The process of academic scientists' knowledge and technology transfer: Initiation, phase transitions and multiple goals

Dissertation

zur Erlangung des akademischen Grades
doctor rerum politicarum
(Dr. rer. pol.)

vorgelegt dem Rat der Wirtschaftswissenschaftlichen Fakultät
der Friedrich-Schiller-Universität Jena
am 06. Dezember 2023

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Datum der Verteidigung: 29.05.2024

Acknowledgments

I would like to express my gratitude to my first supervisor, Prof. Dr. Uwe Cantner, for the opportunity to be part of his research team, for sharing his valuable knowledge with me and for guiding me through my research and my doctorate.

I would like to express my thanks to PD Dr. habil. Holger Graf for his continuous support in all aspects of the daily life of a doctoral student and his constant feedback on my research work.

I am also grateful to Dr. Pablo D'Este for accepting to be my third referee and for sharing his expertise in the field of knowledge transfer from academia to industry at various conferences.

I would like to express my sincere thanks to the Thuringian Ministry for Economic Affairs, Science and Digital Society, which funded the ET^3 research project ("Knowledge and Technology Transfer in Thuringia") in which I was involved and which enabled the financing of my research. Special thanks to all members of the project team Philip Dörr, Lukas Dreier, Dr. Maximilan Göthner, Dr. Martin Kalthaus and Indira Yarullina, for the close cooperation, the fruitful exchange, the mutual encouragement and support in advancing our joint research.

I would also like to thank all the previous and current members of the Graduate Program "The Economics of Innovative Change" for their support, help and advice.

Finally, I would also like to thank my wife, family and friends for their continuous support and motivation.

Thesis overview

Contents

List of Figures

List of Tables

Deutsche Zusammenfassung

Diese Dissertation befasst sich mit dem Prozess des Wissens- und Technologietransfers vom akademischen Sektor in die industrielle Anwendung und untersucht verschiedene Abschnitte des Prozesses. Die Untersuchungseinheit ist dabei stets der/die individuelle Wissenschaftler:in. Kapitel 1 führt in die Thematik ein, zeigt deren volkswirtschaftliche Relevanz auf, stellt die Forschungsziele der Dissertation vor und fasst die nachfolgenden Kapitel kurz zusammen. Die Kapitel 2 bis 4 sind die Kernkapitel dieser kumulativen Dissertation. Sie präsentieren die Ergebnisse der drei Forschungsarbeiten die dieser Thesis zugrunde liegen. Untersuchungsgegenstand dieser Forschungsarbeiten sind dabei die Einflussfaktoren auf die Initiierung des Transferprozesses, das Voranschreiten darin sowie die erfolgreiche Implementierung des Transfers neben der üblichen Forschungsarbeit. Die Dissertation schließt mit Kapitel 5 ab, in welchem die wichtigsten Ergebnisse und Beiträge zusammengefasst sowie politische Implikationen, Limitationen und daraus resultierende weitere Forschungsmöglichkeiten aufgezeigt werden. Für die vorliegenden Untersuchung wurde ein Fragebogen entwickelt und per Online-Umfrage an das wissenschaftliche Personal thüringischer Hochschulen und Forschungsinstitute versendet. Diese Primärdaten wurden mit bibliometrischen Daten der Befragten verbunden und um weitere Sekundärdaten zu den Forschungseinrichtungen der Wissenschaftler:innen ergänzt. Bei den Analysen wurde auf verschiedene Methoden der ökonometrischen Datenanalyse zurückgegriffen. Diese beinhalteten logistische Regressionen, Dominanzanalysen, Seemingly-unrelated Regressionen mit Korrektur möglicher Selektionseffekte sowie multinomiale Regressionen.

Der akademische Transferprozess kann auf konzeptueller Ebene derart beschrieben werden, dass Forschungsresultate an Hochschulen und Forschungsinstituten

generiert und diese anschließend von Wissenschaftler:innenn in die industrielle Anwendung übermittelt werden. Entlang dieses Prozesses muss das aus der Forschung generierte Wissen in eine Anwendungsmöglichkeit konvertiert werden. Dabei ist der Transferprozess, ähnlich wie der Innovationsprozess, von Unsicherheiten bzgl. seiner erfolgreichen Umsetzung geprägt und entlang der Prozessphasen mit verschiedenen Aktivitäten und Herausforderungen für die Wissenschaftler:innen behaftet. Neben den Unterschieden in den Phasen unterscheidet sich der Prozess auch darin, welchen Transferkanal die Wissenschaftler:innen für die angestrebte Transferaktivität nutzen. Die drei Transferkanäle, die für die Untersuchungen dieser Dissertation herangezogen werden, sind die akademischen Ausgründungen, der Schutz von geistigen Eigentum und die Forschungskollaborationen zwischen akademischer Wissenschaft und Industrie. Wie sich dieser Prozess mit seinen phasen- und kanalspezifischen Merkmalen auf der Mikro-Ebene des/der einzelnen Wissenschaftler:in entfaltet, ist in der Literatur bisher noch kaum beleuchtet worden. Diese Arbeit betrachtet daher den Prozess aus verschiedenen Perspketiven und leistet einen Beitrag zur Transferliteratur, indem die erwähnte Verständnislücke angegangen wird. Dabei sollen Erkenntnisse darüber geliefert werden, was Wissenschaftler:innen beeinflusst einen solchen Transferprozess überhaupt zu initiieren. Des Weiteren wird das Voranschreiten im Prozess untersucht. Dafür werden die Phasenübergänge analysiert und überprüft, wie sich die relative Wichtigkeit der Einbettung der Wissenschaftler:innen in die akademische und kommerzielle Sphäre dabei verändert. Schließlich soll auch die Implementierung des Transfers betrachtet werden und wie dies neben der üblicherweise angestrebten hohen Forschungsleistung erreicht werden kann. Hierbei wird die Rolle verschiedener Formen von Sozialkapital bei der Erreichung von Kommerzialisierung und hoher Forschungsleistung bei universitären Wissenschaftler:innen herausgearbeitet.

Da jeder Transfer seinen Ursprung in der Forschungstätigkeit und ihren Ergebnissen hat, bedeutet dies, dass der/die Wissenschaftler:in den Prozess zunächst aktiv initiieren muss. Bisher gibt es in der Literatur zum Wissenstransfer keine Konzeptualisierung der Transferinitiierung. Einig sind sich die Forscher:innen dieses Feldes jedoch darin, dass die Voraussetzung für jeden Transfer das Vorhandensein einer unerkannten Transfermöglichkeit ist und das Erkennen einer solchen die erste Schwierigkeit im Transferprozess darstellt. Das Erkennen einer solchen Möglichkeit erfordert, das kommerzielle Potential der Forschungsergebnisse zu prüfen und potenzielle industrielle Anwendungen ins Auge zu fassen. In Anlehnung an die bestehende Forschung zur Erkennung von unternehmerischen Möglichkeiten aus der Entrepreneurship-Literatur konzeptualisieren wir die Transferinitiierung, indem wir sie in die gleichzeitig stattfindende Erkennung einer Transfermöglichkeit und die Wahl des Transferkanals zur Verfolgung dieser Möglichkeit unterteilen. Wir stellen die Hypothesen auf, dass akademisches und nicht-akademisches Vorwissen, Forschungsqualität und Beziehungen zu industriellen Akteuren die Wahrscheinlichkeit erhöhen, dass Wissenschaftler:innen eine Transfermöglichkeit erkennen. Wir gehen ferner davon aus, dass ihre Forschungsorientierung, ihre Risikobereitschaft und das Vorhandensein kanalspezifischer Vorbilder ihre Wahl des Transferkanals beeinflussen. Unsere deskriptiven Ergebnisse zeigen, dass weniger als die Hälfte der Wissenschaftler:innen in den letzten fünf Jahren eine Transfermöglichkeit erkannt hat. Die Ergebnisse unserer Seemingly-unrelated Regressionen deuten darauf hin, dass sowohl das akademische als auch das nicht-akademische Vorwissen der Wissenschaftler:innen die Wahrscheinlichkeit, eine Transfermöglichkeit zu erkennen, signifikant erhöhen. Wir finden, anders als angenommen, eine statistisch negative Beziehung zwischen der Erkennung einer Transfermöglichkeit und der Forschungsqualität der Wissenschaftler:innen. Darüber hinaus können wir zeigen, dass eine Ausrichtung auf angewandte Forschung die Wahrscheinlichkeit, dass Wissenschaftler:innen den Kanal der geistigen Eigentumsrechte wählen, signifikant erhöht, während diese Beziehung auch für die Grundlagenforschung und die Wahl des Kanals der Ausgründung gilt. Die Ergebnisse deuten ebenfalls darauf hin, dass Risikobereitschaft ein signifikanter Prädiktor für die Wahl des Kanals der Ausgründung ist. Ein positiv signifikanter Einfluss von kanalspezifischen Vorbildern kann für die Wahl des Kanals der geistigen Eigentumsrechte sowie den Kanal zur Ausgründung nachgewiesen werden.

Nachdem der Transfer initiiert wurde, umfasst der Prozess verschiedene Phasen, die der/die Wissenschaftler:in bewältigen muss. Bestehende Modelle für den Transfer von Wissen und Technologien in die Industrie unterscheiden sich sowohl hinsichtlich des betrachteten Transferkanals als auch hinsichtlich der Anzahl der Prozessphasen. Diese Modelle sind oft linear aufgebaut, es ist jedoch allgemein bekannt, dass der Transferprozess, wie jeder Innovationsprozess, einer gewissen Dynamik unterliegt, die Versuch und Irrtum während des Prozesses zulässt. Wir verwenden ein quasi-lineares Modell in der Betrachtung des akademischen Ausgründungsprozesses, das sich durch Rückkopplungsschleifen innerhalb der einzelnen Phasen und kritischen Punkten vor jedem Übergang zur nächsten Phase auszeichnet. In allen Phasen muss der/die Wissenschaftler:in bestimmte Aktivitäten durchführen und mit Hindernissen umgehen, um diese kritischen Punkte zu überwinden und die nächste Phase im akademischen Ausgründungsprozess zu erreichen. Es kann jedoch auch vorkommen, dass der/die Wissenschaftler:in nicht in der Lage ist, die Aktivitäten durchzuführen, dass er/sie an den Hindernissen scheitert oder dass er/sie die Ausgründungsbestrebungen verwirft. Solche Abbrüche von Wissenschaftler:innen im Verlauf des akademischen Ausgründungsprozesses wurden bisher noch nicht quantitativ erfasst. Des Weiteren arbeiten wir aus der Literatur heraus, dass Wissenschaftler:innen an Hochschulen und Forschungsinstituten in die akademische Sphäre eingebettet sind. Die Einbettung in eine Sphäre bestimmt die Beziehung zwischen den institutionellen und sozialen Strukturen und prägt das Verhalten des/der Einzelnen in dieser Sphäre. Sie definiert die dort vorherrschenden Kompetenzen, Aktivitäten und sozialen Verhaltensweisen. Im Falle einer akademischen Ausgründung muss der/die Wissenschaftler:in jedoch in der kommerziellen Sphäre agieren, welche die Merkmale im Kontext der unternehmerischen Aktivitäten abdeckt und sich damit grundlegend von der akademischen Sphäre unterscheidet. Wir stellen die Hypothese auf, dass die Bedeutung der Einbettung in die akademische Sphäre abnimmt, je weiter der/die Wissenschaftler:in im Prozess fortschreitet, während die Einbettung in die kommerzielle Sphäre zunimmt. Unsere Ergebnisse zeigen, dass die kommerzielle Sphäre durchweg eine höhere Bedeutung für den Übergang von einer Phase zur nächsten hat als die akademische Sphäre. Dies trifft auch schon für die frühen Phasen des Prozesses zu, was bestehende Konzeptualisierungen des Ausgründungsprozesses in der Literatur in Frage stellt.

