KNOWLEDGE COMMERCIALISATION IN THE NETHERLANDS

An Analysis of its Determinants with a new Approach to Social Capital

Abstract

This paper expands on the theory on knowledge commercialisation by looking at the determinants for knowledge commercialisation for scientists in all scientific fields. The focus of this research is an empirical analysis of the individual agents, scientists, within the context of valorisation. A new approach towards the determinant social capital was explored with the use of newly gathered data on social networks. The findings suggest that digital social capital plays an important role as a determinant for prompting scientists to engage in knowledge commercialisation.

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Preface

This paper is written as the final thesis of the master's degree Entrepreneurship & Strategy Economics, a specialisation of the Economics master programme at the Erasmus School of Economics, part of the Erasmus University of Rotterdam. For the past months I have worked on this thesis. A lot of time went into gathering the dataset, which had to be done manually from the ground up. I would like to thank my supervisor Professor Roy Thurik for his quick replies and support during the period I was writing my thesis.

Work on this thesis was combined with an internship at Valory. Valory is a company that bridges the gap between science and business by providing scientists opportunities to use their knowledge for solving complex business challenges and by sharing their latest insights. Special thanks go out to Arian Oosthoek who was my mentor during my internship. My internship gave me a close look at the practical aspects of Dutch knowledge commercialisation.

I would like to thank my friend and colleague Remco Castelein for critically proof-reading the first version of my thesis. And finally, I would like to thank my friend Martin Dirksen for proof-reading the final version.

Executive summary

Why do some scientists engage in knowledge commercialisation while others do not? Using newly gathered data on Dutch scientists, this paper will give insight into Dutch knowledge commercialisation. Where previous literature has only analysed determinants amongst beta scientists in the United States, this paper will use a different approach in which scientist of all sciences are included in the analysis. Furthermore, this paper will use a new approach on measuring the determinant social capital by using newly gathered data on scientists professional networks. The findings suggest that this digital social capital plays an important role as a determinant for the propensity to engage in knowledge commercialisation. Higher levels of (digital) social capital will generate more opportunities for a scientist to engage in knowledge commercialising activities. I will argue that the decision to engage in knowledge commercialisation for Dutch scientists is for an important part opportunity-based.

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1. Introduction

1.1 Overview

It is widely accepted that an increase in knowledge transfer leads to economic growth. Dutch government policy is therefore actively aimed at increasing ties between universities and business. At the same time, because of possible conflicting interests, the valorising activities of individual scientists are frowned upon. This leads to conflicting incentives for scientists who stand before the choice of commercialising their knowledge.

My research will focus on valorisation at the individual level: knowledge commercialisation. Literature on knowledge commercialisation has mostly focussed on valorisation at the university (institutional) level. This encompasses ties between the industry and universities and mostly addresses knowledge commercialising activities in the field of beta sciences.

In order to form effective government policy on knowledge commercialisation, it is important to ask what the determinants for knowledge commercialisation activities for Dutch scientists are. The aim of this paper is to broaden the analysis of the incentives for knowledge commercialisation to also include forms of knowledge commercialisation found for alpha and gamma scientists. Thus besides starting businesses for commercialising patents and licenses, this study will also look at activities like consulting. The scientists in this study are all professors (assistant, associate and full) at a Dutch university. A new approach is used to quantify the determinant of social capital in which the size of the online professional network of the scientist is used to make up the digital social capital variable. The results of this study support the thesis that digital social capital is an important determinant for knowledge commercialisation of Dutch scientists.

This paper is structured as follows. In this introduction I will start with explaining the context of this research by exploring the European Paradox and the public discussion surrounding knowledge commercialisation. What follows is a literature review of important authors on scientist entrepreneurship, valorisation and knowledge commercialisation. The introduction ends with the problem statement and a short overview of the results of this paper. Following the introduction is the theoretical framework in which the underlying theories are explained and hypotheses are presented. The data and methodology section gives information on the self-gathered dataset. In the following section the results of the logistical regression analysis are discussed. The conclusion section gives concluding remarks, policy implications, limitations and pointers for further research.

1.2 European Paradox

The topic of knowledge transfer has become a hot topic the last few decades in academic circles, but it has also found its way to politicians and even the public discussion. Although we can speak of a relatively large science output in the western European countries, the level of innovation in these countries remains relatively low compared to that of the United States. This great discrepancy between research and actual innovation has been labelled the Swedish Paradox, or European Paradox. Also in the Netherlands, which aims to be knowledge economy, this European Paradox is apparent (Dijkgraaf & Thurik, 2011).

What underlies the European Paradox is a lack of knowledge transfer in the Western European economies. In the U.S., a decrease in federal funds for universities has been replaced by increasing income flowing from the collaboration between academic research and industries. This started in high-tech fields like bio-technology, but has spread to other beta sciences as well (Etzkowitz, 2010).

The various forms of knowledge transfer, also called valorisation, have gained increasing attention in recent years as an important stimulant of economic growth (Etzkowitz, 2010). Valorisation can be defined as converting the results of scientific research into economic and societal value. Application of new insights from science leads to innovation. It is widely accepted that innovation leads to a competitive advantage and therefore economic growth.

Knowledge transfer of the beta sciences is the focus of literature since the 1980’s. For high-tech companies, scientist entrepreneurship is regarded as the main form of knowledge commercialisation. The Bayh-Doyle act of 1980 allowed scientists and universities to commercialise their own patents by starting small enterprises: a form of valorisation at the individual level (Aldridge & Audretsch, 2011).

In light of the last economic crisis and the budget cuts which followed, the Dutch government attempted to compensate for the decreased funding by stimulating increased valorisation at Dutch universities. Like in the U.S. decreased government funds should be compensated with increased income from collaboration with businesses. Policy is aimed at steering the mainly supply-driven research agenda of Dutch universities to a more demand-driven agenda. Supply-driven research as well as demand-driven research should be more tuned to the Research & Development (R&D) agenda of Dutch businesses. Universities should explore knowledge commercialisation for all sciences, not just high-tech or beta sciences (van der Hoeven, 2005). An interesting point is that valorisation policy is aimed only at the institutional (university) level, while a large share of valorising activities are done at the individual level, even more for the alpha and gamma sciences where consulting is the main form of knowledge commercialisation.

1.3 Knowledge commercialisation

Valorisation is a broad term. The focus of valorisation is the transfer of knowledge of academic research to where it can create value. This transfer can be to businesses in the form of an agreement between university and a firm. The sharing of knowledge can also directly create societal or cultural impact through, for example, public lectures. Knowledge commercialisation, as mentioned before, can be defined as valorisation at the individual level: Scientists sharing their knowledge individually and directly with businesses.

The literature has focussed for a long time on entrepreneurial activities of beta scientists when researching knowledge commercialisation. This paper will take any commercial application of scientist knowledge outside of the university into consideration as knowledge commercialisation. This includes the less tangible forms of knowledge transfers mainly found in the alpha and gamma sciences, such as consulting.

Knowledge commercialisation activities at the institutional level have increased the last few years in the Netherlands. Between 2011 and 2013 a growth in contract-research of 12% was measured. This type of valorisation at the institutional level still reigns supreme in the field of beta sciences. Mostly because it is harder to determine the direct economic value of most alpha and gamma research. As opposed to the tangible and directly applicable results of most medical, chemical or technological research, non-beta research often only proves it worth in the long run.

Contract-research entails research done by universities in collaboration with the industry, which means that the research is (partly) funded by businesses who seek to benefit from this research. The focus of cost-benefit analysis by the industry on the short-term thus naturally favours contract-research agreements with beta faculties. For example, at the Erasmus University of Rotterdam, the most valorisation is done at the Erasmus Medical Center. Valorisation programmes of the gamma and alpha sciences at Woudestein are still in its infancy (van Leeuwen, 2013).

1.3 Public discussion

The funding of scientific research has led to knowledge commercialisation to become a highly controversial topic. The fear that the funding of research by businesses would lead to results favourable for the funding business has led to the belief that all knowledge commercialising activities lead to conflict of interests for scientists. A scientist doing research on the effects of smoking on health while being funded by the tobacco industry is a classic example of conflict of interests. Others belief that science should be pursued for its own sake and that the agenda should not be steered by the industry. It is often fundamental research which leads to more radical scientific discoveries and innovations (Metze, et al., 2014).

A study done in the Netherlands by the Onderzoeksredactie in 2013 contributed to the controversy surrounding entrepreneurial scientists. They gave insights into the nature of extracurricular activities and brought cases of conflicting interests to light. The study showed that, although Dutch scientists are obliged to report all extracurricular activities, most do not report everything or even anything at all: Only 45% of scientists with extracurricular activities reports everything, while 25,3% report nothing of their activities. The percentage of scientists who turn out to have incomplete official reports was found to be 30,1% (Metze, et al., 2014).

The conclusions of the study by Metze et al (2014) led to mixed reactions by universities and new political debate. Wageningen University was concerned by the results, but a spokesperson of the Wageningen University & Research Centre saw no need for concern since most scientists of Wageningen University reported the relevant extracurricular activities on their profile page (Onderzoeksredactie, 2014). The Socialist Party (SP) questioned the Dutch cabinet on the matter and asked for these knowledge commercialising activities to be reduced. The minister of education responded that the ties with industry-leaders should not be a problem as long as they remain transparent (Bussemaker, 2015).

This discussion is not new for the scientific and political world. The discussion on social relevance versus conflict of interests has its roots in the 1960's. Merton (1963) was strongly opposed against the idea of the scientist entrepreneur. He argued that scientific advances should be property of the scientific community and not of an individual researcher. These Mertonian norms had become institutionalized as ideals by the 1970's. Links between universities and industry were cut. Directly profiting from doing research was frowned upon by the scientific community (Stuart & Ding, 2006). During the 1980's these norms were supported with incentive theory from Bok (1982), who argued that commercialization would lead to scientists withholding information from the scientific community until they could file for a patent. This secrecy would undermine the communal ownership of scientific discoveries. During the 1990's, the Mertonian norms began to change to allow for scientist entrepreneurship. This change began in the bio-tech industry. Limited secrecy became normative justification for academic entrepreneurship (Stuart & Ding, 2006). The rise of scientist entrepreneurship was opposed by authors like Brooks (1993) and Krimsky (1991) who feared that scientists would lose their role as independent critics of society. Ironically, the industry also feared increased scientist entrepreneurship as academics could become competitors and keep new technology out of the hands of the industry. They preferred knowledge commercialisation in the form of academic consultants (Etzkowitz, Webster, Gebhardt, & Terra, 2000).

1.4 Relevance

The study done by the Onderzoeksredactie (2013) unintentionally brings to light a flaw in the Dutch university incentive structure. Apparently, scientists have an incentive not to report their activities. Does this also lead to discouragement of knowledge commercialising activities and thus to less transfer of knowledge? In order to answer this question we must seek the answer to the broader question of what the determinants for engaging in knowledge commercialisation at the individual level are.

This analysis of knowledge commercialisation for all sciences can create possibilities for further research, bringing us closer to a model for explaining the determinants for knowledge commercialisation for scientists. This in turn will allow for policy to give incentives for increasing knowledge transfer through stimulating knowledge commercialisation. These insights will in turn also allow for the creation of a new valorisation model for universities with reduced risk of conflicting interests.

The economic and societal value of alpha and gamma sciences has long been underestimated by businesses. Especially the non-technological aspects of innovation can play an important role in the improvement of products, processes and management. Dutch government policy aims to increase knowledge commercialisation in these fields (Ministerie van Onderwijs, Cultuur en Wetenschap, 2014).

Research in this field can help determine the best approach for revision of valorisation policy. As stated earlier, it appears that the Dutch incentive systems gives little room for knowledge commercialisation. The international ranking of universities based on citations has led to the 'publish or perish' culture. Scientists are incentivized to publish as much as possible, which has led to research of lower quality or even fraud. The infamous Tilburg University professor Diederik Stapel who committed statistical fraud claimed that he had done it under pressure of this system (Hamel, 2011).

