in my business model	improve its strengths in my business model	bank on a successful service to avoid risks

DISCUSSION AND LIMITATIONS

This article examines to what extent entrepreneurs rely on heuristics to develop their business model. It focused on the cognitive side of business models by illustrating the power of simple decision mechanisms such as heuristics in making fast and frugal decisions. In so doing, it contributes to business model literature that have recently called for more cognitive oriented studies (Baden-Fuller and Mangematin, 2013). It also contributes to a more practitioner-oriented perspective that has been repeatedly called for by, among others, the recent strategy-as-practice movement (Vaara and Whittington, 2012).

The findings of the survey conducted on a sample of 130 subjects confirmed our preliminary insight that similarity fits with the development of business models. This is consistent with the managerial literature focusing on analogical reasoning (Gavetti and Rivkin, 2005). Actually, our study contributes to advancing the state of the art of the received knowledge by revealing how the similarity heuristic enables the incorporation of innovation in business models. In this regard, findings uncovered a basic set of heuristics that can be used as adaptive strategies in the entrepreneurial context. A central feature of our study on adaptive entrepreneurial strategies is that they are based largely on real-world decisions made in uncertain environments. Particularly, we found that the participants in the survey follow three different decision rules when approaching a business model, i.e., overcoming weaknesses, improving strengths and banking on successful products/services. These belong to the adaptive toolbox entrepreneurs exploit in dealing with the uncertainty of the environment.

Although surveys are widely recognized as an efficient method to acquire information, they impose artificiality on the research. Moreover, we are aware that our sample may not fully reflect entrepreneurial actors' decisions, because we are dealing with students taking classes involving entrepreneurship instead of actual entrepreneurs dealing with real money and uncertainty. As a result, the degree on which results can be generalized all over situations and real world applications are limited. This is why we are motivated to test the same research question with a different methodology, such as an experimental survey which has as its participants real entrepreneurs. This would provide us with a potentially less biased result. Nevertheless, this research deserves the merit to lay the basis for opportunities for further basic and applied research such as on the set of basic heuristic principles, the interaction between heuristics and the entrepreneurial environment, the creation of formal tools for organizational application of heuristics, and an integration of insights from different research programs.

We are hopeful that this study will spur a program of research that will enrich the conceptual foundations of opportunity recognition and evaluation based on a cognitive approach. The end goal, of course, would be that entrepreneurs have a better-developed toolbox of heuristics from which to draw in order to effectively and efficiently make decisions.

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APPENDIX

Please answer the following questions after reading the case study.

Imagine that you have the intention to become entrepreneur and to have an idea for a new business. You like this idea and trust in it.

Your idea is to offer a service that allow student to collaborate throughout their educational career. You know that to create this service you need to invest Euro 5.000. The idea is new and you do not have resources to do an in-depth market research.

You feel that there is money to be made based on the positive feedback received from people around you.

1. In order to elaborate your business model (product, clients, price, partner and resources) which strategy do you chose and how do you behave? (Please circle the letter that best reflect your opinion)

Gamma Option	Beta Option
I start by considering an analog/similar service that I already know and think it can be helpful to elaborate my business model	I have clear in your mind how to develop you business and avoid any influence from existing services

2. Please explain your choice and simulate the reasoning if you were the entrepreneur approaching a business model.

(Ex: How do I select my customers/clients? How do I fix the price? How do I decide on the service's features?)

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Final recap of all the Results (Chapter 1, 2 and 3)

DEPENDENT VARIABLE	HYPOTHESES	ACCEPTDED OR REJECTED?	
	Chapter 1: Are they getting along? Public and Private Funding in University Technology Transfer		
Number of Disclosures	1a: *Federal funding has a stronger effect on invention disclosures than industrial funding*	Accepted	
	1b: *Federal Funding moderates the relationship of industrial funding on disclosures*	Accepted	
Number of Filed Patents	2a: *Federal funding has a stronger effect on patents than industrial funding does*	Rejected	
	2b: *Federal funding moderates the relationship of industrial funding on patents*	Rejected	
Number of Licenses	3a: *Industrial funding has a stronger positive effect on patents than federal funding does*	Rejected	
	3b: *Federal funding moderates the relationship of industrial funding on licenses*	Accepted	
	Chapter 2: Do organizations learn from their past failures? A longitudinal analysis of UTTOs		
Organizational Learning	*Prior organizational failure experience does not reduce the likelihood of future organizational failure more than does prior organizational success experience*	Accepted	
	Chapter 3: The Value of the Heuristic of Similarity in the Development and Understanding of innovation		
Decision Process	*There is an heuristic that fits the best the process of shaping an innovative idea under uncertain conditions: the similarity heuristics*	Accepted	