Ist der/die Wissenschaftler:in in der Lage, die Phasenübergänge zu bewältigen, endet der Prozess mit der Umsetzung des Transfers. Dabei sollte nicht außer Acht gelassen werden, dass Wissenschaftler:innen während ihrer

Transferbemühungen, insbesondere an Hochschulen, auch akademische Ziele verfolgen, die sich auf ihre Forschung auswirken und ihre Karriereaussichten beeinflussen. Ein wichtiges akademisches Ziel für Wissenschaftler:innen ist es, durch einflussreiche Beiträge zum wissenschaftlichen Diskurs hohe Forschungsleistungen zu erzielen. Sie streben dieses Ziel an, um Reputation und Anerkennung unter Fachkolleg:innen zu gewinnen und ihre Chancen auf eine Festanstellung zu erhöhen. Während dieses Ziel auf eine akademische Verwertung von Forschungsergebnissen abzielt, unterliegt die Kommerzialisierung der Ergebnisse unterschiedlichen Normen und Belohnungssystemen, was die Balance zwischen diesen beiden Zielen für Wissenschaftler:innen zu einem schwierigen Unterfangen macht. Dies hat zur Folge, dass transferierende Wissenschaftler:innen multiple Ziele zu erreichen haben, die sie versuchen, miteinander in Einklang zu bringen. Einige Ergebnisse aus der Literatur deuten darauf hin, dass sich diese Ziele nicht zwangsläufig gegenseitig ausschließen, sondern dass es einen Zusammenhang zwischen hoher Forschungsleistung und Kommerzialisierungsaktivitäten von Wissenschaftler:innen gibt. Einer bestimmten Gruppe von Wissenschaftler:innen gelingt es demnach, die verschiedenen Ziele miteinander in Einklang zu bringen. Während sich die bisherige Forschung darauf konzentriert hat, wie Wissenschaftler:innen einzelne Ziele erreichen, fehlt es an Erkenntnissen darüber, was dazu beiträgt, dass Wissenschaftler:innen multiple konfliktbehaftete Ziele erreichen. Diese Lücke wird von mir gefüllt, indem ich ein Quadrantenmodell einführe, welches Wissenschaftler:innen auf der Grundlage ihrer Forschungsleistung und der Kommerzialisierung ihrer Forschungsergebnisse in Profile kategorisiert. Die Hauptannahme ist, dass das soziale Kapital der Wissenschaftler:innen eine entscheidende Rolle bei der multiplen Zielerreichung spielt. Es stellt die Ressourcen dar, auf die sie zurückgreifen und die sie für zielgerichtete Handlungen mobilisieren können, indem sie sich auf die soziale Struktur stützen, in die sie eingebettet sind. Soziales Kapital kann jedoch verschiedene Formen mit unterschiedlichen Merkmalen annehmen, die die soziale Struktur beschreiben. Es kann genutzt werden, indem man sich mit Fachkolleg:innen in der wissenschaftlichen Gemeinschaft verbindet, um sich einen Wettbewerbsvorteil in der Forschung zu verschaffen oder indem man Verbindungen zur Industrie knüpft und das eigene Netzwerk diversifiziert. Es werden drei verschiedene Formen des Sozialkapitals betrachtet, die auf den Kontext von Hochschulwissenschaftler:innen zugeschnitten werden: bindendes (Verbindungen zu Fachkolleg:innen), überbrückendes (Verbindungen zur Industrie) und verbindendes (grenzüberschreitende Aktivitäten innerhalb von Hochschulen) Sozialkapital. Der Einfluss dieser drei Formen des Sozialkapitals auf die multiple Zielerreichung wird anhand einer multinomialen Regression untersucht mit der Profilzugehörigkeit der Wissenschaftler:innen als abhängiger Variable. Die Ergebnisse enthüllen, dass es nur einem kleinen Teil der Wissenschaftler:innen (6,5 %) gelingt, hohe Forschungsleistungen mit der Kommerzialisierung ihrer Forschungsergebnisse in Einklang zu bringen. Alle drei Formen des Sozialkapitals haben dabei einen signifikanten Einfluss auf diese multiple Zielerreichung. Das bindende Sozialkapital begünstigt hohe Forschungsleistungen, während das überbrückende und verbindende Sozialkapital die Kommerzialisierung von Forschungsergebnissen unterstützt. Darüber hinaus gibt es Hinweise auf eine umgekehrt U-förmige Beziehung zwischen bindendem Sozialkapital und der Forschungsleistung, was darauf hindeutet, dass ein Übermaß an solchen Bindungen nachteilig werden kann.

Zusammengefasst lässt sich sagen, dass diese Disertation einen Beitrag zur Literatur über den Wissens- und Technologietransfer leistet, indem sie den Transferprozess aus verschiedenen Perspektiven beleuchtet und dadurch Erkenntnisse über die Einflussfaktoren auf die Transferinitiitiierung, das Voranschreiten im Prozess und die multiple Zielerfüllung von Wissenschaftler:innen liefert. Dieser Beitrag kann als Ausgangspunkt für zukünftige Forschungsarbeiten zum Wissens- und Technologietransfer mit Prozessorientierung angesehen werden, in denen weitere Transferkanäle und weitere mögliche Einflussfaktoren untersucht werden können.

Chapter 1

Introduction

1.1 The process of academic scientists' knowledge and technology transfer

The engagement of scientists from universities and research institutes in knowledge and technology transfer (KTT) into economic application has gained substantial attention over recent decades (e.g. Bozeman, 2000; Fini et al., 2018; Perkmann et al., 2013; 2021; Siegel et al., 2004). Thereby academic scientists bridge the gap between academia and industry enabling the industrial application of scientific insights, which can foster innovation, economic activity and solutions to grand societal challenges (Bornmann, 2013; Fini et al., 2018; George, Howard-Grenville, et al., 2016; Siegel et al., 2007). The underlying process of such an engagement starts with the generation of research results and concludes with their application outside the public science sector (e.g. Philbin, 2008; Vohora et al., 2004). However, this process of transfer is a challenging endeavor for academic scientists and stands in contrast to their usual research activity.

The general problem of transfer activities for academic scientists can be described from an economic perspective on the basis of two general aspects. First, the treatment of knowledge is fundamentally different between academic and industrial actors. Academic scientists produce knowledge with an understanding of it as a public good whose dissemination contributes to the benefit of society. Industrial actors, on the other hand, are interested in the protection and economic exploitation of new knowledge, which gives it the character of a private good. Second, the engagement in transfer activities represents opportunity costs for the scientists. It demands additional time from them that cannot be used for other contractually stipulated tasks such as their own research progress and teaching duties. Furthermore, the publication of their results may be delayed if they are part of a procedure to protect intellectual property rights or if they are part of the project output of joint research with industrial partners who have no interest in disclosing the results. In addition, any involvement in transfer activities is fraught with uncertainties regarding successful implementation. Academic scientists must therefore weigh up whether they are willing to exchange academic returns for potential transfer outcomes.

However, if the focus is on transfer from a procedural perspective, these explanations are not sufficient to fully understand what influences academic scientists to start the process, manage its progression and actually implement the transfer. Furthermore, they do not explain sufficiently why there are some scientists who achieve their academic goal of a high level of research performance and yet are also able to successfully implement transfer.

This thesis sheds light on the process of KTT from academia to industrial applications. The process will be examined from different perspectives, always focusing on the individual academic who carries out the transfer in addition to their academic work. Three different transfer channels are used to analyze the process: Science-Industry collaboration, intellectual property rights and academic spin-off. The latter is given a particularly detailed consideration. Even though this thesis will not be able to uncover all mechanisms responsible for academic scientists' KTT to industry, it contributes to our understanding of the transfer process and the role of the individual scientist along this process, which can improve KTT process theory and accelerate the effectiveness of KTT realization.

The first research objective of this dissertation is to shed light on the initiation of the transfer process. Any transfer process must first be started by an academic scientist, regardless of how far they progress in the process, or even implement the transfer. This element of the transfer process has so far remained untouched in the literature and therefore we need insights into the factors related to the initiation of the process.

Once the transfer has been initiated, the academic scientist has to progress through various phases until implementation. These require different activities and are fraught with challenges that need to be overcome. If this is not successful, the transfer process may be discontinued. The further the scientist progresses in the process, the closer they supposedly come to the industrial sphere. This requires an adaptation to the sphere's logics and norms that differ fundamentally from those of the academic sphere. It is the second research objective to find out how the importance of being embedded in the respective sphere changes along the phase transitions of the transfer process.

The aim of every transfer activity is to reach the end of the process by implementing the transfer. However, this goal is not the only one that academic scientists pursue. In order to advance their own career, it is essential to keep research performance high, which can lead to conflicting goals, especially when it comes to the commercialization of research results. Nevertheless, there are academic scientists who are able to reconcile both. We do, however, not yet know which factors are important in their multiple goals achievement. A first starting point is their social capital in its various forms, which the third research objective seeks to cover.

In the following the three different perspectives on the KTT process — namely its initiation, phase transitions along it and the multiple goals of scientists throughout this process — and the corresponding research objectives of this thesis are discussed in more detail.

1.1.1 Initiation of the transfer process

Any transfer from academia to industry has its origin in the research activity and its results by the scientists. Generally, to get the transfer process started requires linking knowledge to action. The activation of the process occurs through its initiation by the scientist. So far, the literature does not offer a conceptualization of transfer initiation. What the scholars do agree on, however, is that the prerequisite of any KTT is the existence of an unrecognized opportunity and that the recognition of such an opportunity constitutes the first difficulty in the KTT process (Bar-Zakay, 1971; Battistella et al., 2016). According to Etzkowitz (1998), recognizing a transfer opportunity requires the individual scientist to scan research results for their commercial as well as their intellectual potential. By doing so, scientists envision and conceive potential industrial applications and initiate the conversion of their research results into economic value (Sousa-Ginel et al., 2021; Zahra et al., 2007).

In the absence of a conceptualization of transfer initiation, the antecedents of transfer opportunity recognition are also still unknown. However, the entrepreneurship literature and its research on entrepreneurial opportunity recognition offers a suitable source to adapt to the KTT context, since scientists transferring knowledge from academia to industry can be considered as actors in an entrepreneurial manner. This strand of literature emphasizes the importance of individuals‘ prior knowledge as well as their social contacts (e.g. Ardichvili et al., 2003; Arentz et al., 2013; Bhagavatula et al., 2010; George, Parida, et al., 2016). Within the scope of academics‘ KTT, these antecedents are represented in scientific and technical human capital developed by Bozeman et al. (2001). It encompasses scientists' endowment of scientific, technical and social knowledge and skills, including all the resources which are embodied in the individual scientist and on which they can draw due to social relations and network ties.

Inherently connected to the transfer opportunity recognition is the choice of the transfer channel through which the scientist aims to pursue the opportunity. It is an important decision the scientist has to make when initiating the process. Transfer channels differ in various respects, such as the risk involved in engaging in them or the benefits that can arise from them (Arza, 2010; de Fuentes & Dutrénit, 2012). For example, commercializing a discovered algorithm with an industry partner will not only have lower risks but also lower rewards than if the scientist founds their own firm. So far, studies tried to explain this decision retrospectively after the transfer was completed and, thus, suffer from survival bias (e.g. Abreu & Grinevich, 2013; D'Este et al., 2019; Landry et al., 2010).

Thus, the first research objective is to uncover scientists initiation of a transfer process by investigating the antecedents of their transfer opportunity recognition and the factors influencing their choice of a transfer channel.

1.1.2 Phase transitions along the process

After the transfer is initiated the process encompasses distinct phases the scientist needs to master. Existing models regarding academics bridging to industry vary in their considered transfer channel as well as in the number of process phases. These models are often linear in their structure, but it is widely known that the transfer process, like any innovation process, is subject to a certain dynamic that allows trial and error along the process (Fini et al., 2019).