Valorisation at the individual level might be a more efficient alternative for governments trying to steer the agenda of universities. It will allow for scientists to focus on their preferred research and let them transfer this knowledge based on demand when they see fit. Research into the determinants of this decision to engage in knowledge commercialisation can help shape the best environment for this kind of knowledge transfer.

This research will thus fill a gap in the scientific discussion on knowledge commercialisation. While some research on the topic has been done by the Onderzoeksredactie (2014), an analysis using a clear distinction between extracurricular activities and knowledge commercialising activities is needed. This research will take its place in the national discussion on scientist entrepreneurship while also contributing to the scientific discussion on the European Paradox, for which knowledge commercialisation is seen as a solution (Dijkgraaf & Thurik, 2011).

In the discussion for knowledge commercialisation, only whether or not it is a “problem” is discussed. Nauta (2011) argues in his article that there are conflicting incentives for Dutch scientists. They are rewarded for both heavy publishing as well as participating in valorisation programs. At the same time, they risk punishment for engaging in knowledge commercialisation. The recent shaming of scientists with extracurricular activities discourages knowledge commercialisation, but does not bring us closer to a solution for the European Paradox. Studying the underlying determinants for knowledge commercialisation allows working towards a solution which allows both the benefits of efficient knowledge transfer through knowledge commercialisation and reduction of possible academic corruption.

In this paper I will first give an overview of literature on knowledge commercialisation, knowledge transfer and scientist entrepreneurship. The theoretical framework presented in this paper will be based upon theories derived from the literature, along with some new additions on social capital. This section will be followed by an overview and explanation of the data and used methods. The hypotheses will be tested in the results section after which the findings will be discussed. The conclusion section will give a summary of this paper along with concluding remarks based on the findings of this study.

1.5 Literature review

Many authors have written about the determinants of scientist entrepreneurship since its rise in the 1990’s. Sometimes the line between the field of economics, sociology and psychology become blurry. In this paper I focus on the economic papers with where relevant mention of sociology studies on the subject.

Levin & Stephan (1991) used theories from studies on entrepreneurship to explain the decision of some scientists to engage in knowledge commercialisation. They found support for their life-cycle theory in that more mature scientists have a higher propensity to engage in commercialisation activities. They also argued that social capital was an important determinant. Since social capital is hard to measure, they used gender as a proxy. The reasoning was that because of gender inequality, males simply have more social capital on average through their well-connected positions in scientific advisory boards and the like. The main argument of their work is that a scientist will commercialize research only if this is his or her life goal (Levin & Stephan, 1991).

Research done by Joanneum (2001) shifted focus to the institutional level and identified several incentives for scientific institutions to engage in knowledge transfer. He argued that the extra income for the university and diversification of funding would be important along with the increased labor market possibilities for her graduates. At the individual level, increased collaboration would give scientist field knowledge and inspiration for new research. Closer ties between university and industry would thus improve the infrastructure for knowledge (Joanneum Research, 2001).

Michelacci (2003) analysed the low rate of return on R&D and found an opportunity-based explanation in the lack of entrepreneurship amongst scientists. He argues that opportunities are created where new knowledge is created but not commercialised. Thus differences in the level of scientist entrepreneurship for different regions can be explained by looking at investment in knowledge. Scientist entrepreneurship is thus the highest where investments in new knowledge are the highest (Michelacci, 2003).

Jensen & Thursby (2004) use the principal-agent framework for explaining knowledge commercialisation. Incentives for knowledge commercialisation are mostly found in their institutional environment: the university. Scientists gain utility from prestige and income, and also simply on time spent on both applied and basic research. They argue that whether or not a scientist engages in knowledge commercialisation (and for how many hours a week) can be explained by prestige and income they earn both inside and outside the university. This means that simply increased income from knowledge commercialisation is not a sufficient explanation, because increased income from knowledge commercialisation also leads to decreased prestige within the university (Jensen & Thursby, 2004).

Audretsch & Erdem (2004) add a significant number of variables to the model for scientist entrepreneurship. They are the first to link personal motivation of scientist to become an entrepreneur to both public policy and regional context, which until then had been considered to be unrelated. They include the effect of public policies in their model, such as government programs aimed at scientist entrepreneurship. They also expand on the theory of social capital in stating that a demonstration effect is of importance: seeing others engage successfully in knowledge commercialisation could be an incentive for scientists to try it themselves. Like Jensen & Thursby (2004), they argue that scientist entrepreneurs differ from regular entrepreneurs in that they have to balance their scientific career and entrepreneurial activities, which in turn complicates personal utility determinants like income and prestige.

Audretsch & Erdem (2004) also stress the importance of scientist entrepreneurship and point to required further research in the field of knowledge commercialisation. They argue that start-ups created by entrepreneurial scientists are a conduit for knowledge spillovers. Thus scientist entrepreneurship is an important mechanism through which knowledge spills over and becomes commercialised. There are modes for academic research commercialisation which remain unexplored in his study. Audretsch & Erdem (2004) state that modes like consulting are hard to measure. The modes that he includes in his research are limited to patents, licences and start-ups in the field of medical science. This is already a broader approach than previous studies however, which generally only look at the number of licenses granted.

Stuart & Ding (2006) do include scientific advisors in their study which allows them to study the bigger picture on knowledge commercialisation. They too emphasize the importance of social capital along with the demonstration effect, which they labels social influence. They argue that the mere presence of entrepreneurial scientists in an academic environment is likely to have a positive effect on the attitude of other scientists towards entrepreneurship. Contrary to contemporary leading theories on scientist entrepreneurship, the results of their analysis show that higher prestige leads to more entrepreneurial activity. They explain this by the fact that less prestigious scientists don’t have the same access to social capital as more prestigious scientists. Another explanation they give is that prestigious scientists are immune to reputation damage.

A recent study done by Etzkowitz (2010) shows that scientists increasingly choose to allocate their time to consulting activities and research agreements with industrial partners. He finds evidence for a crowding-out effect between publication activities and knowledge commercialisation in the form of commercialising patents. The majority (65%) of scientists in his study report that working with the industry helped them improve as a researcher or sparked new ideas.

Goethner et al (2011) looked at the decision to engage in knowledge commercialisation from both a psychological and economic perspective. They found a direct effect between social capital and the decision for scientists to become an entrepreneur. They argue that high levels of social capital especially affects the early stages of entrepreneurship, when professional connections are most valuable. Besides business opportunities, other scientist entrepreneurs can give them practical help to get started.

Authors touching upon Dutch knowledge commercialisation are more scarce. Hanneman (2007) looks at the decision to engage in knowledge commercialisation (patenting in this case) from a more practical point of view. He mainly looks at reward and career trajectory as main variables and argues that for Dutch universities academic excellence (publishing in peer-reviewed journals) is more important than research with economic relevance. During salary negotiations, the number of refereed publications is far more important than knowledge commercialisation. He concludes that Dutch universities have a publish-or-perish culture instead of a valorisation climate.

Freytag & Thurik (2007) argue that macro-economic circumstances thus determine the preference of scientists to become entrepreneur. However, actual decision is possibly determined by hard economic factors (like taxes and regulatory burdens) or culture. In his study, Jongbloed (2008) also recognizes that the European industry is facing problems in that it takes a long time before results from research become industry innovations. Block et al (2009) even find that the profits of research do not flow back to the region where the knowledge is produced resulting in what is called the European Paradox.

Nauta (2011) compares the situation in the Netherlands directly with that in the United States. He claims that approximately 1 in 10 professors have their own business in the Netherlands where this is 9 out of 10 for their American colleagues. Nauta believes this to be due to the differing incentive structures between Dutch and American universities. American scientists are only payed for three days of work, in the remaining two days they are expected to earn their income with knowledge commercialisation. His policy recommendation is for Dutch universities to adopt this same system.

Literature does not yet provide answers for the determinants of knowledge commercialisation for all sciences. Venditti (2013) acknowledges in a more recent paper that Alpha and Gamma sciences have been ignored by valorisation studies and government programs. This underestimation can be explained by the fact that beta science oriented modes of commercialisation offer more tangible and direct results than, for example, consulting. For example, we can measure the number of patents commercialized and its revenue gained from its application. Alpha and Gamma sciences generally don't work with patents or licences. The inclusion of alpha and gamma scientists will give a more complete picture of the determinants of knowledge commercialisation, although a new approach is needed in which other forms of knowledge commercialisation are included.

This paper aims to fill this gap in the scientific discussion on knowledge commercialisation. Most of the earlier studies on this topic did not include modes of knowledge commercialisation other than scientist entrepreneurship in their models. Modes which are most common for Alpha and Gamma sciences, like consulting, are not researched extensively. To be able to understand the determinants of knowledge commercialisation, all modes of knowledge commercialisation must be included into the model.

Another missing link in the literature is a quantifiable variable for social capital. As we have seen, social capital is considered an important focus point for most literature in determining the decision to engage in knowledge commercialisation. However, the proxy variables used for this are either generalized (gender) or hard to measure for individuals (spatial proximity). Often, social capital is therefore not included as a variable in regression models at all. In this paper I will introduce a new approach for measuring social capital by including a network variable. With this, I will attempt to provide a solution to the intangibility of social capital.

Most studies have used American scientists in their sample. Using data on Dutch scientists will allow for comparative future research on differences in incentives between European and American knowledge commercialisation. Effects of public policy on valorisation could be compared alongside cultural factors. Before national comparisons can be made, comparisons between Dutch universities need to be made. This paper will therefore focus on Dutch universities.

For this novel approach, I will use a newly collected dataset containing real world data. This data on Dutch scientists from all sciences and all universities is collected from university profiles, Linked-in profiles and several other sources publicly available on the internet. It will include a new approach on measuring social capital in which data is used on the size of the digital social capital, allowing for a more precise measurement.

1.6 Problem statement

The objective of this paper is to explore what variables cause scientists to engage in knowledge commercialisation, using newly gathered data on Dutch professors. An attempt is made to extend the theory of social capital for knowledge commercialisation by including digital social capital. Also, this study broadens the research on knowledge commercialisation by including data on scientists from all sciences, not just Beta sciences. Furthermore, this paper will use a statistical analysis to find evidence for an explanation using differences in culture between universities. In sum, this paper will attempt to answer the question of what the determinants are for Dutch scientists to engage in knowledge commercialisation.

In this paper I will statistically test a model based on incentive theories found in the literature on knowledge commercialisation, scientist entrepreneurship and valorisation. To the model I will add university culture variables and digital social capital. This paper will thus contribute to the literature by using a new, more complete approach towards knowledge commercialisation. The empirical analysis in this paper can be seen as a first attempt and will hopefully lead to further exploration digital social capital and university incentive structures.

This study offers a number of interesting findings on the determinants of knowledge commercialisation. Evidence is found for a positive relationship between digital social capital and knowledge commercialisation, ceteris paribus. Also, a significant positive effect of nationality on knowledge commercialisation is found which may also support social capital theory. The found positive relation between age and knowledge commercialisation may support the scientist life-cycle and career-trajectory theories. No evidence for any significant difference between universities on the level knowledge commercialisation of their scientists was found. Based on these results, this paper will argue that the decision to engage in knowledge commercialisation for scientist is mainly opportunity-based.

The apparent problem of valorisation policy lies in the lack of focus on the actual incentives for the knowledge commercialising scientists. In this paper I will argue that instead of discouraging individual pursuits of knowledge commercialisation of professors, universities and businesses can possibly benefit from this mode of knowledge transfer. Instead of trying to steer the research agendas of universities, policy could focus on stimulating universities to facilitate knowledge commercialisation activities of scientists. This will increase their window of opportunity which in turn increases the level of knowledge commercialisation. Facilitation of knowledge commercialisation by the university will decrease the high number of scientists who commercialise their knowledge in secret and will allow monitoring and prevention of conflict of interest.

This new policy of transparent and facilitated valorisation can only succeed when universities change their stance on extracurricular activities of scientists. A complicating factor is the increasing international competition between universities based on the citation ranking system. To steer this system more towards competition based on valorisation is beyond the scope of this paper but worth investigating in further research.

More extensive data collection on all scientist in the Netherlands would allow for more conclusive evidence to support this policy recommendation. Ideally this would include qualitative data such as interviews to gain more insight into scientists intentions. This study did not include analysis of effects over time which is only possible when data is collected over time with help of all Dutch universities. This way data on wages could ideally be collected and neo-classical entrepreneurship theory on the effect of income could be included in the model. Future comparative studies could look at differences in determinants between American and European scientists to further explore knowledge commercialisation in the context of the European Paradox.

2. Theoretical framework

2.1 Entrepreneurship

In the literature on valorisation and scientist entrepreneurship we can find several theories exploring determinants for engagement in knowledge commercialisation. While several theories are applicable to regular entrepreneurs as well as scientist entrepreneurs, there are important differences. Although knowledge commercialising activities may include starting a new business, this mode is not in the majority when including Alpha and Gamma scientists. A lot of knowledge commercialising activities are not especially risky, except for the risk of being punished by the university when risking conflict of interest. The risk-taking personality factor, which is important in general theories on entrepreneurship, is therefore relatively less important here. For this reason, these factors are not included in the model.

2.2 University incentive structure

Stuart & Ding (2006) point out that studies done on the culture of the universities of California, Berkeley and Stanford show that the values at Stanford are much more supportive of scientist entrepreneurship. They argue that this supportive work environment has a positive effect on scientist entrepreneurship. Could this positive effect also be the case for Dutch universities? Nauta (2011) thinks that this indeed is the case. He states that professors from Dutch universities are less likely to engage in knowledge commercialisation compared to British and American universities. This statement assumes that university context is an important influence on the decision to engage in knowledge commercialisation. In the literature we can find that both the incentive structure and university culture can be influencing factors. These two factors are intertwined, since incentives like wage, promotions and punishment arguably come forth from the norms on knowledge commercialisation. An environment which discourages or even punishes knowledge commercialisation will have a negative effect on the likelihood of scientists trying these activities for the first time. As Goethner et al (2011) argues, the effect is greatest in the first stages of scientist entrepreneurship.

This study has its focus on Dutch universities. As Stuart and Ding (2006) has shown, universities in the same geographical area can have different stances on knowledge commercialisation. It is important to see whether there are significant differences between Dutch universities in their stance and support on knowledge commercialisation before comparing this effect with foreign universities.

In general, the incentive structure follows the same guidelines for universities in the Netherlands. Dutch scientists are encouraged to inform the university of their extracurricular activities. If they fail to report ‘relevant activities’ they are labelled as showing misbehaviour. What activities are exactly relevant is open for interpretation, which results in reported activities widely differing. Some scientists report even voluntary charity activities while others don’t report anything at all because they don’t deem it relevant. In contrast, rules are more clearly defined for university medical centres (UMC's). Scientists working at UMC's are only required to report activities which could damage the UMC's interests or the scientists integrity (VSNU, 2013).

Differences between universities become more noticeable when looking at how universities follow these official statements in practice. The Onderzoeksredactie has done some research on this matter but they mostly only state official university guidelines on valorisation. For example, Delft allows professors one day each week to engage in extracurricular activities. While scientist in Utrecht and Leiden need to report every extracurricular activity, other universities like Delft, Eindhoven and Twente only require reporting of activities with potential conflict of interest (Metze, et al., 2014). It is hard to get a complete picture of the stance on knowledge commercialisation for each university. Official statements might not necessarily reflect the university's real stance on knowledge commercialisation. Further qualitative research on this matter may shed more light on the case.

Looking at the results of valorisation activities for each university might provide a proxy for university incentive structures. The argument is that more supportive incentive structures lead to increased quantity of valorisation activities. A ranking of valorising universities was made by Elsevier every two years. The last one was made in 2013 and contained an extensive analysis on valorisation on multiple fronts such as entrepreneurship, collaboration with industry and profits (van Leeuwen, 2013).

Is there a difference in the effect of the incentive structures of these valorising universities compared to less valorising universities? My expectation is that the incentive structure which supports other forms of valorisation for these universities also supports knowledge commercialisation at the individual level. Therefore I hypothesize the following:

Hypothesis 1: The likelihood to engage in knowledge commercialisation is greater for scientists working at universities with a higher valorisation ranking compared to universities with a lower ranking.

2.3 Social capital

2.3.1 Network effect

Many authors on scientist entrepreneurship use social capital as an important determinant (Goethner et al., 2012). Social capital is the expected economic benefits derived from an individual's social network. These benefits can be for example preferential treatment or (business) opportunities which open up for an individual.

These benefits are hard to observe so models including social capital use proxies to observe the effect of social capital. Certain factors which enhance opportunities can arguable be used as a fitting proxy.

For example, literature has used gender as a proxy variable for a long time. Being male would give access to higher levels of social capital, because they are more often member of a scientific advisory board or other influential positions (Audretsch & Erdem, 2004). In a world of increasing gender equality, it has to be seen whether gender still holds up as a proxy variable.

In the same fashion it can be argued that nationality can be used as a proxy variable for social capital when examining knowledge commercialisation within one country. Being Dutch in the Netherlands automatically gives you a head start because you speak the language, know the culture and already have connections through your personal network. This increases the amount of opportunities and thus the benefits gained.

One could argue that since social capital is a measure of the benefits derived from ones social network, a larger social network should lead to larger benefits. Thus the most direct practical way of measuring social capital would be measuring the size of the social network. This used to be impossible to measure, since no one held a list of their known connections. Nowadays, with the advent of social media, more and more information on peoples social network becomes available. The professional social network website Linked-In has its focus on business connections and can thus arguably be seen as a fairly accurate measure of the real size of one's social network.

A possible argument is that the size of the social network is not the sole factor for measuring social capital. An important factor for making this network generate opportunities is the quality of the connections. Is it a distant relative in a different country or a well-placed friend in business? Also, how do you use this social network? Becoming visible for your connections is important for showing what your capabilities and interests are. When it is clearly visible for others what your expertise is, opportunities will present themselves more easily.

Higher levels of social capital generate more opportunities for scientists to engage in knowledge commercialisation. This lowers the threshold, by reducing the time and effort for a scientist to look for opportunities. Therefore, a more connected academic world will increase the number of scientists who commercialise their knowledge. Especially for activities like consulting, the threshold is lower than for a more risky decision like becoming an entrepreneur.

2.3.2 Demonstration effect

Another effect closely tied to social capital is social influence: the influencing of another individual's behaviour. A scientist entrepreneur who has successfully commercialised his knowledge might become an example to other scientists in his department, faculty or university. Social influence thus spreads through one social network. It can be argued that having a larger social network thus increases the chance of becoming influenced (or influencing) others (Stuart & Ding, 2006).

Stuart & Ding (2006) argue that this effect is especially true in work-environments and when there in closer spatial proximities. Having a scientist who engages in knowledge commercialisation in the same office thus has a larger influence than someone in another faculty in another building. However, the world has become more closely connected and contact between people has shifted to the digital realm. Networking also shifts to the national level instead of just the local. It can be argued that spatial proximity is less important as a factor for this reason. Thus it is interesting to study social influence through online social networks such as Linked-In. Examples of online social influence might be a scientist who shares his experiences working with the industry with his network. Furthermore, Linked-In connections arguably reflect ones real professional network, on condition that one regularly uses Linked-In to add new connections.

Hypothesis 2: The likelihood to engage in knowledge commercialisation is positively related to the level of social capital of a scientist.

2.4 Scientist career-trajectory and life-cycle

The scientists personal life can be an important factor in the decision to change his or her focus towards commercialising knowledge. Audretsch & Erdem (2004) state that, for scientists, the career can be seen as an important factor. A scientist who has a focus on his scientific career may feel less for doing jobs outside of the university. The design of the university incentive system can play an important role in steering this trajectory.

At the moment, Dutch universities do not take into consideration any valorisation efforts through knowledge commercialisation when negotiating for promotion or salary. An assistant professor may thus feel that the need to publish is more important because it is the only way of advancing his or her career (Jongbloed & van der Sijde, 2008). On the other hand, full professors already have the prestige and desired rank within the university. For this reason, their focus may shift towards gaining prestige outside of the university.

The life-cycle hypothesis focusses more on the age of the scientist. Levin & Stephan (1991) found evidence for a negative relation between age and scientific productivity. Younger scientists focus more on their scientific career, which they advance through publishing. Possible, the ambition of older scientists might shift towards entrepreneurial activities as they have reached the limit of their academic career.

The incentive structure of universities may have an effect on the decision to engage in knowledge commercialisation through the life-cycle effect. A negative stance on knowledge commercialisation may result in an incentive structure discouraging scientific staff to commercialise knowledge. This could manifest itself in punishment, reputation loss and lower chances of promotion. Young scientists will therefore more likely solely pursue the more rewarding path of research and publishing (Jensen & Thursby, 2004). On the other hand, older scientists of higher rank (full professors) are to some extent immune to the taboo surrounding knowledge commercialisation because of their proven, prestigious and influential position. I therefore hypothesize the following:

Hypothesis 3: The likelihood to engage in knowledge commercialisation is positively related to the age of a scientist.

Hypothesis 4: The likelihood to engage in knowledge commercialisation is positively related to the level of academic rank of a scientist.

2.5 Public policy context

Public policy can be used to steer universities towards being more supportive for valorisation efforts. Dutch government funding for universities have been reduced (the first cash flow) and this loss of funding needs to be balanced by extra income from valorisation. Dutch policy is mostly focussed on steering the research agenda of universities from basic research to applied research (van der Hoeven, 2005). The net effect of this policy on the stance on universities is hard to measure. On the one hand it increases the ties between scientists and industry, but on the other hand it could have the effect of creating a government versus university situation. This situation might influence the stance of universities on valorisation in a negative way. Since public policy is the same for all Dutch universities, we do not include it in our model. Further comparative research with foreign universities might need to analyse this effect further.

3. Data & Methodology

3.1 Data source

In order to statistically test the hypotheses, data on Dutch scientists is needed. Since this data was not available, I collected this data myself. Personal data on scientists was collected using publicly available personal profiles from university pages and Linked-In, often supplemented with information from CV's and media articles. This proved to be more difficult than expected, since most university websites were not up-to-date. Information was thus completed using activities stated on Linked-In profiles and CV's. When these profiles did not show any activities either, the professor was googled and the first 20 hits were browsed for any knowledge commercialising activities. Despite these efforts, this dataset might not give a true representation of the knowledge commercialisation of scientist due to the real possibility of them not reporting all activities (Metze, et al., 2014).

A random sample of 273 scientists was taken from the population of university scientists working at Dutch universities. This sample was equally distributed over 13 Dutch universities (Erasmus University Rotterdam, Leiden University, Nyenrode Business University, Radboud University Nijmegen, Delft University of Technology, Eindhoven University of Technology, Tilburg University, University of Amsterdam, University of Groningen, University of Twente, Utrecht University, VU University, Wageningen University). The samples of each university were equally distributed over the university's faculties.

The number of observations used in the model is 188 since 85 scientists did not have Linked-In or their profiles were not available to me because of privacy setting or due to the fact that I did not use a premium Linked-in profile. This study's level of analysis is at the individual level. The scientists in this sample are all either assistant-, associate- or full-professor.

3.2 Variable descriptions

3.2.1 Knowledge commercialisation

The dependent variable for this model is a dummy variable (*dknowcom*) which takes the value of 1 if the observed individual engages in knowledge commercialising activities.[1] Of all reported extracurricular activities of the scientists in this dataset, a clear distinction needed to be made between non-commercialising and commercialising activities. An extracurricular activity is seen as knowledge commercialisation when we can speak of knowledge transfer with commercial benefits for the scientist. The most common examples of this are consulting jobs for a wide range of businesses and

[1] A subdivision was initially made between knowledge commercialising scientist who were business owners and those who had part-time jobs, but this distinction proved not to be relevant for this research.