Based on their case study, Vohora et al. (2004) developed a quasi-linear model of the academic spin-off creation process featuring feedback loops within the individual phases and critical junctures before each transition to the subsequent phase. These critical junctures arise because different phases of spin-off creation require distinct configurations of resources, capabilities, network ties and support. In all phases the scientist needs to accomplish specific activities and deal with barriers to overcome these critical junctures to reach the next phase in the spin-off creation process. However, it may also occur that the scientist is unable to accomplish the activities, fails due to the barriers, or simply disengages from the transfer engagement. Such dropouts of scientists along the spin-off creation process have not yet been measured on a quantitative level.

Scientists at universities and research institutes are embedded in the academic sphere, which defines the prevailing sets of competencies, activities, and social behavior there (Dasgupta & David, 1994; Stephan & Levin, 1996). Being embedded in a sphere determines the relationship between the institutional and social structures and shapes an individual's behavior within that sphere (Beckert, 2003; Granovetter, 1992; Le Breton-Miller & Miller, 2009; Zukin & DiMaggio, 1990). In the case of a spin-off creation, however, the scientist must operate in the commercial sphere with different characteristics covering the context of entrepreneurial efforts. In his theory paper on the academic spin-off creation process of scientists, Rasmussen (2011) derives a continuous shift in the importance of scientists‘ embeddedness in the academic and commercial sphere along this process. According to his conceptual framework, the importance of being embedded in the academic sphere decreases as the scientist progresses along the transfer process, while the embeddedness in the commercial sphere increases.

The multi-phased model with its transitions provided by Vohora et al. (2004) lends itself to the empirical analysis of the conceptualized change in the importance of scientists' embeddedness within the two opposing spheres by Rasmussen (2011). Adopting a micro-level perspective by analyzing the phase transitions from the viewpoint of the individual scientist emphasizes the transfer agent, since previous research has remained predominantly at the spin-off project level, neglecting individual characteristics and tensions.

The second research objective aims to add to our understanding of how scientists' embeddedness within the academic and commercial spheres influences their phase transitions along the transfer process.

1.1.3 Scientists' multiple goals

If the scientist is able to master all phase transitions, the process ends with the implementation of the transfer. Every engagement in knowledge and technology transfer has the consequential goal of actually implementing the transfer. However, initiating it and progressing in the process is fraught with challenges and effort for the scientist. It should not be ignored that scientists, especially those at universities, also pursue academic goals that affect their research and drive their career prospects. As a consequence, transferring scientists have multiple goals to achieve, which they try to reconcile with each other.

An important academic goal for scientists is to achieve high research performance through impactful contributions to the scientific discourse. They aim to achieve this goal to gain reputation and peer-recognition and also to increase their chances of awarded tenure (Lissoni et al., 2011). While this goal aims at an academic exploitation of research results, the commercialization of these results is subject to different norms and reward systems, which makes balancing them a difficult endeavor for scientists (Ambos et al., 2008; Sauermann & Stephan, 2013). Yet, the literature already indicates, that these goals are not mutually exclusive but that there is a relationship between high research performance and commercialization activities by scientists (e.g. Geuna & Nesta, 2006; Gulbrandsen & Thune, 2017; Siegel et al., 2007; van Looy et al., 2006; 2011). This means, there is a certain group of scientists who can manage to reconcile these multiple goals.

For each of these goals, scientists rely on their social capital to achieve it. It constitutes the set of resources they can access and mobilize for purposive actions by drawing on the social structure in which they are embedded (Lin, 2017; Portes, 1998). However, social capital can take on various forms with different characteristics describing the social structure. Scientific peers, for example, can help solve emerging problems in the research process, while contacts with industry can be important companions in the commercialization process. Social capital theory proposes a distinction between three forms of this capital: bonding, bridging and linking social capital. They differ in terms of their network type, strength of ties, type of relationships, trust and benefits.

The missing link in the literature is the influence of different forms of social capital on the multiple goals achievement by scientists, which is why the third research objective is dedicated to this study.

1.2 Structure of the thesis

This cumulative thesis is composed of three papers identified as the core chapters 2-4. Each chapter sheds light on the process of knowledge and technology transfer from the academic sector to industrial application and examines different stages of the process, with the scientist as the unit of investigation. Chapter 2 looks at the onset of the transfer process, examining the influences on the recognition of transfer opportunities and the choice of channel to pursue this opportunity. Chapter 3 examines the entire transfer process from knowledge generation to commercial application for the academic spin-off channel and the conditions for the progress of scientists in this channel. Chapter 4 deals with the multiple goals achievement of scientists who commercialize their research results in addition to their high research performance, and the role of their social capital in this. Table 1.1 summarizes the key characteristics of the chapters. Additionally, each chapter is summarized in the following.

1.2.1 Chapter 2

The second chapter "Initiation of knowledge and technology transfer from academia to industry: Opportunity recognition and transfer channel choice" aims to understand how the initiation of a transfer process unfolds, an area that has received relatively little attention in existing research. Focusing on the beginning of the process, however, is crucial because it determines whether and how knowledge generated within academia finds its way into practical applications beyond the academic realm.

To address this gap in the literature we conceptualize the initiation of the transfer process for the first time in KTT research. Based on our conceptualization it encompasses two key components: the recognition of a transfer opportunity and the simultaneous choice of a transfer channel to act on the opportunity. Our approach draws upon the literature on entrepreneurial opportunity recognition and adapts it to the KTT context (Ardichvili et al., 2003). We focus on the three most common and economically relevant KTT channels: Science-Industry collaboration, intellectual property rights and academic spin-off creation. These channels are particularly significant in cases where the impetus for transfer arises from internal research within the academic environment.

Our aim is to provide a comprehensive understanding of the process initiation of KTT, shedding light on why some scientists recognize transfer opportunities while others do not, and which factors guide their choice of channels for pursuing these opportunities. We derive hypotheses regarding the factors that influence scientists in recognizing transfer opportunities and their decision-making process when choosing a KTT channel.

Table 1.1: Thesis overview.

	Chapter 2	Chapter 3	Chapter 4
Title	Initiation of knowledge and technology transfer from academia to industry: Opportunity recognition and transfer channel choice	A procedural perspective on academic spin-off creation: The changing relative importance of the academic and the commercial sphere	University scientists' multiple goals achievement: Social capital and its impact on research performance and research commercialization
Co-authors	Philip Doerr, Martin Kalthaus	Uwe Cantner, Maximilian Goethner, Philip Doerr, Martin Kalthaus	
Theoretical foundation	Scientific and technical human capital, Opportunity recognition	Sphere embededdness, Multiple institutional logics	Multiple goals, Social capital
Process view	Initiation of transfer process	Phase transitions along process	Implementation of the transfer (alongside research performance)
Transfer channels	Science-Industry collaboration, intellectual property rights, academic spin-off	Academic spin-off	Academic spin-off, intellectual property rights
Data	Survey and bibliometric data	Survey and bibliometric data	Survey, bibliometric and funding data
Methodology	Seemingly unrelated regressions	Logit regression with dominance analysis	Multinomial logit regression
Own contribution	Significant contribution to the design of the study, data collection,theoretical and empirical elaborations, and interpretation of the results	Significant contribution to the design of the study, data collection,theoretical and empirical elaborations, and interpretation of the results	-
Status	First revision received and resubmission in Industrial and Corporate Change is being prepared. Available as working paper in JERP: No. 2023-002	Published in Small Business Economcis. DOI: 10.1007/s11187-023-00815-w	Under review in Technovation

We conducted an online survey of scientists in the German state of Thuringia between December 2019 and January 2020. This survey inquired about the scientists' involvement in KTT activities through the three considered transfer channels. Our sample of respondents from universities and research institutes is representative for Germany. We utilize seemingly unrelated regressions to account for selection and multiple channel choices in our econometric approach.

The findings of this study revealed a positive relationship between scientists' probability to recognize a transfer opportunity and different kinds of prior knowledge. Contrary to our expectation, scientific quality reduces the likelihood of recognizing a transfer opportunity. For the choice of the transfer channel, the results show a positive relationship between choosing the spin-off channel and basic research as well as risk willingness. Applied research increases the likelihood to choose intellectual property rights as a channel. Furthermore, role models are positively associated with both of these channels.

This chapter is co-authored with Philip Doerr and Martin Kalthaus. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations as well as to the interpretation of the results. Currently we have received first review results from the Journal *Industrial and Corporate Change* and are preparing a revised resubmission. The Chapter has been published as working paper in the Jena Economic Research Paper (JERP) series: No. 2023-002.

1.2.2 Chapter 3

The third chapter "A procedural perspective on academic spin-off creation: The changing relative importance of the academic and the commercial sphere" focuses on the multi-phase process and the transitions along it for one specific transfer channel: Academic spin-offs (ASOs). ASOs are considered significant contributors to economic growth, job creation and addressing societal challenges (Fini et al., 2018; Rasmussen et al., 2020; Vincett, 2010). Despite the increasing number of ASOs in recent years, many of these enterprises fail during the founding process, representing untapped potential (Braunerhjelm, 2007; Fini et al., 2017). Extensive research has been conducted to understand the ASO founding process, focusing on its phases and the challenges faced by academic entrepreneurs. These challenges often manifest as "critical junctures", complex issues that hinder progress from one phase to the next (Vohora et al., 2004).

We underscore the importance of scientists' embeddedness in both the academic and commercial spheres, as these spheres have contrasting institutional and normative structures that influence scientists' behavior (Dasgupta & David, 1994; Rasmussen, 2011; Stephan & Levin, 1996). Scientists pursuing their research are embedded in the academic sphere, where Mertonian norms prevail and knowledge is considered a public good. However, engaging in the ASO creation process requires an additional embeddedness in the commercial sphere, which operates under substantially different attitudes, norms, and logics, such as rent-seeking and secrecy. During the founding process, academic entrepreneurs are often confronted with tensions arising from the differences between these two spheres. Successfully founding a new enterprise requires scientists to navigate and resolve these tensions.

In this chapter we examine how the relative importance of scientists' embeddedness in the academic and commercial spheres changes throughout the ASO creation process. The study divides the process into four phases, including the research phase, opportunity framing, pre-spin-off phase, and spin-off phase, with three transitions between them. The main assumption is that the importance of the academic sphere decreases while the importance of the commercial sphere increases.

We employ our survey data collected from 1,149 scientists at universities and research institutes in Thuringia, Germany. The survey also gathered information about the scientists' involvement in various phases of ASO founding. Different proxies from survey data and additional publication data of the scientists are used to capture the embeddedness in each of the two spheres. We estimate the probability of individual scientists' transitions from one phase to the next and use dominance analysis to assess the changing relative importance of embedding in both spheres.

We observe that the level of embeddedness in both spheres directly impacts the success of these transitions. The results support the main assumptions, showing a decreasing relative importance of the academic sphere as the

ASO founding process advances and an increasing relative importance of the commercial sphere. However, there is an exception during the transition to the final phase, where the importance of the commercial sphere decreases. The study also reveals that the relative importance of the commercial sphere is higher than that of the academic sphere from the early stages of the process, challenging existing notions in the ASO literature that prioritize the academic sphere in the early stages of ASO creation.

This chapter is co-authored with Uwe Cantner, Philip Doerr, Maximilian Goethner and Martin Kalthaus. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations as well as to the interpretation of the results. The chapter is published in *Small Business Economics* and in the following chapters referred to as Cantner et al. (2023).

1.2.3 Chapter 4

The fourth chapter "University scientists' multiple goals achievement: Social capital and its impact on research performance and research commercialization" delves into the evolving role of university scientists, shedding light on the increasing demands placed upon them. While their primary goal has traditionally been to conduct high-quality research and distinguish themselves from their peers by making impactful contributions to scientific discourse, recent years have witnessed a significant expansion in the scope of their responsibilities (Etzkowitz & Leydesdorff, 2000; Fromhold-Eisebith & Werker, 2013; Perkmann et al., 2021). Notably, they are now expected to engage in outreach activities that bridge the gap between academia and industry or society at large.