(government) institutions; partner at a firm; (small) business owner; giving courses or seminars at firms; specialist professions like doctors, dentists and psychiatrists; scientist in residence at a firm or the commercialising patents and licenses. Admittedly, the line can sometimes be blurry. In many cases it is not clear whether or not the scientist was paid for the knowledge transfer. The following common extracurricular activities are not considered knowledge commercialisation: Editor or reviewer of scientific journals; jury; visiting professor; guest lectures at scientific institutes; organising conferences; a board position within a scientific institute; research activities within a scientific institute; committee position; incidental readings or talks; memberships (KNAW, Royal Academy).

In the table below we can see the distribution of the dummy variable for knowledge commercialisation (*dknowcom*).

Table 1: Distribution of the dummy variable for knowledge commercialisation

1 if Knowledge Commercialisation	Freq.	Percent	Cum.
0	159	58,24	58,24
1	114	41,76	100
Total		273	100

As shown in this table, the majority of scientists (58%) in this sample does not engage in knowledge commercialisation.

3.2.2 Rank

The lifecycle and scientist career trajectory theories found in the literature look at both rank and age. As argued in the theoretical framework, the propensity to commercialise knowledge might be influenced by the rank of the scientist. The scientists in this dataset are either full professors, associate professors or assistant professors. This information was collected from university profiles. A dummy variable was made for all three ranks. In the table below we can see the distribution for every rank.

Table 2: Distribution of the Rank variable

rank	Freq.	Percent	Cum.
Assistant Professor	48	17,58	17,58
Associate Professor	31	11,36	28,94
Professor	194	71,06	100
Total	273	100	

As shown in this table, the majority of the dataset contains full professors. This is due to the fact that university websites had very inconsistent scientist profile databases. Even within universities, these differed greatly between faculties. Some faculties only had information on full professors, therefore the distribution probably does not reflect the real population. This might cause bias for the university dummy variables, since some universities only had information on full professors.[2] Included in the model are the full- and associate professor dummy variables, with the assistant professors as the reference group.

3.2.3 Age

The other explanatory variable for the scientist career trajectory theory is age. The age of every scientist in the dataset was collected from university profiles. When the age was not available, the age was calculated based on the date of graduation or start of a study.[3] This way of calculated guessing means that some of the observations might be off by a few years. In the table below we can see the summary statistics of age.

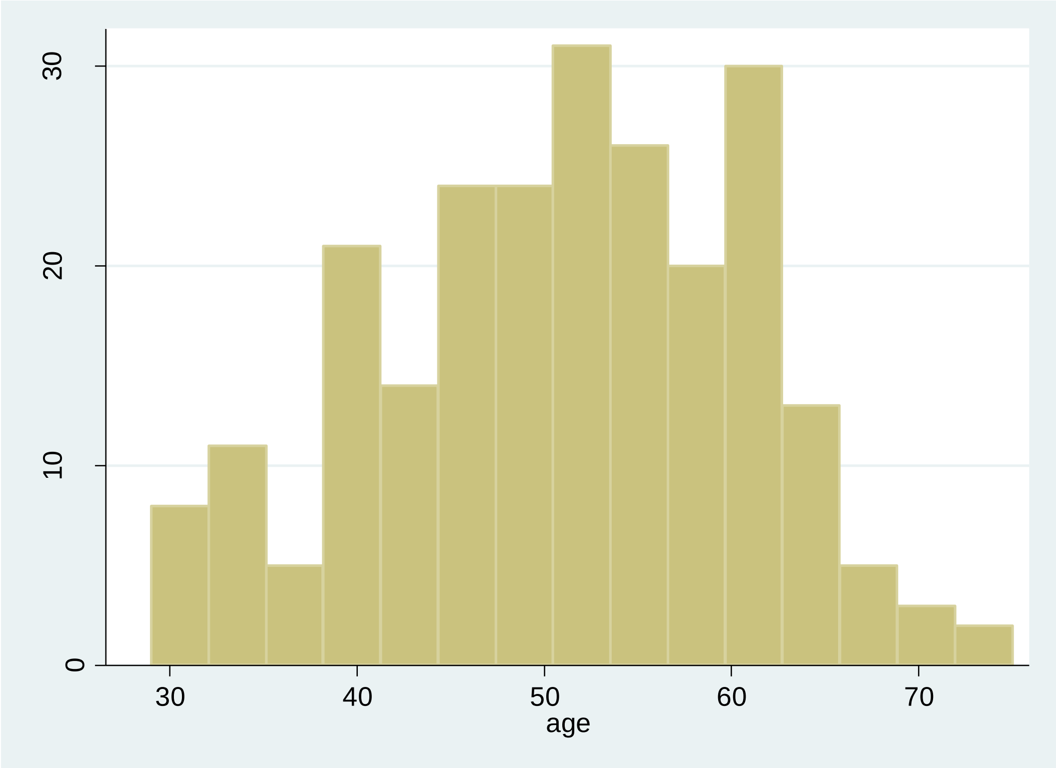
Table 3: Summary statistics of the age variable

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	237	51	9,53	29	75

As can be seen in the table above, the average age of scientists in this sample is 51 with a standard deviation of 9,5 years. The youngest scientist in this dataset is 29 years old and the oldest is 75. Indeed, some professors in this sample who are beyond the age of retirement are still active at the university, or outside of the university. In the histogram below we can see the distribution for *age*.

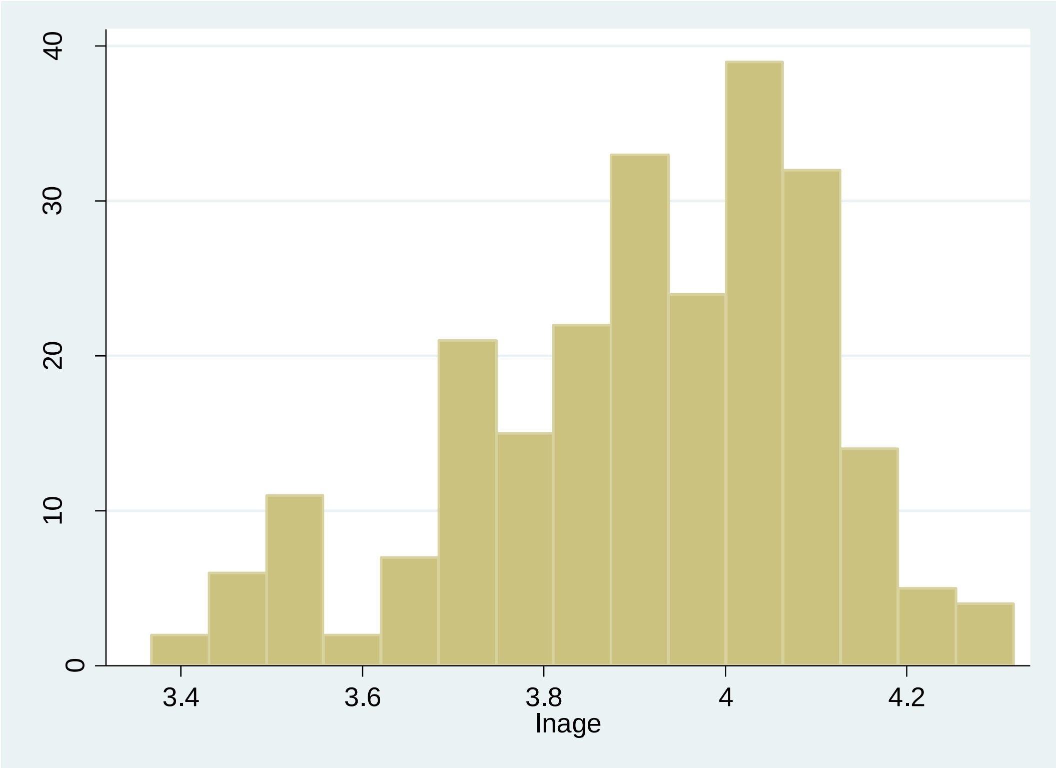
[2] A possible solution would be to only compare the full professors of each university. However, rank turned out to be insignificant either way. Therefore it should not have an effect on the university variable.
[3] The calculations was based on the assumption that a scientist was 18 years old when starting a study and around 22 or 25 years old when finishing (depending on the number of studies).

Figure 1: Distribution of the age variable



As we can see, the distribution of the age variable approximates a normal distribution. The variable was transformed in a log-variable which gives the variable *lnage*. In the histogram below we can see that the distribution of *lnage* fits the shape of a normal distribution better. Therefore *lnage* is used in the logistical regression model.

Figure 2: Distribution of the lnage variable



3.2.4 Science

Three dummy variables were created to represent the three scientific fields: *Alpha*, *Beta* and *Gamma*. When looking at knowledge commercialisation for different sciences in this sample, we find that the percentage of scientists engaged in knowledge commercialisation is highest among Gamma scientists (43%), closely followed by Beta (42%) and lastly the Alpha sciences (36%). Interestingly, the focus of literature has long been on Beta knowledge commercialisation while this sample suggests that knowledge commercialisation occurs as often for Gamma scientists.

The gathering of scientist observations was evenly spread over all the faculties of every university in the sample. As we can see in the table below, this means that the spread of scientists in this sample is uneven.

Table 4: Distribution of the science variable

Science	Freq.	Percent	Cum.
Alpha	42	15,38	15,38
Beta	118	43,22	58,61
Gamma	113	41,39	100
Total	273	100	

Beta and Gamma sciences are better represented in this sample compared to Alpha sciences. This however makes sense since Alpha sciences are in the minority in Dutch universities. Since most studies focus on Beta sciences, I include Alpha and Gamma sciences in the model with Beta as a reference group.

3.2.5 Social capital

In the theoretical framework we have distinguished several variables which could act as proxy variables for social capital. The size of the social network, measured by the number of Linked-in connections; nationality and gender.

Linked-In is an online platform for social networking.[4] It focusses on professional networking and offers multiple tools to enlarge your network and get in contact with others. By regularly updating your profile, others can see your skills and experience. The number of Linked-In connections a scientist has was collected and this creates the variable for *socialcapital*. Checks were done for every scientist and information from Linked-In profiles were only used when it was sure (based on job description) that it was the scientist in question. In the ideal situation this number would represent the size of the individuals real world network. Strictly, it would be more fitting to use the term digital social capital. In the table below we can see the summary statistics for the variable *socialcapital*.

Table 5: Summary statistics for the socialcapital variable

Variable	Obs	Mean	Std. Dev	Min	Max
socialcapital	211	529	480	0	2832

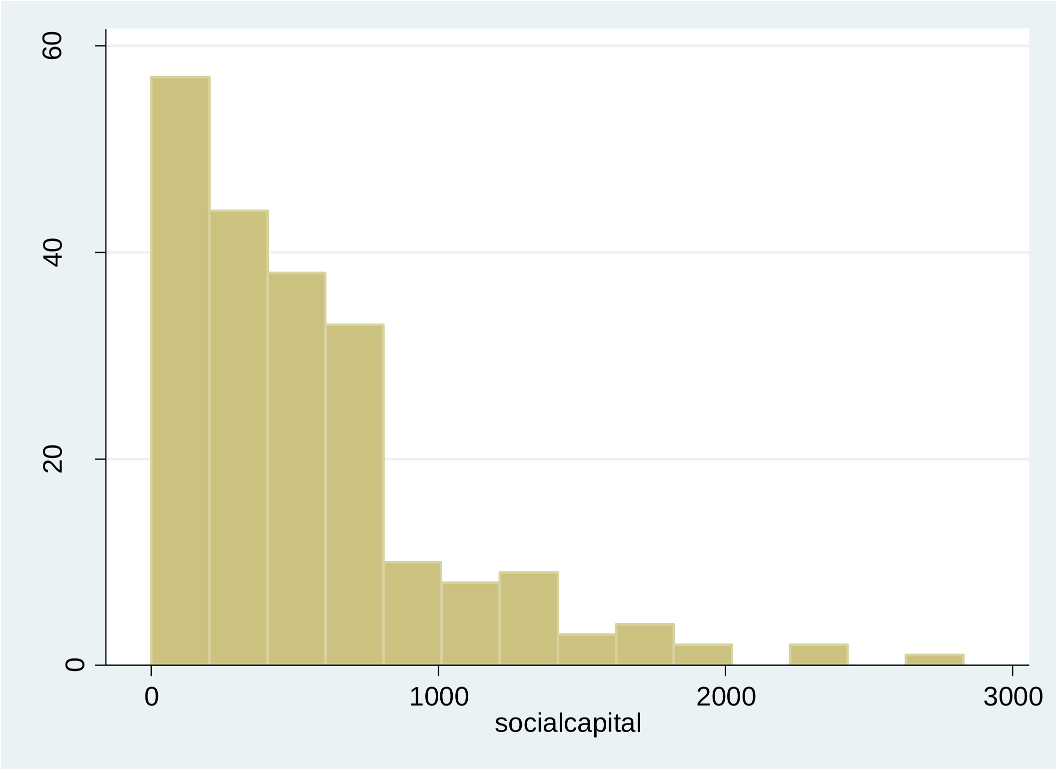
As shown in the table, the number of observations for *socialcapital* is lower than the total number of observations in this sample. This is due to the fact that some scientists did not have a Linked-In profile, or that their profile couldn't be accessed by me.[5] Due to this constraint, people without a Linked-In profile gained a missing value in de dataset instead of a zero. The possibility exists that they have a large digital network while I would have reported them of having none, which would cause bias. The lowest number of connections in this sample is zero while the highest is 2832 connections. Indeed,

[4] www.linkedin.com

[5] Some profiles can only be seen when using a Premium-profile.

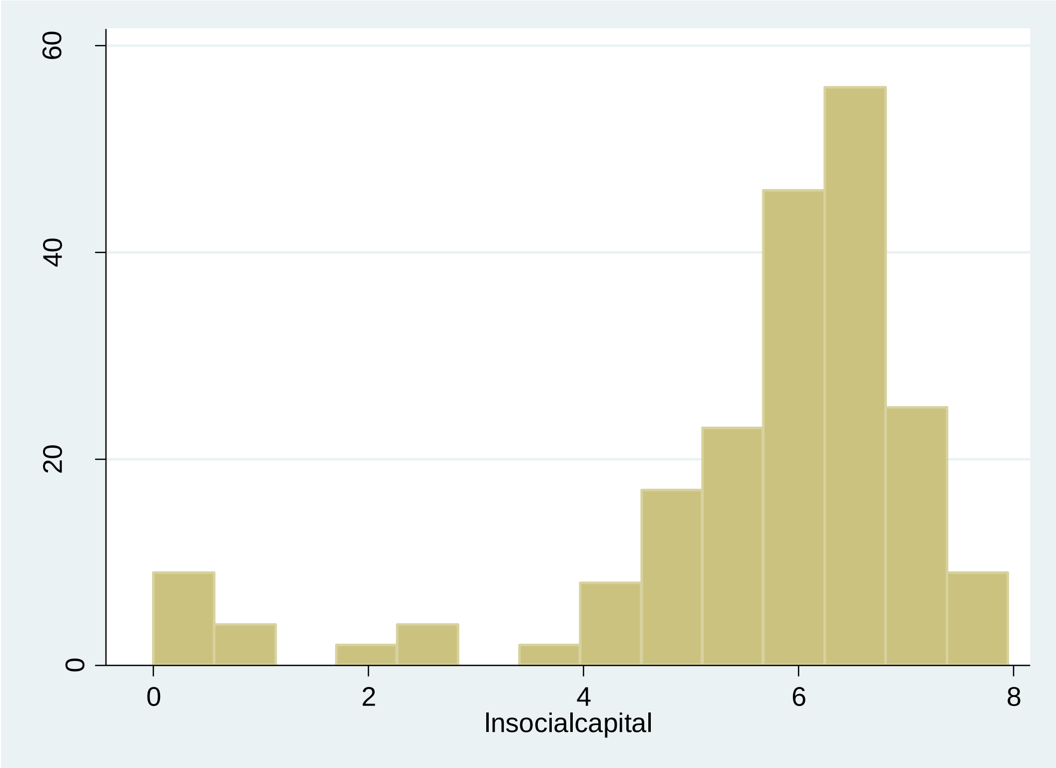
there are some scientists who do have a Linked-In profile but have zero connections, which means that they probably never use it. The mean and standard deviation are very high. This can possibly be explained by a snowball effect in social networking. More connections leads to better visibility and thus even more connections. The histogram for the *socialcapital* variable is presented below.

Figure 3: Distribution of the socialcapital variable



As shown in the figure, the distribution for *socialcapital* is skewed to the right. Therefore the *socialcapital* variable is transformed into a log-variable (*lnsocialcapital*). In the histogram below we can see the distribution of *lnsocialcapital*.

Figure 4: Distribution of the lnsocialcapital variable



The new distribution is slightly skewed to the left, but approximates more of a normal distribution. Therefore the *lnsocialcapital* variable is used in the model instead of *socialcapital*.

3.2.6 Nationality

As argued in the theoretical framework, nationality can influence an individual's social capital. An individual has a starting social capital in the country he is native too. Furthermore he benefits from speaking the language and knowing the culture. In the table below we can see the nationalities and their frequencies for this dataset.

Table 6: Distribution of the nationality variable

nationality	Freq.	Percent	Cum.
American	3	1,1	1,1
Argentinian	1	0,37	1,47
Australian	1	0,37	1,84
Belgian	7	2,57	4,41
Brazilian	2	0,74	5,15
British	3	1,1	6,25
Chinese	3	1,1	7,35
Dutch	222	81,62	88,97
French	1	0,37	89,34
German	14	5,15	94,49
Greek	1	0,37	94,85
Indian	2	0,74	95,59
Irish	1	0,37	95,96
Italian	6	2,21	98,16
Macedonian	1	0,37	98,53
Polish	1	0,37	98,9
Russian	1	0,37	99,26
Turkish	2	0,74	100
Total	272	100	

As we can see, the large majority of scientist in this dataset is Dutch (82%). The second-largest nationality is German (5%), followed by Belgian (3%) and Italian (2%). The majority of non-Dutch scientists are western-European.

The importance of nationality for this research lies within the distinction between Dutch and non-Dutch in this sample. A dummy variable was added to distinguish Dutch scientists from foreign scientists who reside in the Netherlands. The distribution of the *Dutch* variable can be seen in the table below.

Table 7: Distribution of the Dutch variable

1 if Dutch		Freq.	Percent	Cum.
	0	51	18,68	18,68
	1	222	81,32	100
Total		273	100	

The variable *Dutch* take the value of 1 when the individual has the Dutch nationality and 0 if non-Dutch. The correlation matrix in appendix B1 shows a relatively high correlation between *age* and *Dutch*. Foreign professors tend to be younger than the average scientist in this sample.

3.2.7 Gender

The last variable used as a proxy for social capital is gender. As we have seen, gender is often used as a proxy for social capital in literature. It is argued that males have access to greater social capital, because they more often take place in boards and other influential positions than females. In the table below we can see the distribution of the variables *male*, which takes the value of 1 if the individual is male and 0 if female.

Table 8: Distribution of the male variable

1 if male		Freq.	Percent	Cum.
	0	50	18,32	18,32
	1	223	81,68	100
Total		273	100	

As we can see, the number of male scientists (82%) heavily outweighs the number of female scientists in this sample (18%). The number of female scientists in the Dutch scientist population is reportedly low (14,8% of full professors in 2012 were women), thus this sample reflects the population in this matter (Gerritsen, Verdonk, & Visser, 2012).

3.2.8 Institutional incentives

Institutional incentives are hard to quantify and thus dummy variables are a necessity. Dummy variables for all 13 universities in the dataset are included in the first model: *Erasmus* (Erasmus University Rotterdam), *Leiden* (Leiden University), *Nyenrode* (Nyenrode Business University), *Radboud* (Radboud University Nijmegen), *Delft* (Delft University of Technology), *Eindhoven* (Eindhoven University of Technology), *Tilburg* (Tilburg University), *UvA* (University of Amsterdam), *RUG* (University of Groningen), *Twente* (University of Twente), *Utrecht* (Utrecht University), *VU* (VU University), *Wageningen* (Wageningen University). The Erasmus University is used as the reference group. The number of observations of every university is 21, since the data was evenly gathered.

A second model is made to see the difference between the top five valorising universities and other Dutch universities (van Leeuwen, 2013). The dummy variable *dvalortop5uni* was created for this purpose where *dvalortop5uni* take the value of 1 for the following universities: University of Twente, Utrecht University, Eindhoven Technical University, Delft Technical University and Wagingen University.

3.3 Methodology

Because the dependent variable is a dummy variable, a logistic regression analysis is used. In this paper I use two models. The first model is used to analyse the difference in effect between all Dutch universities. In the second model these university dummy variables are replaced by one dummy variable for the top 5 valorisation universities (*dvalortop5uni*).

The economic model is as follows:

$$Knowledge\ Commercialisation = \beta_0 + \beta_1 Rank + \beta_2 Science + \beta_3\ University + \beta_4\ Age + \beta_5 Nationality + \beta_6\ Gender + e$$

Based on the theoretical framework and formed hypotheses, the expected signs of the effects of the explanatory variables are shown in the table below.

Table 9: Expected signs of the explanatory variables explaining the propensity to engage in knowledge commercialisation

Variable	Expected sign
Professor (*prof*)	+
Associate professor (*associateprof*)	+
Gamma (*Gamma*)	+
Alpha (*Alpha*)	-
University (*dvalortop5uni*)	+
Age (*lnage*)	+
Nationality (*Dutch*)	+
Gender (*male*)	+

4. Results and discussion

4.1 Regression analysis

The marginal effects of the logistical regression analysis measuring the propensity to engage in knowledge commercialisation are presented in the table below. Both models are shown: Model 1 with the individual university dummies and model 2 with the valorising university dummy.

Table 9: The Average Marginal Effects of Model 1 and 2 explaining the propensity to engage in knowledge commercialisation using a logistical regression analysis

	(1)		(2)	
prof	-0.0746	(-0.69)	-0.128	(-1.26)
associateprof	-0.135	(-1.08)	-0.153	(-1.19)
Alpha	-0.0478	(-0.41)	-0.0284	(-0.25)
Gamma	-0.137	(-1.58)	-0.0741	(-0.88)
lnsocialcapital	0.0807*	(3.65)	0.0859*	(3.68)
Leiden	-0.0794	(-0.44)		
Nyenrode	0.0846	(0.49)		
Radboud	-0.0710	(-0.38)		
Delft	-0.00763	(-0.04)		
Eindhoven	-0.114	(-0.65)		
Tilburg	-0.0460	(-0.28)		
UvA	-0.181	(-1.01)		
RUG	-0.426*	(-2.15)		
Twente	-0.255	(-1.47)		
Utrecht	0.00227	(0.01)		
VU	-0.162	(-0.95)		
Wageningen	-0.137	(-0.79)		
lnage	0.436*	(2.13)	0.448*	(2.16)
Dutch	0.239*	(2.61)	0.244*	(2.60)
male	-0.0923	(-1.03)	-0.0780	(-0.88)
dvalortop5uni			0.0195	(0.24)
N	188		188	

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$

Model 1 includes all university dummies individually, except for the Erasmus university, which functions as the reference group. The pseudo R-squared is 16,5% for 188 used observations.[6] First we will interpret the average marginal effects before accepting or rejecting the hypotheses.

The first two variables, *prof* (full professors) and *associateprof* (associate professor), both have insignificantly different effects from the reference group *assistantprof* (assistant professor).

[6] For the STATA output of the logistical regression analysis see appendix A.

The same is true for the next two variables *Alpha* and *Gamma*. Being a Alpha or Gamma scientist yields no significantly different effect from being a Beta scientist.

One of the statistically significant effects found in the model is that of the proxy variable for social capital (*lnsocialcapital*), which is significant at a 5% significance level. On average, an increase in a scientists Linked-in network size of 1% thus leads to a 0.08 percentage point increase in the chance of this individual engaging in knowledge commercialisation activities, ceteris paribus.