This shift challenges the traditional image of the scientist ensconced in an ivory tower, solely focused on research. Universities have become more actively involved in economic development, prompting scientists to reconcile the pursuit of research excellence with the commercial exploitation of their research results. Achieving these goals is not without its challenges, as they are subject to different norms and reward systems (Ambos et al., 2008; Sauermann & Stephan, 2013). Literature shows that these goals are not mutually exclusive but that there is a relationship between high research performance and commercialization activities by scientists (e.g. Geuna & Nesta, 2006; Gulbrandsen & Thune, 2017; Siegel et al., 2007; van Looy et al., 2006; 2011), indicating that some scientists can resolve the conflicts between those goals. However, how those scientists manage to achieve multiple goals remains unclear.

While existing research has focused on how scientists achieve individual goals, there is a dearth of information on what sets apart scientists who excel in multiple conflicting goals. This chapter aims to fill this gap by introducing a quadrant model that categorizes scientists based on their research performance and the commercialization of their research results. Four profiles are derived based on scientists' citations per year and publication and the prevalence of commercialized research results: normal scientists with a low research performance and no commercialized research results, star scientists with a high research performance but without commercialized results, ambidextrous scientists with a low research performance but with commercialized results and ambidextrous stars with both, a high research performance and commercialized results.

The key assumption presented in this study is that social capital, which encompasses the resources scientists can access and mobilize through their social networks, plays a vital role in helping them achieve multiple goals (Granovetter, 1973; Putnam, 2001; Szreter & Woolcock, 2004). Social capital can be harnessed by connecting with peers in the scientific community to gain a competitive edge in research, as well as by forging connections with industry and diversifying one's network. Three different forms of social capital are considered and are adapted to the context of university scientists: bonding (connections with peers), bridging (connections with industry), and linking (boundary-spanning activities within universities) social capital.

The research methodology involves the aforementioned survey conducted in the German state of Thuringia, covering scientists' commercialization activities and industry connections. This chapter focuses solely on university scientists and combines the survey data with information on their publication records and university funding structures. Multinomial logistic regressions are used to assess the impact of different forms of social capital on scientists' profile affiliations.

The findings reveal a range of insights: Only a small fraction of scientists (6.5%) manage to balance high research performance with research commercialization. All three forms of social capital have a significant impact on this multiple goal achievement. Bonding social capital benefits high research performers, while bridging and linking social capital support the commercialization of research results. There is also evidence of an inverted U-shaped relationship between bonding social capital and research performance, suggesting that an excess of such ties can become disadvantageous.

This Chapter is single-authored and currently under review in *Technovation*.

Chapter 2

Initiation of knowledge and technology transfer from academia to industry: Opportunity recognition and transfer channel choice

2.1 Introduction

The transfer of academic research into application, so-called knowledge and technology transfer (KTT), fosters innovation, economic activity and can contribute to solutions to grand societal challenges (Bornmann, 2013; Fini et al., 2018; George, Howard-Grenville, et al., 2016; Siegel et al., 2007). The KTT does not take place instantaneously but is a process that starts with knowledge generation in academia and ends with its application outside academia (Fabiano et al., 2020; Siegel et al., 2004; Wood, 2011). Previous research examines phenomena along the process, especially barriers and facilitators (Bozeman et al., 2015; Perkmann et al., 2013; 2021), or focuses on the end of the process, i.e. the transfer outcomes and impacts of the transferred knowledge and technologies (e.g. Abreu & Grinevich, 2013; Audretsch et al., 2012; Bonaccorsi et al., 2014; de Fuentes & Dutrénit, 2012;

D'Este et al., 2019). However, the start of the process, the initiation of KTT, has been mostly neglected, despite its importance in understanding if and how transfer takes place and how to mobilize unused transfer potential.

Bar-Zakay (1971, p. 324) already emphasized in his KTT model that "[a] prerequisite for any case of [knowledge and] technology transfer is the existence of an (unrecognized) opportunity for technology transfer." Even though it seems immanent that an opportunity for KTT needs to be recognized to initiate the transfer process, research on this phenomenon has remained absent over the past decades. While Battistella et al. (2016) acknowledged that the difficulty in initiating transfer lies in recognizing a transfer opportunity, research on how transfer opportunities are recognized and which antecedents for such an opportunity recognition are necessary is missing. While some scholars focus on the intention to conduct KTT (e.g. Goethner et al., 2012; Huyghe & Knockaert, 2015), the intention does not necessarily require a recognized opportunity. Furthermore, the initiation of KTT encompasses not only the recognition of a transfer opportunity but also the choice of a transfer channel to follow-up on the opportunity. The choice of the KTT channel is inherently connected to the transfer opportunity recognition and therefore an important decision in the initiation of the transfer process. Previous research has tried to retrospectively explain the choice of a KTT channel after the transfer was completed (e.g. Abreu & Grinevich, 2013; D'Este et al., 2019; Landry et al., 2010) but not at the initiation of the transfer process. A detailed understanding of the initiation of the transfer process gives insights on why some scientists recognize a transfer opportunity while others do not and what influences their channel choice to pursue the opportunity. Furthermore, such insights allow for the contextualization of research on phenomena along the transfer process and on transfer outcomes, which are usually analyzed retrospectively and suffer from survival bias.

Given the lack of understanding of the initiation of the KTT process, we provide insights on, first, the antecedents of scientists' recognition of a transfer opportunity to commercialize research and, second, which factors influence scientists' choice of a KTT channel. We conceptualize the initiation of the KTT process as a simultaneous event encompassing the recognition of a transfer opportunity and the accompanying choice of a transfer channel to pursue the opportunity. Therefore, we build on research on entrepreneurial opportunity recognition (e.g. Ardichvili et al., 2003; Baron, 2007; George, Parida, et al., 2016; Mejri & Umemoto, 2010; Shane, 2000; 2001) and adapt and generalize it for KTT. For the channel choice, we consider Science-Industry (S-I) collaboration, disclosure of Intellectual Property Rights (IPR) and spin-off creation since they are the most frequent and economically relevant KTT channels. They also represent those channels in which, as Battistella et al. (2016) puts it, the stimulus for transfer initiation arises from internal research — i.e., in the academic environment. We utilize previous findings from retrospective analyses on channel choices (e.g Abreu & Grinevich, 2013; Haeussler & Colyvas, 2011; Landry et al., 2010) to derive potential factors that are relevant for the choice at the initiation of the transfer activity. We center our analysis around the individual scientist and derive hypotheses on the antecedents for the opportunity recognition and the factors influencing the choice of the transfer channel.

To gain empirical insights into the transfer initiation and to test our hypotheses, we developed a novel online survey. We surveyed scientists in the German state of Thuringia between December 2019 and January 2020. We asked them about their transfer activity for the three different channels in the last five years. Our sample of respondents from universities and research institutes is representative for Germany. Since the transfer initiation consists of the simultaneous opportunity recognition and the KTT channel choice, we need to account for the selection into recognizing a transfer opportunity. To account for a potential selection bias, we propose two novel exclusion restrictions. Furthermore, we need to account for the possibility that multiple KTT channels can be chosen to realize the transfer opportunity. Our empirical strategy builds on Seemingly Unrelated Regressions (SUR) (Roodman, 2011), which allows us to simultaneously estimate a selection equation for the opportunity recognition and outcome equations for each KTT channel. In addition, SUR takes into account the possibility of multiple channel selection and can thus reveal interdependencies between channels.

Our results show that fewer than half of the surveyed scientists recognized a transfer opportunity in the last five years. Decisive for such a recognition is prior knowledge, either gained by academic or non-academic work. However, scientists who produce high quality-research are less likely to recognize an opportunity. With these results, we contribute to the literature on academic engagement and commercialization by shifting the focus to the antecedents of scientist's transfer opportunity recognition (e.g. Abreu & Grinevich, 2013; Perkmann et al., 2013; 2021; Rothaermel et al., 2007). With respect to the channel choice, the scientist's research orientations show heterogeneous influences across the channels. Furthermore, risk-willingness is highly relevant for choosing the spin-off channel. Role models have a positive influence on the choice of the IPR and spin-off channel but a negative influence for S-I collaboration. These results contribute to the growing literature devoted to the choice of KTT channels. While other scholars took a retrospective view from transfer implementation (e.g. Abreu & Grinevich, 2013; D'Este et al., 2019; Haeussler & Colyvas, 2011; Landry et al., 2010; Llopis et al., 2018), we capture the recognition directly which overcomes a survival bias in previous analyses. Overall, our findings provide first empirical insights on the initiation of KTT and the full transfer potential. The insights on the characteristics that influence an opportunity recognition, as well as the factors that are decisive for the channel choice, can be used not only to refine existing theoretical models on the transfer process but also to guide policy makers and management of research organisations.

In the following Section 2.2, we conceptualize the transfer initiation and derive hypotheses for the opportunity recognition as well as the choice of KTT channel. In Section 2.3 we discuss our data and empirical approach followed by the results and robustness tests in Section 2.4. We discuss and conclude in Section 2.5.

2.2 Initiating the knowledge and technology transfer process

2.2.1 Conceptualizing the initiation phase

A precursor of KTT is the creation of knowledge (Graham et al., 2006; Stephan, 1996). However, the subsequent knowledge transfer from academia to industry does not occur automatically. It requires that scientists deliberately engage with industry through activities which transfer knowledge (Bercovitz & Feldman, 2006; Louis et al., 1989). Although knowledge is considered a public good and sharing is a common procedure in scientific discourse (Gerbin & Drnovsek, 2020), the logic behind the use of research results for potential commercial exploitation is fundamentally different (Dasgupta & David, 1994). For the scientists, acting within academia and industry is subject to conflicting logics (Sauermann & Stephan, 2013) and evokes tensions that have to be managed and balanced (Ambos et al., 2008; Cantner et al., 2023). Especially at the beginning of the KTT process, these tensions are relevant for the scientists to engage in transfer in the first place.

KTT is usually understood as a process (e.g. Fabiano et al., 2020; Maresova et al., 2019) which can be separated into distinctive, successive phases (e.g. Bradley et al., 2013; Siegel et al., 2003; Wood, 2011; Zuniga & Correa, 2013). The starting point of every KTT process is its phase of initiation, which includes the recognition of a transfer opportunity and the choice of a transfer channel. The process ends with the integration of the knowledge and technology by the recipient (Battistella et al., 2016). In most conceptualizations of the KTT process, the decisive step from research activity to the pursuit of transfer activity is neglected or not conceptualized. Vohora et al. (2004) is among the few who, in the context of spin-off creation, discuss the recognition of an opportunity as a critical juncture from doing research to being engaged in transfer activity. However, they do not investigate what influences a scientist's recognition of a transfer opportunity. In the context of S-I collaboration, Philbin (2008, p. 499) refers to a "collaboration opportunity landscape" where scientists would, based on their research, need to provide technical solutions that might contribute to firms' product or service development. Opportunity recognition would require an alignment of such technical solutions with market trends.