The following variables are the university dummies. It is interesting to see that only the dummy variable *RUG* (University of Groningen) shows a statistically significant effect at a 5% significance level. It appears that on average, RUG scientists have a 42.6 percentage point lower chance of being engaged in knowledge commercialisation compared to Erasmus scientists, ceteris paribus. The results for the other universities dummies suggests that there is no significant difference in the effect of working for any of these universities compared to working for Erasmus on the propensity to commercialize knowledge.

Lnage shows a significant effect at a 5% significance level. This means on average, an increase in a scientists age of 1% leads to a 0.44 percentage point increase in the chance of this individual engaging in knowledge commercialisation activities, ceteris paribus.

We can also interpret the coefficient of the nationality variable *Dutch*, since it is significant at a 5% significance level. On average, scientists with a Dutch nationality have a 24 percentage point higher chance of being engaged in knowledge commercialisation than non-Dutch scientists, ceteris paribus. Finally, although the expected sign for *male* was positive, no significant effect was found for gender.

For model 2 the university variables were grouped into one variable: *dvalortop5uni*. As explained earlier, this variable takes the value of 1 for every scientist working for a top 5 valorisation university (University of Twente, Utrecht University, Eindhoven Technical University, Delft Technical University and Wagingen University). The other variables are the same as in model 1.

As we can see, the results for the other variables are mostly the same except for a slight increase in coefficients. As a result, the interpretation of these variables only changes slightly. On average in this model, an increase in a scientists Linked-In network size of 1% leads to a 0.09 percentage point increase in the chance of this individual engaging in knowledge commercialisation activities, ceteris paribus. An increase in a scientists age of 1% leads to a 0.45 percentage point increase in the chance of this individual engaging in knowledge commercialisation activities, ceteris paribus. Also, on average, scientists with a Dutch nationality have a 24.4 percentage point higher chance of being engaged in knowledge commercialisation compared to non-Dutch scientists, ceteris paribus. These effects are all significant at a 5% significance level.

More interestingly, *dvalortop5uni* turns out to be a highly insignificant variable. Just like the results from model 1, this suggests that there is no significant difference between Dutch universities in their effect on a scientists propensity to commercialise knowledge.

4.2 Interaction variables

There is a possibility that the interpretation of our model is biased due to multicollinearity. The correlation matrix shows some variables within the model to be highly correlated. The correlation matrix can be found in appendix B1. In order to see whether there were any interaction effects between the explanatory variable I ran some logistical regression including interaction terms.

There exists a high correlation between age and academic rank in this sample. This can be expected, since the senior rank of full professor can only be gained after sufficient years of academic experience.[7] The possibility exists that the insignificance of the academic rank variables (*prof, associateprof, assistantprof*) were caused by there being an far less observations for associate professors and assistant professors compared to full professors in this dataset. I therefore ran another logistical regression with only one dummy variable for professor (*prof* = 1 if full professor and *prof* = 0 if associate- or assistant professor), which can be found in appendix C2. This had no significant effect on the model. I have also included an interaction variable between age and rank in the model (see appendix D1), but this effect was insignificant.

Theoretically, simply becoming older shouldn't affect the likelihood to engage in knowledge commercialisation. Increasing age does lead to an increased network, and therefore social capital. The underlying factor for the effect of age could thus be social capital. Theoretically, the effect of *lnage* should thus be greater when not controlling for the effect of social capital. In order to test this, I have ran a logistical regression model omitting *lnsocialcapital* from the model. This model can be found in appendix C1. The results show that the variable *lnage* becomes insignificant after omitting *lnsocialcapital* from the model, which is the opposite of what was expected.[8] This can be explained from the fact that social capital in this sample is represented by the number of Linked-in connections. This digital networking is less adopted by the older scientists, which is also visible in the correlation matrix. The correlation between *lnage* and *lnsocialcapital* for this sample is negative (-0.1335). It is therefore important to keep the distinction between digital social capital and social capital in mind.

[7]

[8] Omitting the age variable (*lnage*) from the model had the same result but inverted.

An interaction term was added to the model (see appendix D1). In contrast to the other added interaction variables, this showed a significant effect. This significant interaction between age and social capital shows that the effect of age is different for different levels of social capital (i.e. the size of the digital network). This means that increasing age leads to an increasing effect of social capital on knowledge commercialisation. However, as can be seen in the model in appendix D1, this effect is negligible since the magnitude of the interaction variable is close to zero.

4.3 Discussion

4.3.1 Hypothesis 1

The results from the two models give support to two of the four hypotheses. The first hypothesis states that the likelihood to engage in knowledge commercialisation is greater for scientists working at universities with a valorisation culture. Model 1 showed us that there was no significant difference between the individual universities, with the University of Groningen being the only exeption. The significant difference between Erasmus University and the University of Groningen is, however, not relevant for this hypothesis. The second model showed that there is no significant difference between the top 5 valorising universities and other Dutch universities in their scientists propensity to commercialise knowledge. Therefore, hypothesis 1 is rejected.

Although the found difference between Erasmus and Groningen is not directly relevant for supporting or rejecting the first hypotheses, the magnitude of the effect is striking. On average, scientists working for the University of Groningen have a 42.6 percentage point lower probability of being involved in knowledge commercialisation compared to Erasmus university scientists, ceteris paribus. Although this large difference could point to the effect incentive structures and university culture has on knowledge commercialistion, other factors could also be of effect here. It is possible that geographical factors like infrastructure and position relative to business play a role. Erasmus university has a strategic position in the heartland of the Netherlands, the randstad area, where all major firms are concentrated. The high level of infrastructure makes it well accesible. Groningen University, on the other hand, lies far in the north of the Netherland with little major companies in the area (with some large gas firms being the exception). This relatively close proximity of Erasmus university to business makes collaboration between scientists and firms more easy. Because of these confounding factors, the university dummy variable variables are not the most accurate proxies of university incentive structures. Grouping based on this particular factor is thus needed to analyse its effect on knowledge commercialisation.

For this reason the divide between valorising and less-valorising universities was made. No significant difference between the valorising and less-valorising universities was found. This could be due to the fact that the ranking is gradual. In other words, the difference in valorisation efforts between number 5 and number 6 on the Elsevier valorisation ranking is small. The valorisation ranking was build up from a lot of different factors, which might explain the small difference in total valorisation (van Leeuwen, 2013).

The sample was taking evenly from every university faculty because of the original plan to include a faculty variable. Since the faculties are not homogenous across universities, they could not be compared. With hindsight this distribution does not give a representative sample of universities (and thus the whole population) since some faculties are larger than others. Future research could collect data more targeted on incentive structures for knowledge commercialisation as opposed to valorisation in general.

Nevertheless, the rejection of the first hypothesis suggests that there is no difference in incentive structure between the Dutch universities or at least no difference in effect on knowledge commercialisation. This relative homogeneity in incentive structure may point to a common factor behind it which influences the incentive structures. This might be Dutch scientific culture, which makes it interesting to compare with for example the U.S. scientific culture. The incentive structures might also be influenced by government policy. Further comparative research is needed in order to find out whether this is true.

4.3.2 Hypothesis 2

The second hypothesis states that the level of social capital of a scientist is positively related to his or her propensity to engage in knowledge commercialisation. The results of the regression analysis support this hypothesis in two ways. The first is that the effect of digital social capital (*lnsocialcapital*) was found to be significant and positive. On average, an increase in the number of Linked-in connections of 1% increases the likelihood of the scientist engaging in knowledge commercialising activities by 0.09 percentage points (in model 2). Also, a positive and significant effect was found for the Dutch variable. It was found that on average, Dutch scientist have an increased probability of being engaged in knowledge commercialisation of 24.4 percentage points compared to non-Dutch scientists, ceteris paribus. These finding supports the second hypothesis, although gender, a proxy for social capital often used in literature, did not have a significant effect.

The findings suggest a significant positive effect for social capital, measured for both the size of the digital social network as well as nationality. The possibility exists that social capital increases exponentially instead of regularly because of a snowball-effect. A larger network with more connections might lead to a higher growth of the network through second degree connections. These “friends of friends” might more easily become new connections, thus leading to an exponential growth of network and thus benefits.

This exponential growth in social capital is only realised when the individual puts effort into the network. Therefore we have to be careful in interpreting the correlation between social capital and knowledge commercialisation. Simply doubling the Linked-in network of a scientist in this sample will not automatically lead to more knowledge commercialisation; the network and its benefits needs to be used. Although more opportunities are presented, the intention of the scientist must be to use his social capital for knowledge commercialisation in the first place. When a scientist increases his or her social capital beyond a certain threshold, it makes them (their skills, knowledge and experience) more visible for firms. This leads to increased opportunities for scientists and thus more knowledge commercialisation.

The nationality variable was used as a proxy for social capital in this analysis. This variable faces the same problems as the university variables however; it may be interpreted in multiple ways. In this case the university variables were interpreted as proxies for incentive structures and culture. Nationality can also be interpreted as a proxy for culture. For example, one might say that the Dutch culture is less entrepreneurial than American culture. To limit this interpretation problem I have separated the nationalities in Dutch and non-Dutch only. This pools all non-Dutch cultures into one category. As seen in the data description section of this paper, the non-Dutch scientists in this sample are mostly western European. Using a larger dataset with data from other western European universities allows more accurate measurement of cultural effects.

The finding that gender (*male*) has no statistically significant effect on the probability of a scientist engaging in knowledge commercialisation brings up an interesting point. In the literature we can find gender as a proxy for social capital for two reasons. The first is that gender was more linked to social capital a few decades ago. Because of gender inequality, it was more difficult for women to get influential positions and were thus denied access to high levels of social capital. Secondly, there no was no practical way of collecting real world data on the size of an individual network. Only proxies based on generalized assumptions such as gender were available. This study shows that gender as a proxy for social capital is no longer valid.

4.3.3 Hypothesis 3

Support was also found for the third hypothesis. The results from the logistical regression analysis show that, on average, a 1% increase in age increases the chance of engaging in knowledge commercialisation by 0.44 percentage points, ceteris paribus. This finding suggests that the age of a scientist is positively related to the propensity to engage in knowledge commercialising activities.[9]

[9] Using *age* as compared to *lnage* makes for a better interpretable variable. The decision was made in favour of *lnage* because its probability distribution approached the normal form.

The positive and significant effect found for age fits within the life-cycle theory as explored in the theoretical framework section. After many years of research, a scientist might long for variation in work or new ways to get inspiration for new research. Besides these personal factors, the positive effect of age might be interpreted in several other ways. Increased age is arguably highly correlated with experience and possession of knowledge. Therefore a possible explanation might be that older and thus wiser scientists are in higher demand for firms.[10] The possibility exists that the effect of age is nonlinear. Further research might delve into the possible nonlinear properties of the effect of age. The knowledge gains of doing research might show decreasing returns after a certain number of years. Teaching others or sharing this knowledge could then become a more efficient use of time than research after a certain point.

4.3.4 Hypothesis 4

The fourth hypothesis states that scientists with a higher rank are more likely to engage in knowledge commercialisation than those of lower rank. No statistically significant results were found for the rank dummy variables. Therefore, these results suggest that rank has no effect on the propensity to commercialise knowledge. Because no support has been found, the fourth hypothesis is rejected.

It is interesting to see that there is no significant difference between ranks in the probability of being engaged in knowledge commercialisation. The scientist career-trajectory theory states that scientists of lower rank might be more focussed on their career than on commercialising knowledge. These results suggest that this is not the case. A possible explanation is that several other factors are at work here which counteract the positive effect of rank. A scientist of a lower rank might have a lower work-load and thus more time to spend on knowledge commercialising activities. The high correlation of rank with age suggests means that explanations based on the younger age of lower ranked scientists are unsupported. Further research is needed in which the differing motivations of assistant-, associate- and full professors are explored.

Even though all publicly available information was used for the construction of the main dependent variable, this variable likely doesn't cover all knowledge commercialising activities for all scientists in this dataset. Interviews with scientists done by the Onderzoeksredactie (2014) show that many scientists do not want their colleagues or the university to know of their extracurricular activities. An unknown number of professors hide their activities, therefore further research is needed which uses data collected through anonymous surveys.

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[10] This same argument can be made for rank. Multicollinearity might thus be a problem if you follow this interpretation. The correlation matrix in the appendix indeed shows a relatively high correlation of 0.46 between *lnage* and *prof*.

5. Conclusions

5.1 Concluding remarks

This paper has expanded on the theory on knowledge commercialisation by looking at the determinants for knowledge commercialisation for scientists of all sciences. The focus of this research was a statistical analysis of individual agents within the context of valorisation. A new approach towards the determinant social capital was explored with the use of newly gathered data on social networks.

The results of this paper suggest that there is no difference between universities in their effect on the propensity to engage in knowledge commercialisation of their scientists. Even when the valorising universities were grouped together, the results point to no statistically significant effect on knowledge commercialisation at the individual level.

Social capital was found to be a positive and significant determinant for knowledge commercialisation. Scientists with a larger network had a higher probability to be engaged in knowledge commercialisation. This larger network generated more opportunities for the scientist to commercialise their knowledge. Thus, increased benefits from higher levels of social capital come in the form of more opportunities for the scientist to commercialise their knowledge.

Contradicting results were found for the effect of age and rank on knowledge commercialisation. Based on the life-cycle and career-trajectory theories, both age and rank were predicted to have a positive effect. However, the results showed only a significant and positive effect for age. An increase in age leads to a higher probability of being engaged in knowledge commercialisation. On the other hand, there is no statistically significant difference between full professors, associate professors and assistant professors in this sample. The correlation between age and rank is relatively high (it takes years of research and experience to become a professor), therefore it is possible that there are counteracting factors for rank. Further research is needed to identify these factors.

5.2 Limitations

It is important to point out several limitations of this study. Although this paper contains hypotheses based upon well-established theories derived from literature, the correlations found must not strictly be interpreted as causal relationships. Other limitations have to do with the availability and the nature of the data. No dataset was available and therefore all the data had to be collected manually. Due to this being a time-consuming effort, the resulting number of observations is lower than preferable. Also, only publicly available data could be used. As a result, not all required information for every scientist could be found or was outdated. Furthermore, sometimes it was difficult to determine whether or not an extra-curricular activity should be deemed a knowledge commercialising activity. This was made difficult by the lack of information on the nature of the activity. It could sometimes be unclear if a scientists was payed for, for example, consulting. Also, some cases of knowledge commercialisation were ambiguous: Is writing a scientific book knowledge commercialisation? What if it is a popular scientific book? For this study I drew the line at knowledge transfer to only firms, the public sector and NGO's.

The new approach of using the size of scientist's Linked-In network as a proxy for social capital suffers from some limitations as well. Not everyone uses Linked-In to the same extent. Some add everyone they meet to their network but never use it, others only add important connections and keep close ties with them through updates and comments. Some made an account and never used it again, and some don't have an account at all. The way people use their network is hard to check.

5.3 Policy implications

There are several implications following from the findings of this study. The public debate surrounding knowledge commercialisation revolves around the possibility of science losing its objective nature and conflict of interests. On the other hand, knowledge transfer is direly needed for innovation in Europe. Governments are pushing universities to steer their agendas to be in line with industry R&D, but at the same time knowledge commercialisation on the individual level is frowned upon.

With the right incentives, knowledge commercialisation can be a highly efficient form of knowledge transfer. The incentives for knowledge transfer are offered by the firm in the form of wage, prestige and new practical insights. This form of collaboration stimulates scientists to focus their research on topics valuable for society and industry. At the same time, stronger ties between science and industry will give a higher rate of return on public spending on science. This higher rate of return on public spending on science can be achieved through universities embracing knowledge commercialisation as a mode of valorisation.

As shown in this paper, higher levels of social capital will allow for more opportunities to commercialize knowledge. Investing in the social capital of scientists will thus stimulate the occurrence of knowledge transfer which will increase innovation and therefore economic growth.

Government and university policy could thus steer towards stimulating knowledge commercialisation by investing in the social capital of the scientific community. In other words, by making scientists and their knowledge more visible and accessible for the industry. Investing in a network for knowledge transfer matching the supply of knowledge with the demand of the industry is a possibility. Part of the revenues from knowledge commercialisation can then be reinvested in education and academic research.

This still leaves the question on how to limit possible conflict of interests. Conflict of interest occurs when the scientist's research is directly funded by a firm. Facilitation of knowledge commercialisation by the university or through a neutral third party would allow for monitoring of activities. The aim should be to make it easy and attractive for the scientist to commercialise knowledge through this network. As a condition this has to be knowledge gained through independent university research. This would make it relatively unattractive to continue with hidden extracurricular activities.

For this to happen, it is important that the stigma on knowledge commercialisation is lifted. Universities can sharpen their definitions on what activities are harmful and which are beneficial for the university and society. The incentive structure of the university should reflect this by rewarding beneficial knowledge commercialisation.

In order to break out of the European Paradox, Dutch government policy on valorisation needs to change. Knowledge commercialisation can become a major form of knowledge transfer if handled correctly. If the Dutch knowledge-economy wishes to remain competitive with more innovative knowledge economies, stimulating knowledge commercialisation at the individual level is needed. Government policy should stimulate universities to engage in open valorisation, in which scientists are supported in commercialising their knowledge by helping them grow their social capital. This facilitation, possibly in the form of a transparent valorisation network, would allow for monitoring of activities.

5.4 Further research

In order to effectively stimulate knowledge transfer, future research should continue to explore the effects of different forms of valorisation on the rate of innovation. Available data should be gathered from scientific institutions along with qualitative data such as interviews with scientists. Further research could focus on building a more complete model using possible determinants not used in this study due to data limitations, like wages. Also, the possible snowball effect of social capital could be explored. A comparison with other European countries and ideally a global comparison should be the next step, allowing for control of cultural factors. Finally, to see the effect of public policy over time, longitudinal data should be gathered.

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Appendix

A. Regression tables

Table A1: Model 1 and 2 explaining the propensity to engage in knowledge commercialisation using a logistical regression analysis

	(1) dknowcom		(2) dknowcom	
prof	-0.379	(-0.68)	-0.605	(-1.24)
associateprof	-0.687	(-1.07)	-0.724	(-1.17)
Alpha	-0.243	(-0.41)	-0.134	(-0.25)
Gamma	-0.697	(-1.54)	-0.350	(-0.88)
lnsocialcapital	0.410*	(3.28)	0.406*	(3.30)
Leiden	-0.403	(-0.44)		
Nyenrode	0.429	(0.49)		
Radboud	-0.361	(-0.38)		
Delft	-0.0388	(-0.04)		
Eindhoven	-0.580	(-0.64)		
Tilburg	-0.233	(-0.28)		
UvA	-0.919	(-1.00)		
RUG	-2.162*	(-2.06)		
Twente	-1.294	(-1.44)		
Utrecht	0.0115	(0.01)		
VU	-0.821	(-0.94)		
Wageningen	-0.697	(-0.79)		
lnage	2.217*	(2.04)	2.118*	(2.06)
Dutch	1.216*	(2.45)	1.152*	(2.44)
male	-0.469	(-1.02)	-0.369	(-0.87)
dvalortop5uni			0.0921	(0.24)
_cons	-10.63*	(-2.49)	-10.77*	(-2.67)
N	188		188	
Pseudo R^2	0.1654		0.1179	

t statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$

Table A2: STATA output of Model 1 explaining the propensity to engage in knowledge commercialisation using a logistical regression analysis

```
Iteration 0:   log likelihood = -129.92843
Iteration 1:   log likelihood = -108.76015
Iteration 2:   log likelihood = -108.43458
Iteration 3:   log likelihood = -108.43412
Iteration 4:   log likelihood = -108.43412

Logistic regression                             Number of obs   =        188
                                                LR chi2(20)     =      42.99
                                                Prob > chi2     =     0.0021
Log likelihood = -108.43412                     Pseudo R2       =     0.1654
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.3786454	.5541463	-0.68	0.494	-1.464752	.7074614
associateprof	-.6872475	.6444164	-1.07	0.286	-1.95028	.5757856
Alpha	-.2429006	.5982811	-0.41	0.685	-1.41551	.9297089
Gamma	-.6974525	.4521524	-1.54	0.123	-1.583655	.18875
lnsocialcapital	.4097949	.1250006	3.28	0.001	.1647982	.6547916
Leiden	-.4031577	.9199468	-0.44	0.661	-2.20622	1.399905
Nyenrode	.4294312	.8832935	0.49	0.627	-1.301792	2.160655
Radboud	-.3607525	.9436066	-0.38	0.702	-2.210188	1.488682
Delft	-.0387659	.9358854	-0.04	0.967	-1.873068	1.795536
Eindhoven	-.5795292	.8992521	-0.64	0.519	-2.342031	1.182973
Tilburg	-.2334734	.8371807	-0.28	0.780	-1.874317	1.407371
UvA	-.9186673	.9160382	-1.00	0.316	-2.714069	.8767346
RUG	-2.162345	1.049726	-2.06	0.039	-4.21977	-.1049203
Twente	-1.293773	.8955079	-1.44	0.149	-3.048936	.4613907
Utrecht	.0115071	.8048678	0.01	0.989	-1.566005	1.589019
VU	-.8213567	.8695522	-0.94	0.345	-2.525648	.8829343
Wageningen	-.6969428	.8860058	-0.79	0.432	-2.433482	1.039597
lnage	2.216611	1.086166	2.04	0.041	.0877648	4.345457
Dutch	1.215996	.4953688	2.45	0.014	.2450914	2.186901
male	-.4689051	.4596893	-1.02	0.308	-1.369879	.4320694
_cons	-10.62589	4.273483	-2.49	0.013	-19.00176	-2.250017

Table A3: STATA output of Model 2 explaining the propensity to engage in knowledge commercialisation using a logistical regression analysis

```
Iteration 0:   log likelihood = -129.92843
Iteration 1:   log likelihood = -114.82894
Iteration 2:   log likelihood = -114.60906
Iteration 3:   log likelihood = -114.60848
Iteration 4:   log likelihood = -114.60848

Logistic regression                               Number of obs   =        188
                                                  LR chi2(9)      =      30.64
                                                  Prob > chi2     =     0.0003
Log likelihood = -114.60848                       Pseudo R2       =     0.1179
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.605147	.4876943	-1.24	0.215	-1.56101	.3507163
associateprof	-.7240112	.6182587	-1.17	0.242	-1.935776	.4877537
Alpha	-.134047	.54351	-0.25	0.805	-1.199307	.931213
Gamma	-.3501204	.3990941	-0.88	0.380	-1.13233	.4320896
lnsocialcapital	.4056915	.1230398	3.30	0.001	.1645379	.6468451
dvalortop5uni	.0921172	.3833096	0.24	0.810	-.6591559	.8433902
lnage	2.117945	1.026129	2.06	0.039	.1067679	4.129121
Dutch	1.152429	.4719032	2.44	0.015	.2275162	2.077343
male	-.3685788	.4237268	-0.87	0.384	-1.199068	.4619104
_cons	-10.76659	4.030144	-2.67	0.008	-18.66553	-2.867653

B. Correlations

Table C1: Correlation matrix

(obs=188)

	dknowcom	prof	associ~f	assist~f	Alpha	Beta	Gamma	lnsoci~l	dvalor~i	lnage	Dutch	male
dknowcom	1.0000											
prof	0.0516	1.0000										
associatep~f	-0.0762	-0.5589	1.0000									
assistentp~f	0.0024	-0.7214	-0.1711	1.0000								
Alpha	0.0110	0.0014	0.0397	-0.0348	1.0000							
Beta	0.0600	0.0283	-0.0099	-0.0253	-0.3842	1.0000						
Gamma	-0.0693	-0.0300	-0.0184	0.0510	-0.3263	-0.7474	1.0000					
lnsocialca~l	0.2516	0.0496	-0.1151	0.0371	-0.1082	0.0324	0.0446	1.0000				
dvalortop5~i	0.0348	0.0334	0.0135	-0.0510	-0.2990	0.5292	-0.3266	0.0318	1.0000			
lnage	0.1582	0.4651	-0.1166	-0.4553	0.1034	0.0759	-0.1521	-0.1335	0.0276	1.0000		
Dutch	0.2296	0.1367	0.0041	-0.1658	0.1569	-0.1264	0.0166	0.0315	-0.0478	0.3324	1.0000	
male	-0.0435	0.1275	-0.0495	-0.1101	-0.0503	0.0966	-0.0627	-0.0156	0.1239	0.1320	-0.0052	1.0000