At the beginning of the KTT process stands the individual scientist and their research results from which transfer opportunities can be derived (Ndonzuau et al., 2002). The initiation of the transfer process is the recognition of the transfer opportunity. Borrowing from research in entrepreneurial opportunity recognition (e.g. Ardichvili et al., 2003; Baron, 2007; Shane, 2001), we define a transfer opportunity as an idea based on the scientist's research for which they see potential in application outside the academic context. This opportunity can lead to financial or non-financial rewards for the individual scientist or their institution, either through direct research commercialization or indirectly through facilitated access to additional resources. The recognition of such a transfer opportunity is a cognitive process that initiates the KTT process, regardless of whether the pursuit of the opportunity commences and whether the transfer is accomplished. To discover such a transfer opportunity, the individual has to scan research results for their commercial as well as their intellectual potential to translate scientific results into industrial application (Etzkowitz, 1998). It requires from the scientist that they envision and conceive potential industrial applications, which constitute the start for the conversion of knowledge into economic value (Sousa-Ginel et al., 2021; Zahra et al., 2007). This perspective is frequently coined science push (Callaert et al., 2015; D'Este et al., 2019; Nemet, 2009; Walsh, 1984). Alternatively, a transfer opportunity can also be triggered by an industry pull, where industry actors with specific application-oriented problems seek knowledge and expertise from academia and approach scientists to transfer their knowledge (D'Este et al., 2019; Nemet, 2009; Walsh, 1984). In any case, a scientific discovery paves the way for a potential transfer endeavor. Thereby, the transfer opportunity recognition is the first critical juncture in the overall KTT process that needs to be overcome for the actual initiation of the process (Siegel et al., 2003; Vohora et al., 2004). Thus, the process of KTT starts with the scientist's recognition of transferable research results into industrial application.[1]

The recognition of a transfer opportunity is necessary but not sufficient for KTT because the transfer also requires the choice of a transfer channel through which transfer will take place (e.g. Abreu & Grinevich, 2013; D'Este et al., 2019; Ponomariov & Boardman, 2012). In the initiation phase of the transfer process, the recognition of a transfer opportunity coincides with the choice of transfer channel through which the opportunity can be realized. The choice of the transfer channel is therefore a decision that takes

[1]It is important to disassociate transfer opportunity recognition from intentions towards KTT. In contrast to opportunity recognition, intentions, e.g. entrepreneurial intentions, are considered as a state of mind directed towards a specific behavior (Bird, 1988). While there is, for example, a relationship between entrepreneurial intention and entrepreneurial behavior (Goethner et al., 2011), we do not consider a transfer intention as a necessary prerequisite for opportunity recognition. In the case of an existent transfer intention, it is formed before the opportunity recognition according to action theory (Achtziger & Gollwitzer, 2018; González-López et al., 2021), but an opportunity might not be recognized and the transfer process not initiated.

place simultaneously with the transfer opportunity recognition. Thereby, the channel through which the transfer is realized is inherently connected to the opportunity that is recognized and to scientists' personal and research characteristics.[2] For example, the discovery of a new algorithm would not be subject to patent protection, but it could be developed into a product by the scientist in a spin-off or in collaboration with industry.

Multiple transfer channels are identified in the literature and can be differentiated by several typologies, e.g., in terms of formality (Bercovitz & Feldman, 2006), risk (Arza, 2010) or the benefits for scientists inherent in the engagement within the transfer channel (de Fuentes & Dutrénit, 2012). The most frequent and economically relevant transfer channels for research commercialization are S-I collaborations, protection and commercialization of IPR and the creation of academic spin-offs (Leitner et al., 2021).[3] Transfer via these channels usually is seeded in the academic environment stimulated by scientists' research activities and contains a commercial character either in a narrow sense by selling research results or in a broad sense by co-producing or enabling access to research results to non-academic recipients such as industrial actors. The transfer can lead to a direct economic impact on companies and subsequently on industries, regions or national economies. For the scientists, engaging in these transfer channels can result in scientific and financial returns (Lam, 2011). The transfer channels are associated with different risk-reward trade-offs, and the scientists have to decide upon them. To continue with the above example, commercializing the discovered algorithm with an industry partner will not only have lower risks but also lower rewards than if the scientist founds their own firm. In the literature, the factors that influence the choice of a transfer channel have only been retrospectively analyzed based on the final outcome of the transfer activity (D'Este et al., 2019; Llopis et al., 2018).

[2] While it is widely acknowledged that the initially chosen channel can be subject to change along the overall transfer process (e.g. Hayter et al., 2020; Schaeffer et al., 2020), the scientist's first channel choice is associated with the transfer opportunity recognition at the beginning of the transfer process.

[3] The protection and commercialization of IPR includes not only the sale of patents and other protectable new creations, but also the licensing of these. S-I collaborations represents any form of intended co-production of marketable knowledge and technologies, such as funded research collaborations or contract research. It excludes consultancy which constitutes a commercialization channel not requiring any opportunity recognition by the scientist.

In the following, we focus on potential antecedents for the transfer opportunity recognition and factors which might influence the channel choice. First, we derive a set of hypotheses to empirically test antecedents of transfer opportunity recognition. We derive our hypotheses from the literature on opportunity recognition in entrepreneurship (e.g. Ardichvili et al., 2003; Baron, 2007; George, Parida, et al., 2016; Mejri & Umemoto, 2010; Shane, 2000; 2001) and generalize it for KTT from academia to industry. Second, we derive a set of hypotheses that test the factors influencing the choice of a transfer channel among the scientists who have an opportunity recognition. For the choice of a transfer channel, we draw on the literature regarding scientists' transfer engagement, which provides several factors that allow for the establishment of potential relationships for the choice of the transfer channel (e.g Abreu & Grinevich, 2013; D'Este et al., 2019; Landry et al., 2010). Our approach to conceptualizing the initiation stage of the KTT process allows us to explain, first, why some scientists recognize a transfer opportunity while others do not and, second, what influences the choice of the transfer channel for the subsequent pursuit of the transfer opportunity.

2.2.2 Antecedents for the transfer opportunity recognition

Central to the initiation of the transfer process is the recognition of a transfer opportunity based on research activity and outcomes. Such recognition is a cognitive process that can be influenced by the individual's scientific and technical human capital encompassing scientists' endowment of scientific, technical and social knowledge and skills (Bozeman et al., 2001). It includes all the resources which are embodied in the individual scientist and on which they can draw due to social relations and network ties (Bozeman & Corley, 2004). In essence, we assume that a higher scientific and technical human capital leads to an increased likelihood of a recognized transfer opportunity. In the following we capture scientific and technical human capital by three factors. First, we argue that prior knowledge possessed by the scientist can be such a factor. Furthermore, the quality of the research results can influence the recognition of an opportunity, since the higher the quality of research results, the greater can be the opportunities for its application. Lastly, interaction with economic actors can be influential in understanding and recognizing the relevance of industrial application of the generated scientific results. In the following, we derive hypotheses for potential relationships of influential antecedents for the recognition of a transfer opportunity.

Prior knowledge

Prior knowledge is an important antecedent for the recognition of a transfer opportunity, as shown in the literature about entrepreneurial opportunity recognition (e.g. George, Parida, et al., 2016; Mejri & Umemoto, 2010; Shane, 2000). Prior knowledge reflects the sum of an individual's knowledge at a given point in time (Arentz et al., 2013). Shepherd and DeTienne (2005) show that the more prior knowledge an individual possesses, the more capable they are to recognize important connections between concepts, which in turn increases the ability to recognize transfer opportunities. Individuals who possess a wide range of prior knowledge and experience are inclined to recognize opportunities characterized by problem-solving and economic value (Hsieh et al., 2007). Especially multiple domains of knowledge and experience increase scientists' ability to recognize transfer opportunities (Cliff et al., 2006; Corner & Ho, 2010). In particular, scientists can accumulate knowledge both from their academic work and from other professional activities, such as work experience outside academia. The knowledge scientists acquire in their academic work is usually highly specialized in a specific research field and results from their research skills and techniques (de Grande et al., 2014). Additionally, scientists might be endowed with non-academic knowledge gained through work experience outside the academic sector (Gulbrandsen & Thune, 2017). Such knowledge contains work practices, market or customer knowledge and other knowledge related to economic activity. Both types of prior knowledge, academic and non-academic, can influence opportunity recognition.

An increasing body of research shows that scientists' prior academic knowledge is positively associated with their KTT activity (e.g. D'Este et al., 2019; Haeussler & Colyvas, 2011; Landry et al., 2007). Prior academic knowledge also positively affects the frequency of such engagements (Tartari & Breschi, 2012), as well as the variety of knowledge transfer channels used for its implementation (D'Este & Patel, 2007; Iorio et al., 2017). The accumulation of research activity and output increases scientists' academic knowledge resources that they can "sell" (Louis et al., 1989). Also, a larger pool of prior knowledge increases the options for knowledge recombination and subsequently the recognition of transfer opportunities. According to the entrepreneurship literature, individuals only recognize entrepreneurial opportunities that are related to their prior knowledge (D'Este, Guy, & Iammarino, 2012; Shane, 2000). For scientists, this means that a larger body of academic knowledge yields a higher chance of recognizing a transfer opportunity. In line with the high relevance of prior knowledge for successful transfer activities (D'Este et al., 2019; Llopis et al., 2018), we hypothesize for the transfer opportunity recognition that:

Hypothesis 1a: *The scientist's stock of academic knowledge increases the likelihood of recognizing a transfer opportunity.*

Similar to prior academic knowledge, prior non-academic knowledge, especially economic knowledge, can influence a scientist's transfer opportunity recognition. Shane (2000) points out the importance of prior knowledge about markets, how to serve them, and prior knowledge of customer problems to recognize opportunities. Building on this argument, related empirical findings show that experience outside academia decreases scientists' perception of Mertonian-related barriers to activities with industrial involvement (Merton, 1973; Tartari et al., 2012). Therefore, this reduction of perceived barriers might increase the willingness of scientists to keep their eyes open for transfer opportunities. Furthermore, scientists who have prior commercial experience, e.g. acquired in non-academic employment, accumulate context-specific skills, idiosyncratic information and economic knowledge (Vohora et al., 2004). Such knowledge from experiences outside the usual field of work gives a combined advantage and thereby facilitates the recognition of opportunities (Salter et al., 2015). This allows scientists to use their previously acquired knowledge from other domains to identify potential transfer opportunities that have a benefit for those same other domains. Also, experience outside academia gives insights into practical challenges and needs for which solutions are welcome. Given the relevance of non-academic prior knowledge, especially acquired in non-academic employment, we hypothesize that:

Hypothesis 1b: *The scientist's work experience outside academia increases the likelihood of recognizing a transfer opportunity.*

Scientific quality

The academic knowledge scientists generate can be characterized by its quality, e.g. in terms of its scientific relevance or how the findings shift the knowledge frontier. Especially high-quality knowledge influences scientific discourse and impacts subsequent research. Also, higher quality knowledge shows a higher relevance for the recognition of transfer opportunities for industrial applications (Murray & Stern, 2007). However, for finalized transfer activities, the quality of knowledge a scientist possesses provides ambiguous results (Perkmann et al., 2021). While Ding and Choi (2011) find a positive relationship between research quality and engagement in transfer activities, Tartari et al. (2014) and Giuliani et al. (2010) find a negative but insignificant relationship. For the recognition of a transfer opportunity, however, the quality of the generated knowledge can be highly relevant. The inherent novelty of high-quality research bears potential for as yet unrecognized opportunities for the industry. For example, scientists who generate high-quality knowledge have a comparative advantage in achieving breakthroughs that are of great importance to industry (Zucker et al., 1998). Especially, the recombination of existing and new knowledge increases novelty and usefulness (Xiao et al., 2022). Following this argument, Veugelers and Wang (2019) find a link between high-quality publications and technological impact. In related research, D'Este, Mahdi, et al. (2012) show that individual scientific quality, measured by the average number of citations to papers, significantly facilitates the discovery of IPR. Given the high relevance of the quality of knowledge a scientist posses, we hypothesize:

Hypothesis 2: *The quality of the scientist's research increases the likelihood to recognize a transfer opportunity.*

Relations to industrial actors

The recognition of a transfer opportunity can also be influenced by various interactions with industrial actors, a phenomenon frequently associated with relational capital (see, e.g. Bozeman & Corley, 2004; Davidsson & Honig, 2003; Dietz & Bozeman, 2005; Mosey & Wright, 2007; Wu et al., 2015). The access to sources for complementary knowledge acquisition can be achieved by relational assets and knowledge exchange and, thus, increase the potential for knowledge recombination (Andries et al., 2021; Ardichvili et al., 2003; Bhagavatula et al., 2010; Ramos-Rodríguez et al., 2010; Shane & Venkataraman, 2000). In particular, interaction with external market actors increases the recognition of opportunities as it creates awareness of current needs and problems of industrial actors (Gruber et al., 2013; Snihur et al., 2017). Landry et al. (2007) show that connections with industry are in general a good predictor for the successful implementation of technology transfer efforts. Having ties to the industry gives scientists commercial insights, leads to an envisioning of industrial applications and changes their perspective to an industrial one, enabling them to be boundary-spanning scientists (Dolmans et al., 2022). Furthermore, they can draw on their relationships to discuss their research results, or they are approached for solutions in the industry or gain inspiration for ideas on what can be done with their knowledge (Fritsch & Krabel, 2012; Nicolaou & Birley, 2003). Given the high relevance of interaction with industry in understanding the relevance of its own research for industry application, we hypothesize:

Hypothesis 3: *The scientist's relations to industrial actors increases the likelihood of recognizing a transfer opportunity.*

2.2.3 Choice of transfer channel

Since in the initiation phase of the KTT process the opportunity recognition coincides with the choice of a transfer channel, we argue that different factors can influence this choice. We argue that, in contrast to the influence of the scientific and technical human capital on the opportunity recognition by the scientist, the following factors have a discriminatory effect between transfer channels and influence the scientist's choice. Given the three most frequent and economically relevant transfer channels S-I Collaboration, IPR and spin-off creation, we, first, consider scientists' research orientation toward basic and applied research as potential factors. Second, we argue that scientists' willingness to take risks influences the transfer channel choice due to a distinct risk associated with the transfer channels. Third, we consider the social context of the scientists through departmental role models they are exposed to as relevant for choosing a transfer channel.

Research orientation

Scientists' research orientation, i.e. the kind of research they are conducting, can be separated into basic research and applied research (Stokes, 1997). Basic research is defined as the fundamental advancement of scientific knowledge, such as the discovery of new relationships, materials, chemicals or any other fundamental discovery that shifts the scientific frontier. Basic research generates knowledge that is fundamental and considered to be temporally distant from and less certainly lead to commercial application. The economic value of basic research is difficult to forecast, making its economic payoff uncertain and in the case of foreseen economic relevance, often taking many years to unfold (Bartunek & Rynes, 2014; Dasgupta & David, 1994). Applied research, in contrast, discovers new scientific knowledge with specific practical or commercial objectives (Bartunek & Rynes, 2014; Godin, 2006). It is considered rather short- and mid-term oriented to time-to-capitalization. In a simplified transfer process of successive phases, it is closer to commercialization than basic research (Aghion et al., 2008). Therefore, applied research is closer to offering solutions to potential market needs with practical purposes and often addresses existing or potential market demands (Aghion et al., 2008; Bartunek & Rynes, 2014). Furthermore, applied research draws on user inspiration based on existing knowledge, which sometimes is even combined with existing technology to improve future technology (Stokes, 1997).

Given the differences in the nature of the two orientations toward research, the choice of the transfer channel can be influenced by familiarity or understanding of it. In the case of basic research orientation, results can be of importance to industry, but due to its fundamental nature, the discovery might require further application-oriented research to fulfill an economic purpose (David et al., 1992). This additional research and development often cannot be pursued by the scientist alone due to a lack of financial resources, equipment or skills and knowledge (Ankrah et al., 2013). Therefore, upon the recognition of the transfer opportunity, the involvement of industrial partners becomes paramount for its realization. In such a S-I collaboration, corporate partners not only fill the resource gaps but can also set the direction of potential applications (Ankrah & AL-Tabbaa, 2015). If, however, the scientist has the required complementary assets and skills or can acquire them over time, the realization of the transfer opportunity can be done directly via a spin-off. Through this channel, the research results can be directly translated to customers via products or services by the scientist (Pirnay et al., 2003; Rappert et al., 1999). Based on this consideration, we propose that basic knowledge is relevant for the S-I collaboration and spin-off channel:

Hypothesis 4a: *The higher a scientist's extent of basic research orientation, the higher the likelihood to choose the S-I collaboration channel.*

Hypothesis 4b: *The higher a scientist's extent of basic research orientation, the higher the likelihood to choose the spin-off channel.*

Scientists who have a focus on applied research generate results that are closer to application and therefore commercialization (Leitner et al., 2021). The overall aim of generating knowledge that is close to application makes them aware of potential ways to commercialize it, especially via spin-off creation (Hossinger et al., 2021). The idea to bring its own research to the market and having entrepreneurial aspirations can increase the likelihood to choose the spin-off channel. However, the development of new products or services might require some adaptation and exploitation of existing knowledge (Vohora et al., 2004). Additionally, if such entrepreneurial aspirations are not present in the scientist (yet), intermediaries, such as technology transfer offices or venture capitalists, might approach scientists based on their research outcomes encouraging them to engage in spin-off creation (Duchek, 2013; Karnani, 2012). If the scientist does not want to actively engage in commercialization, a recognized opportunity can be legally protected and potentially commercialized as an IPR. It is a frequent outcome of applied research activities and some scientists might perceive IPRs as validation of their research and see them as potential quality signals to strengthen their reputation (Blind et al., 2018; Göktepe-Hulten & Mahagaonkar, 2010; Moutinho et al., 2007). Furthermore, in publicly funded applied research projects, IPR can be relevant to meet funding requirements. Besides their signaling value, scientists might perceive property rights as a risk-free additional source of income (Owen-Smith & Powell, 2001). Especially financially motivated scientists might be more interested in property rights promising considerable or fast returns. Based on these approaches to how applied research can be translated into commercial outcomes, we hypothesize the following:

Hypothesis 4c: *The higher a scientist's extent of applied research orientation, the higher the likelihood of choosing the spin-off channel.*

Hypothesis 4d: *The higher a scientist's extent of applied research orientation, the higher the likelihood of choosing the IPR channel.*

Risk willingness

Another influential factor can be a scientist's perception of risk and their willingness to engage in risky activities. Pursuing a recognized transfer opportunity can be associated with different degrees of risk, conditional to the transfer channel of choice. An individual's risk willingness is a personality characteristic describing an individual's disposition towards seemingly risky endeavors (van Gelderen et al., 2005), whereas risk defines the likelihood that an actual outcome will deviate from an expected outcome (Audretsch et al., 2002). In the following, we discuss the risk in terms of costs and benefits associated with different transfer channels and how the individual's risk willingness therefore influences the channel choice.

The choice of an S-I collaboration to pursue a recognized opportunity is usually associated with low or no opportunity costs, since the research is already an integral part of the scientist's activity (Arza, 2010). However, one could argue that there could be foregone opportunities to explore new research avenues with potentially higher impact. Nevertheless, the expected research output is subject to the same uncertainty as any other open-ended research activity (Stephan, 1996). Since such collaborations involve an industrial partner who acts as a sponsor, personal financial costs for the scientist are absent; however, there could be transaction costs in establishing the collaboration in the first place. Furthermore, there could be issues of appropriability of the generated results, since the industry partner could claim its exclusivity on the results and prohibit publication (AL-Tabbaa & Ankrah, 2016). Usually, contractual agreements can solve such problems ex-ante via non-disclosure agreements (Lee, 2000) or other arrangements. On the other hand, there can be several benefits from such activity, such as access to resources and knowledge (Lam, 2010). Also, the engagement may lead to new research ideas, scientific outcomes and repeated engagements (Cantner et al., 2022; de Fuentes & Dutrénit, 2012). Overall, S-I collaboration seems to have low financial and transactional costs which can be outweighed by the benefits of such engagement. We, therefore, do not assume that scientists require a high-risk willingness to choose S-I collaboration as a channel to realize their recognized transfer opportunity.

Disclosing a recognized opportunity for IPR protection can be associated with opportunity costs. The scientist can be constrained by being well advised to not publish their results before the IPR is filed to maintain the novelty of the claims (Florida, 1999; van Looy et al., 2004). Furthermore, a granted patent, for example, can be challenged and infringement claims be put forward. However, usually the institution as a patent applicant would be challenged and bear the legal risk. With respect to these potential opportunity costs, empirical evidence suggests that scientists do not perceive a reduction in their opportunities or a decline in their research activity (Tartari et al., 2012). Furthermore, there are no financial costs for scientists to file for IPR protection, since such costs are usually covered by the host institution which carries the entire financial risk (Czarnitzki et al., 2011). With respect to the benefits, the successful commercialization of an IPR can result in substantial financial rewards for the individual. Furthermore, IPRs are considered a signaling instrument for scientific success, prerequisites in some funding applications or starting points for further commercialization (Blind et al., 2018; Göktepe-Hulten & Mahagaonkar, 2010). Overall, the institutional setup with respect to IPRs and the empirical evidence suggests that the costs of choosing this channel are very low, but the benefits can be substantial. Therefore, the risk willingness should not have an influence on the choice of the IPR channel.

Founding a spin-off as the chosen transfer channel for a recognized opportunity bears high opportunity costs as well as personal financial costs. Haeussler and Colyvas (2011) explicate that the creation of an academic spin-off is the most binding and riskiest transfer channel for scientists. With respect to the opportunity costs, the process of founding a company is an extensively time-consuming endeavor that binds substantial resources that cannot be devoted to research (Lacetera, 2009). This is often perceived as a major barrier in the process of spin-off creation (Hossinger et al., 2020; Neves & Franco, 2018). Furthermore, since the founding of a spin-off entails leaving the academic system, it can bear substantial financial risk because it often requires personal financial investment to found and run the firm and also foregone salary if the scientist reduces or quits the academic activity. However, some scientists consider the creation of a spin-off as a second-best alternative to an academic career if they cannot get tenure (Civera et al., 2020; Horta et al., 2016; Vismara & Meoli, 2016). Nevertheless, if the scientist leaves the academic position to work full time in the spin-off, financial risks can become dire (Åstebro et al., 2013; Forlani & Mullins, 2000). With respect to the benefits, academic spin-offs can be highly successful and provide large financial returns and reputation, as some leading examples show. However, the distribution of success is highly skewed and the survival rate of academic spin-offs is quite low (Criaco et al., 2014; Gurdon & Samsom, 2010; Rodeiro-Pazos et al., 2021; Rothaermel & Thursby, 2005; Wennberg et al., 2011). Overall, choosing to commercialize the recognized transfer opportunity via a spin-off can entail a high risk for the scientists. Consequently, scientists who choose this channel must possess a high risk willingness. Therefore, we hypothesize that:

Hypothesis 5: *The higher the scientist's risk willingness, the higher the likelihood of choosing spin-off creation as a transfer channel.*

Role models

Finally, the social context in which the scientist recognizes the transfer opportunity might affect the scientist's choice of a transfer channel. In general, a scientist's relationship with intra-organizational peers has a significant effect on their behavior, e.g. mimicking the behavior of peers (Bercovitz & Feldman, 2008; Broström, 2019). For the case of KTT activities, the engagement of peers in such endeavors creates awareness of such activities and potentially influences an individual's orientation towards such engagement (Aschhoff & Grimpe, 2014; Ding & Choi, 2011; Greven et al., 2020; Tartari et al., 2014). Marquis and Tilcsik (2013) argues that *alignment* is the underlying mechanism that leads to the "imprinting" of characteristics and behaviors of individuals that reflect the specifics of the environment in which they operate. This mechanism is especially prominent in role models who can have a formative impact on scientists' alignment with peers' behavior and, thus, adaptation to their social context. Gibson (2004) characterizes role models as encompassing individuals' cognitive construction based on attributes of people in social roles observed in the environment. Accordingly, role models are those who are perceived by the observer as having similar characteristics and whose behavior is considered worth striving for. The cognitive process of role modeling is an observation and adaptation of the attributes of multiple role models. Thereby, attributes that are considered negative can also be rejected.