C. Multicollinearity checks

Table C1: Logistical regression analysis and Average Marginal Effects explaining the likelihood to engage in knowledge commercialisation with lnsocialcapital omitted

```
Iteration 0:   log likelihood = -161.37585
Iteration 1:   log likelihood = -151.89716
Iteration 2:   log likelihood = -151.81065
Iteration 3:   log likelihood = -151.81058
Iteration 4:   log likelihood = -151.81058

Logistic regression                             Number of obs     =        237
                                                LR chi2(8)        =      19.13
                                                Prob > chi2       =     0.0142
Log likelihood = -151.81058                     Pseudo R2         =     0.0593
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	.0984506	.4062938	0.24	0.809	-.6978705	.8947718
associateprof	-.5632988	.5457916	-1.03	0.302	-1.633031	.5064331
Alpha	-.6206376	.4539892	-1.37	0.172	-1.51044	.2691648
Gamma	-.1848953	.339121	-0.55	0.586	-.8495603	.4797696
dvalortop5uni	-.0435193	.3267437	-0.13	0.894	-.6839252	.5968866
lnage	.4197043	.8437685	0.50	0.619	-1.234052	2.07346
Dutch	1.34233	.4395323	3.05	0.002	.4808629	2.203798
male	-.2451355	.37086	-0.66	0.509	-.9720077	.4817367
_cons	-2.708525	3.171554	-0.85	0.393	-8.924657	3.507607

```
Average marginal effects                        Number of obs     =        237
Model VCE    : OIM

Expression   : Pr(dknowcom), predict()
dy/dx w.r.t. : prof associateprof Alpha Gamma dvalortop5uni lnage Dutch male
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	.0222192	.0916527	0.24	0.808	-.1574168	.2018552
associateprof	-.12713	.1221886	-1.04	0.298	-.3666152	.1123552
Alpha	-.1400707	.1008933	-1.39	0.165	-.337818	.0576766
Gamma	-.0417287	.0763598	-0.55	0.585	-.1913911	.1079337
dvalortop5uni	-.0098218	.0737308	-0.13	0.894	-.1543315	.1346879
lnage	.0947224	.1900514	0.50	0.618	-.2777714	.4672162
Dutch	.3029484	.092348	3.28	0.001	.1219496	.4839472
male	-.0553242	.0834092	-0.66	0.507	-.2188032	.1081548

Table C2: Logistical regression and Average Marginal Effects explaining the likelihood to engage in knowledge commercialisation including the prof variable (prof=1 if scientist is full professor, 0 if associate- or assistant professor)

```
Logistic regression                               Number of obs   =        188
                                                  LR chi2(8)      =      29.24
                                                  Prob > chi2     =     0.0003
Log likelihood = -115.30629                       Pseudo R2       =     0.1125
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.2824693	.3983644	-0.71	0.478	-1.063249	.4983106
Alpha	-.1462198	.5402139	-0.27	0.787	-1.20502	.9125799
Gamma	-.354066	.3977123	-0.89	0.373	-1.133568	.4254357
lnsocialcapital	.4082126	.1224691	3.33	0.001	.1681776	.6482476
dvalortop5uni	.067188	.3817339	0.18	0.860	-.6809967	.8153726
lnage	1.951298	1.010757	1.93	0.054	-.0297494	3.932346
Dutch	1.116921	.4691539	2.38	0.017	.1973962	2.036446
male	-.3790991	.4222796	-0.90	0.369	-1.206752	.4485538
_cons	-10.38978	4.002085	-2.60	0.009	-18.23372	-2.545835

```
Average marginal effects                          Number of obs   =        188
Model VCE    : OIM

Expression   : Pr(dknowcom), predict()
dy/dx w.r.t. : prof Alpha Gamma lnsocialcapital dvalortop5uni lnage Dutch male
```

	Delta-method					
	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.0603034	.0846244	-0.71	0.476	-.2261642	.1055575
Alpha	-.031216	.1152349	-0.27	0.786	-.2570722	.1946403
Gamma	-.0755883	.0842553	-0.90	0.370	-.2407257	.0895491
lnsocialcapital	.0871479	.0233684	3.73	0.000	.0413466	.1329492
dvalortop5uni	.0143437	.0814755	0.18	0.860	-.1453453	.1740327
lnage	.4165758	.2078352	2.00	0.045	.0092263	.8239253
Dutch	.2384475	.0944877	2.52	0.012	.053255	.4236401
male	-.0809325	.0894491	-0.90	0.366	-.2562496	.0943846

Table C3: Logistical regression and Average Marginal Effects explaining the likelihood to engage in knowledge commercialisation with the lnage variable omitted

```
Logistic regression                               Number of obs   =        205
                                                  LR chi2(8)      =      28.64
                                                  Prob > chi2     =     0.0004
Log likelihood = -127.22785                       Pseudo R2       =     0.1012
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.2206102	.4149318	-0.53	0.595	-1.033862	.5926412
associateprof	-.6322711	.604604	-1.05	0.296	-1.817273	.552731
Alpha	.0107863	.5248934	0.02	0.984	-1.017986	1.039558
Gamma	-.3003956	.3733091	-0.80	0.421	-1.032068	.4312769
lnsocialcapital	.3445879	.1078402	3.20	0.001	.133225	.5559507
dvalortop5uni	.0586005	.3641182	0.16	0.872	-.655058	.772259
Dutch	1.386659	.4285574	3.24	0.001	.5467021	2.226616
male	-.5227142	.4033312	-1.30	0.195	-1.313229	.2678004
_cons	-2.514163	.8460684	-2.97	0.003	-4.172427	-.8558993

```
Average marginal effects                          Number of obs   =        205
Model VCE    : OIM

Expression   : Pr(dknowcom), predict()
dy/dx w.r.t. : prof associateprof Alpha Gamma lnsocialcapital dvalortop5uni Dutch
```

	Delta-method					
	dy/dx	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.047733	.0895428	-0.53	0.594	-.2232337	.1277678
associateprof	-.1368032	.1294975	-1.06	0.291	-.3906136	.1170072
Alpha	.0023338	.1135689	0.02	0.984	-.2202571	.2249247
Gamma	-.064996	.0803176	-0.81	0.418	-.2224155	.0924236
lnsocialcapital	.0745578	.0212196	3.51	0.000	.0329681	.1161475
dvalortop5uni	.0126793	.0787639	0.16	0.872	-.1416952	.1670538
Dutch	.3000286	.0835554	3.59	0.000	.136263	.4637943
male	-.1130986	.0859597	-1.32	0.188	-.2815766	.0553794

Table C4: Logistical regression and average marginal effects explaining the likelihood to engage in knowledge commercialisation with the Dutch variable omitted

```
Logistic regression                               Number of obs   =        188
                                                  LR chi2(8)      =      24.16
                                                  Prob > chi2     =     0.0022
Log likelihood = -117.84754                       Pseudo R2       =     0.0930
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.6059111	.478398	-1.27	0.205	-1.543554	.3317319
associateprof	-.6152414	.6041046	-1.02	0.308	-1.799265	.5687818
Alpha	.0846722	.5303449	0.16	0.873	-.9547848	1.124129
Gamma	-.2176103	.3886579	-0.56	0.576	-.9793659	.5441452
lnsocialcapital	.4304079	.1259491	3.42	0.001	.1835523	.6772635
dvalortop5uni	.0972972	.3756342	0.26	0.796	-.6389322	.8335266
lnage	2.741095	.9791941	2.80	0.005	.8219099	4.66028
male	-.3855164	.413661	-0.93	0.351	-1.196277	.4252442
_cons	-12.46601	3.882465	-3.21	0.001	-20.0755	-4.856515

```
Average marginal effects                          Number of obs   =        188
Model VCE    : OIM

Expression   : Pr(dknowcom), predict()
dy/dx w.r.t. : prof associateprof Alpha Gamma lnsocialcapital dvalortop5uni lnage
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	-.1330168	.1033836	-1.29	0.198	-.3356451	.0696114
associateprof	-.1350652	.1312385	-1.03	0.303	-.392288	.1221577
Alpha	.0185882	.1163998	0.16	0.873	-.2095512	.2467277
Gamma	-.0477724	.0850681	-0.56	0.574	-.2145029	.118958
lnsocialcapital	.0944883	.0245936	3.84	0.000	.0462858	.1426908
dvalortop5uni	.0213599	.0824065	0.26	0.795	-.1401538	.1828735
lnage	.601758	.1971848	3.05	0.002	.2152829	.9882331
male	-.0846332	.0900213	-0.94	0.347	-.2610718	.0918054

D. Interaction variables

Table D1: Logistical regression and average marginal effects explaining the likelihood to engage in knowledge commercialisation including interaction variables

```
Logistic regression                             Number of obs     =        188
                                                LR chi2(13)       =      38.07
                                                Prob > chi2       =     0.0003
Log likelihood = -110.89248                     Pseudo R2         =     0.1465
```

dknowcom	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	2.239345	8.242537	0.27	0.786	-13.91573	18.39442
associateprof	-.9175785	.6410329	-1.43	0.152	-2.17398	.3388229
Alpha	-.113783	.5445064	-0.21	0.834	-1.180996	.95343
Gamma	-.4248969	.4120998	-1.03	0.303	-1.232598	.3828038
lnsocialcapital	-.2241434	.3290543	-0.68	0.496	-.8690779	.4207912
dvalortop5uni	.1308578	.3914125	0.33	0.738	-.6362966	.8980122
lnage	5.306203	2.54363	2.09	0.037	.3207801	10.29163
Dutch	11.42189	9.59355	1.19	0.234	-7.381122	30.2249
male	-.4467208	.4528288	-0.99	0.324	-1.334249	.4408073
lnageXprof	-.7987439	2.139336	-0.37	0.709	-4.991766	3.394278
lnageXlnsocialcapital	.0002865	.000151	1.90	0.058	-9.50e-06	.0005826
lnsocialcapitalXDutch	.4151548	.3273277	1.27	0.205	-.2263957	1.056705
lnageXDutch	-3.298921	2.442582	-1.35	0.177	-8.086294	1.488453
_cons	-19.64947	9.722869	-2.02	0.043	-38.70594	-.5929944

```
Average marginal effects                        Number of obs     =        188
Model VCE    : OIM

Expression   : Pr(dknowcom), predict()
dy/dx w.r.t. : prof associateprof Alpha Gamma lnsocialcapital dvalortop5uni lnage Dutch
               lnageXlnsocialcapital lnsocialcapitalXDutch lnageXDutch
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
prof	.4556541	1.676242	0.27	0.786	-2.82972	3.741028
associateprof	-.1867056	.1275959	-1.46	0.143	-.4367891	.0633778
Alpha	-.0231522	.1107475	-0.21	0.834	-.2402132	.1939089
Gamma	-.0864565	.0829996	-1.04	0.298	-.2491328	.0762198
lnsocialcapital	-.0456079	.0666599	-0.68	0.494	-.176259	.0850432
dvalortop5uni	.0266265	.079559	0.33	0.738	-.1293063	.1825593
lnage	1.079687	.499088	2.16	0.031	.1014928	2.057882
Dutch	2.324086	1.933342	1.20	0.229	-1.465194	6.113366
male	-.0908972	.0913048	-1.00	0.319	-.2698512	.0880569
lnageXprof	-.1625256	.4348063	-0.37	0.709	-1.01473	.6896791
lnageXlnsocialcapital	.0000583	.0000297	1.96	0.050	7.90e-08	.0001165
lnsocialcapitalXDutch	.0844742	.0655389	1.29	0.197	-.0439797	.2129282
lnageXDutch	-.6712528	.4904982	-1.37	0.171	-1.632611	.290106