In the context of KTT, Huyghe and Knockaert (2015) find evidence for a positive relationship between channel-specific role models, i.e. observable successful peers in a particular transfer channel, and scientists' intention to engage with the respective channel. For the particular channels, Scherer et al. (1989), for instance, find that role models are decisive to follow an entrepreneurial career path, while Bercovitz and Feldman (2008) provide such evidence for invention disclosure activities. In a similar vein, Tartari et al. (2014) find that departmental peers affect scientists' collaborative engagement with industrial partners. For each channel, role models can lead by example and increase scientists' awareness of a specific transfer channel. In this sense, role models can be important factors in forming activity and even career preferences (Gibson, 2004; Scherer et al., 1989). Based on these arguments, we hypothesize a positive relationship between the presence of role models for a specific transfer channel and the choice of this transfer channel to pursue the recognized opportunity. The corresponding hypothesis states:

Hypothesis 6: *The extent of departmental role models for (a) S-I Collaboration, (b) protection of IPR or (c) spin-off creation is positively related to scientists' choice of the respective transfer channel.*

2.3 Data and Method

2.3.1 Data

To investigate scientists' transfer initiation, we conducted a novel online survey of academic staff at both universities and research institutes in the German Federal State of Thuringia. Thuringia captures the variety in the German research landscape well, as there are four universities and about 25 research institutes. More precisely, one of these universities is a technical university and one is affiliated with a university hospital. Furthermore, the university landscape is enriched with seven universities of applied sciences, including one music college. The research institutes cover the whole range from basic science-oriented institutes to applied science-oriented institutes (e.g. Max Planck Institute, Fraunhofer Society, etc.). This heterogeneity of organizations guarantees coverage of a wide range of disciplines and organizational research orientations (for an overview, see Table 2.9).

We collected publicly available contact information and characteristics of the scientists from their organizations' web presence. Overall, we identified 7,785 scientists to whom we sent the invitation for our web-based survey in December 2019 and January 2020. We received 1,409 responses (18.1% response rate) of which we excluded 265 observations due to incomplete answers and run our analysis with a working sample of 1,149 observations. The differences between this working sample of respondents and the initial population are marginal, and we consider a non-response bias unlikely.[4] Comparing the working sample with the overall population of scientists at universities in Germany (Statistisches Bundesamt, 2020), we can claim representativeness of our sample in terms of academic rank and gender (Table 2.8).

[4]We compared the characteristics position, gender, organizational focus and academic discipline between the overall population and the working sample (Armstrong & Overton, 1977) in Table 2.7. There are some statistically significant differences concerning the disciplines. There is especially an under-representation of scientists from medicine in our respondents. We believe that our initial data collection included many medical doctors with an affiliation with the university hospital but who are not involved in research anymore.

Our online survey consists of a set of questions on the scientist's transfer activities in the three channels S-I collaboration, the protection of IPR and the creation of an academic spin-off. For each channel, we included a question regarding the transfer initiation during the last five years. We developed the items to capture the potential of KTT at the very beginning of the transfer process. This is opposed to many studies looking at the end of KTT processes, i.e. KTT outputs in terms of realized transfer such as created spin-offs or licensed IPRs. To ensure the reliability of these items, we discussed them with colleagues specialized in the field and practitioners from technology transfer offices. Subsequently, we conducted a pre-test of our survey in a comparable German state with a random sample of scientists, as suggested by Sue and Ritter (2007). Furthermore, in our survey, we collected information on scientists' characteristics regarding their socio-demographic situation, research activity and personality.

In addition to the survey data, we gathered data on the respondents' publication records from Web of Science (WoS) and Scopus.[5] For the scientists' publications, we collected the respective source normalized impact factor (SNIP), retrieved from the journal record of Scopus.

2.3.2 Empirical strategy

In our empirical approach, we have to account for the whole initiation process, the antecedents of scientists' recognition of a transfer opportunity and the simultaneous choice of the transfer channel. In this setting, however, a transfer channel is chosen only by those scientists who have transfer opportunity recognition (TOR). This implies that the choice of the transfer channel is of non-random character and requires an account of the respective selection process in our empirical approach. If we would ignore the selection and estimate the channel's choice by treating the transfer initiators' choice of the transfer channel as a random sample, we would generate inconsistent

[5] Our primary source for publication data is WoS. If there was no publication record in WoS for a respondent, we went to Scopus which has a larger coverage for some disciplines esp. for social sciences and humanities (Martín-Martín et al., 2021). If, again, there were no publications in Scopus listed, we assumed zero publications, which is especially plausible for PhD researchers at the beginning of their academic careers. In doing so, we might underestimate the influence of our respondents' publications.

estimates (Heckman, 1979). Furthermore, including the recognition of a transfer opportunity as an exogenous variable when estimating the channel choice would not take into account the endogeneity between the choice of the transfer channel and the recognition of a transfer opportunity. Therefore, a proper solution to this is to include the scientists' self-selection in the choice of the transfer channel in our econometric model. Consequently, we estimate a selection equation which corrects for potential selection bias in the opportunity recognition, while the choice of the three transfer channels is the outcome equations. Given that the three transfer channels are non-exclusive, scientists can recognize multiple transfer opportunities for which they can choose different transfer channels. To account for the possibility of multiple channel choices by a scientist, we allow the error terms of the outcome equations to be correlated.

We use a multivariate probit model with a correction for self-selection and the possibility of choosing multiple transfer channels. To account for the meaningful correlations between the error terms of the different relationships between the dependent variables, we rely on seemingly unrelated regressions (SUR) (Roodman, 2011). In this setting, the SUR estimates will be more efficient than those derived from single-equation regressions because SUR take into account those correlations. SUR account for simultaneous relationships between the dependent variables by allowing the error terms of each equation in the model to correlate and let them share a multivariate normal distribution. This enables us to control for our selection bias and to allow for scientists' multiple channel choices. However, when correcting for a self-selection bias, it is necessary to include an exclusion restriction. This requires identifying at least one variable in the selection equation that affects the probability of recognizing a transfer opportunity but does not influence the outcome, i.e. the choice of the transfer channel. We explain our chosen variables for the exclusion restriction in more detail below in section 2.3.3.

Our regression model is separated into the selection equation and three outcome equations capturing the three considered transfer channels. Equation 2.1 depicts the selection equation where the probability of each scientist i to have a transfer opportunity recognition (TOR_i) or not is explained by the vector PK_i, capturing academic and non-academic prior knowledge, SQ_i for scientific quality and RI_i for relations to industrial actors. $Excl_i$ is a vector of two variables for the exclusion restriction, X_i is a vector of the control variables and $\varepsilon_{i,S}$ is the error term for the selection equation.

$$Pr(TOR_i = 1) = \beta_0 + PK_i\beta_1 + SQ_i\beta_2 + RI_i\beta_3 + Excl_i\beta_4 + X_i\beta_5 + \varepsilon_{i,S} \quad (2.1)$$

The outcome equation 2.2 for the scientist i's choice among the three transfer channels is the probability to choose channel C defined by $Pr(C_i = 1)$ with $C = \{$S-I collaboration, IPR, spin-off$\}$. Our explanatory variables for i' channel choice are the research orientation (RO_i), a vector containing applied and basic research, the risk willingness ($Risk_i$) and channel-specific role models ($Role_{i,C}$). $\varepsilon_{i,C}$ are the channel-specific error terms.

$$Pr(C_i = 1) = \beta_0 + RO_i\beta_2 + Risk_i\beta_3 + Role_{i,C}\beta_{4,C} + X_i\beta_5 + \varepsilon_{i,C} \qquad (2.2)$$

Due to the correlation among the dependent variables, the error terms are potentially correlated, too. The error terms follow a multivariate normal distribution with a mean of zero and variance-covariance matrix with off-diagonal elements $\rho_{i,j} = \rho_{j,i}$. They capture an unknown variable that connects the outcomes. To simplify denotation, we introduce: $TOR = 1$, $C_{S-I\,Collaboration} = 2$, $C_{IPR} = 3$, $C_{Spin-off} = 4$.

$$\left(\begin{array}{c|c} \varepsilon_1 & \\ \varepsilon_2 & \\ \varepsilon_3 & \mathrm{X} \\ \varepsilon_4 & \end{array} \right) \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{1,2} & \rho_{1,3} & \rho_{1,4} \\ \rho_{2,1} & 1 & \rho_{2,3} & \rho_{2,4} \\ \rho_{3,1} & \rho_{3,2} & 1 & \rho_{3,4} \\ \rho_{4,1} & \rho_{4,2} & \rho_{4,3} & 1 \end{pmatrix} \right] \qquad (2.3)$$

2.3.3 Variables

Dependent variables

To understand the transfer initiation, we need one dependent variable for the recognition of a transfer opportunity (selection) and three dependent variables for the different channels a scientist can choose from (outcome). Since transfer opportunity recognition coincides with the channel choice, we can use the information on the channel choice in the initiation phase of the KTT process to construct the *transfer opportunity recognition (TOR)*. For each of the different channels, we asked the scientists whether they identified or developed an idea for the respective channel within the last five years. In particular, for the transfer channel *S-I Collaboration* we asked respondents how many times in the last five years they had been involved in the "development of an idea for a cooperation with company participation, i.e. identification of a research question or problem for which cooperation between universities and companies could be helpful". For the IPR channel respondents should indicate how often they had an "identification of an idea or invention that can be attributed to potential industrial exploitation or can be legally protected". For the *Spin-off* channel we asked how often the respondent was involved in the "development of an idea to found a firm, e.g. discussion of the idea with others, assessment of the economic potential or application of creative techniques". We recoded the responses of each of the three transfer channels into binary variables, since we are not interested in the frequency of recognition but only if a recognition happened at all. We end up with the three outcome variables *S-I Collaboration (=1)*, *IPR (=1)* and *Spin-off (=1)*. We use the three outcome variables to construct our variable for transfer opportunity recognition which is equal to 1 for every scientist who initiated the transfer process in any of the three channels (*TOR (=1)*).

Explanatory variables for the transfer opportunity recognition

To understand what influences the probability of a transfer opportunity recognition, we use two variables to capture scientists' prior academic and non-academic knowledge. First, we operationalize the stock of academic knowledge by the scientists' overall *Number of publications*. The scientist's publication output is a frequently used measure to account for the scientific performance and the accumulated knowledge in transfer-related studies focusing on successfully implemented transfer (Perkmann et al., 2021). We log-transform the variable to account for its right-skewed distribution. Second, our proxy for scientists' non-academic prior knowledge is the scientist's *Work experience outside academia*. It is obtained from a survey item capturing the years a scientist has worked outside academia. Previous research shows that scientists who accumulate work experience outside academia are more likely to successfully engage in commercial activities and to better adapt to their requirements (Gulbrandsen & Thune, 2017).

Furthermore, we account for the scientific quality of the scientists' research output. We argue that scientists' research output must also have a certain quality to draw promising ideas for KTT from it. We use the *Average impact factor*, representing the average of the publications' source normalized impact factor (SNIP) as provided in the journal record of Scopus. SNIP accounts for differences across disciplines when calculating the impact of a publication.

To capture scientists' relations to industrial actors, we again draw on the scientists' publication record. We measure how frequently their research is co-published with industry partners. While co-publishing is an important relational asset for the implementation of transfer opportunities (D'Este, Mahdi, et al., 2012; Fritsch & Krabel, 2012; Krabel & Mueller, 2009), we argue that it is also relevant for the recognition of transfer opportunities. We calculate the fraction of papers with at least one co-author affiliated to industry over the total number of publications, which results in the *Share of publications with industry*.

Exclusion restriction

To account for the bias introduced in the channel choice due to the selection into having a transfer opportunity recognition, we need to include at least one variable that is correlated with the recognition of the transfer opportunity but is independent of the channel choice (Wilde, 2000). We use two variables that fulfill this exclusion restriction. The first variable is the general *Organizational transfer orientation* which is, according to Jacobson et al. (2004), a proxy for the priority universities and research institutes given to transfer activities via policies and practices. Throughout the last decades, universities and research institutes have been required to act more "entrepreneurial" (Etzkowitz et al., 2000; Guerrero & Urbano, 2012), which affects their strategic alignment towards third mission activities, as well as their research commercialization culture (Giuri et al., 2019). This orientation towards transfer into industrial application reduces the boundaries between academia and industry by institutionalizing commercial norms and logics that coexist with academic ones. This increases the likelihood that scientists see opportunities to transfer their research (Colyvas, 2007; Murray, 2010; Perkmann et al., 2019). Consequently, research results regarding this relationship show a strong association between universities' orientation towards third mission activities and its impact on KTT activities (Balasubramanian et al., 2020; Kalar & Antoncic, 2015; Todorovic et al., 2011).

However, this established transfer culture and the respective environment that supports such activity does not discriminate between the different channels. Research organizations aim in their third mission activities and respective strategies to strengthen these activities in general (Horner et al., 2019). The respective infrastructure, such as TTOs, are usually one-stop shops for scientists who want to bring their recognized ideas into industry application and provide tailor-made support for the idea, which covers all the different transfer channels (Zhou & Tang, 2020). Furthermore, most evaluations of transfer activities assess the whole range of activities so that the organizations do not focus on particular channels but instead cover the whole range. Overall, the *Organizational transfer orientation* should therefore influence scientists to recognize transfer opportunities but should not influence the subsequent choice of the transfer channel.[6] We measure the *Organizational transfer orientation* via the share of scientists who recognized at least one transfer opportunity affiliated with the same organization as the focal scientist.

The second exclusion restriction accounts for whether the scientist's position is based on *Internal funding* or not. We exploit the peculiarity of the German science system that a scientist's position can be financed via money from the budget of the organization or via third-party funding, such as grants or scholarships. The latter is, however, short term and prolongation of a position is highly uncertain. Scientists funded with internal money,

[6]At this point it should be mentioned that scientists are not randomly assigned to institutions. However, we do not consider this as a severe problem, since scientists do not choose their employment at an academic institution according to its transfer orientation and the transfer structures provided, but rather according to research-relevant criteria and teaching.

however, either hold a permanent position or an extension of the contract is more likely.[7] We argue that this kind of funding influences the likelihood to recognize transfer opportunities. First, internal funding, especially a permanent position, ties the scientist more strongly to their organization. This increases their embeddedness in the academic system and strengthens a role characterized by a focus on research and teaching (Dasgupta & David, 1994; Merton, 1973) and reduces the need to search for alternatives. Landry et al. (2010), for instance, show that if the scientist's position is funded internally, KTT activities are reduced. Scientists, however, who are financed via external funding know that a follow-on position is highly uncertain and that they need to search for potential alternatives or ways to extend their position. Related empirical results show that industrial funding increases scientists' interaction with industry (Boardman & Ponomariov, 2009; Gulbrandsen & Smeby, 2005; Landry et al., 2010) indicating that such third-party funding is helpful to establish further interaction. Second, the *Internal funding* is typically associated with significant teaching duties, while third-party funding does not require teaching. Since a high teaching load can disincentivize scientists' appeal for transfer activities (Landry et al., 2007), scientists with a position that is internally funded should be less likely to recognize a transfer opportunity.

While the funding of a position should have an influence on the likelihood to recognize a transfer opportunity, it should not influence the transfer channel choice. The different channels can all provide an opportunity for externally funded scientists to result in the potential prolongation of contracts or alternative employment. But also internally funded scientists can benefit from the different channels. Industry collaboration can increase financial means to finance one's own position or to hire additional scientists (Ankrah et al., 2013). Patents can be counted as scientific output to gain reputation or to signal industry applicability (Blind et al., 2018; Göktepe-Hulten & Mahagaonkar, 2010; Moutinho et al., 2007). Academic entrepreneurship can be the sole employment or be done in parallel to an academic position (Civera et al., 2020; Horta et al., 2016; Vismara & Meoli, 2016). In this

[7] The German law governing the non-permanent positions at research organizations (Wissenschaftszeitvertragsgesetz) grants up to six years of employment for pre-doc scientists and six years for post-doc scientists (as well as several exceptions, such as extra years for childcare).

sense, the rewards that can be derived from the different channels do not depend on the initial financial background of the individual scientists. For our econometric approach, to indicate whether a scientist's position is based on *Internal funding*, we asked a respective question in our survey (see Table 2.3) and created a binary variable based on the response.

Explanatory variables for channel choice

To test our hypotheses with respect to channel choice, we rely on four variables that we expect to influence the scientists' choice. We include the two variables *Basic research* and *Applied research* to capture scientists' research orientation within the last five years. Following Amara et al. (2019), respondents were asked to indicate the extent to which they consider their research as basic or applied. *Basic research* is characterized by contributions to fundamental understanding whereas *Applied research* is characterized by the consideration of use. Both variables were assessed on a 4-point Likert scale, ranging from "not at all" to "a lot".

To measure the scientist's willingness to take risks and test its influence on the channel choice, we asked the participants about their *Risk willingness* according to SOEP-IS Group (2014, p. 36) with the following question: "How do you see yourself? Are you generally a person who is fully prepared to take risks or are you trying to avoid risks?" Respondents were asked to assess their *Risk willingness* on an 11-point Likert scale ranging from "risk averse" to "fully prepared to take risks". The 11-point Likert scale proves to be a valid and reliable survey method to capture the willingness to take risks (Beierlein et al., 2014).

To capture the relevance of channel-specific *Role models*, we create three different variables tailored to the respective transfer channel. In our understanding, role models are scientists who have successfully exploited an opportunity. This means that they have successfully realized a transfer activity in the respective channel, which is in line with Huyghe and Knockaert (2015). Furthermore, we argue that role models must be observable to have an impact. Therefore, we refer to role models as the scientist's colleagues at the same department or research institute who successfully realized a transfer opportunity at least once in a specific channel. For instance, a colleague who founds a firm would be considered a spin-off role model. Since all survey participants were asked to state their realized transfer activities in the last 5 years, we can utilize this information to create such role models. For S-I collaboration, we asked for the "Realisation or participation in a research cooperation with company participation", for IPR whether "Selling or licensing of an idea or invention, e.g. selling a patent to a company" took place and for spin-off if the scientists "Completed foundation of a firm, i.e. the launch of business activities". Each variable for channel-specific *Role models* is created as the share of scientists at a university department or research institute with successfully realized transfer in all scientists at that organizational unit.

Control variables

We control for several factors that can influence the recognition of a transfer opportunity in the selection equation and the channel choice in the outcome equations. First, to control for differences in academic rank, we create a dummy variable distinguishing between *Professor (=1)* and other types of researchers, e.g. post-docs, Phd students, ... (Perkmann et al., 2021).[8] Second, we control for scientists' gender and distinguish between *Female (=1)* and others. This is motivated by the strong gender gap identified in the KTT-related literature (see, e.g. Abreu & Grinevich, 2017; Tartari & Salter, 2015). Third, we control for differences between *Disciplines* to account for differences in their transfer propensity (see, e.g. Abreu & Grinevich, 2013; Perkmann et al., 2011). We distinguish between seven *Disciplines*: *Engineering*, *Humanities*, *Life Sciences*, *Medicine*, *Physics*, *Chemistry*, *Social Sciences* and *Computer Science and Mathematics*. Lastly, we control for organizational heterogeneity in the type of generated knowledge that might influence scientists' cognitive proximity to research commercialization (e.g. Bercovitz & Feldman, 2008). We create a categorical variable to account for the *Organizational focus*. It distinguishes the research focus of the scientists' organization into three groups: *Basic*, *Between basic and applied* and *Applied*.

[8] We treat junior professors at universities as well as directors or heads of departments in research institutes equal to full professors.

For the categorization, we rely on the German Ministry for Science and Education (Bundesministerium für Bildung und Forschung, 2014).[9]

2.4 Results

2.4.1 Descriptive results

Descriptive statistics are provided in Table 2.1 and distinguished for variables of the selection equation and the outcome equations. The statistics give first indications of the frequencies of opportunity recognition and the characteristics of the scientists who have it. The descriptive results show that 44% (504 out of 1,149) of the scientists have a transfer opportunity recognition. Among the scientists who recognized transfer opportunities, we observe that they most frequently chose S-I collaboration with 82% (412 out of 504). Considerably fewer pursue their recognized transfer opportunity in the IPR and the spin-off channel with 47% (235 out of 504) and 49% (249 out of 504), respectively. Since scientists can recognize several transfer opportunities for which they can consider different transfer channels, we represent the combinations of channels in Figure 2.1. In the Venn diagram, overlapping circles indicate scientists' pursuit of transfer opportunities through multiple channels. For instance, we can see that 119 of the 504 scientists (23.6%) recognized in all three channels at least one transfer opportunity. Furthermore, 79 (15.7%) of the scientists chose the combination of the channels S-I collaboration and IPR, 15 (2.98%) combined IPR and spin-off and 60 (11.9%) decided to pursue their transfer opportunities through the channels spin-off and S-I collaboration. Overall, more than half of the scientists (54.18%) recognized transfer opportunities in more than one channel.

Among the explanatory variables for the transfer opportunity recognition, we observe that the average *Number of publications* is comparatively low, presumably because of the high share of scholars who have not reached professorship. In line with that, the *Average impact factor* is low. *Work*

[9] Research institutes of the Leibnitz Association, the Max Planck Society and similar are allocated to basic research. Universities are located between basic and applied research and universities of applied sciences as well as institutes such as the ones from the Fraunhofer Society and similar are allocated to applied research (see Table 2.9).

experience outside academia seems to be the exception in our sample with the low mean and larger variance. Also, there is a low average *Share of publications with industry*. For the variables explaining the channel choice, we observe that on average, more scientists consider their work as *Applied research* than as *Basic research*. The scientists' *Risk willingness* centers around the mean of the 11-point Likert scale. Among the role models, *Role models: S-I Collaboration* are very frequent, while the other two role models are rather scarce.

With respect to the control variables, the share of *Professors* is around one fifth and there is a slight increase of their frequency in the scientists who recognized a transfer opportunity. By contrast, the share of *Female* scientists drops from 37% in the overall sample to 31% who recognized a transfer opportunity. Among the disciplines, we observe a quite equal distribution of disciplines from 10% to 20% in the overall sample but a more heterogeneous distribution for the scientists who recognized an opportunity. However, the changes are not surprising: increases for *Engineering*, *Physics and Chemistry* and *Computer Science and Mathematics* and decreases especially for *Humanities* and *Social Sciences*. The organizational focus indicates that the majority of respondents works in universities. There are some small changes from the overall sample to the scientists who recognized an opportunity, indicating that scientists in application-oriented organizations have a higher likelihood to recognize opportunities. If we turn to the correlation between the explanatory variables (Tables 2.10 and 2.11), there are no substantial correlations in the data.

2.4.2 Regression results

The results of our empirical analysis are presented in Table 2.2. The first column shows the estimates of our selection equation which is relevant to test hypotheses 1a, 1b, 2 and 3. The remaining columns represent the three transfer channels scientists can choose for the pursuit of their recognized transfer opportunity. Since scientists can choose multiple channels, we estimate a multivariate probit model which provides correlation coefficients of the error terms that we present in the lower part of the table. The error terms show for the prevalence of selection mechanisms in column (1) that these occur

Table 2.1: Descriptive statistics.

	Selection TOR (=1)				Outcomes S-I-C (=1), IPR (=1), Spin-Off (=1)			
	mean	sd	min	max	mean	sd	min	max
Dependent variables								
Transfer opportunity recognition (=1)	0.44	0.50	0	1				
S-I Collaboration (=1)					0.82	0.39	0	1
IPR (=1)					0.47	0.50	0	1
Spin-off (=1)					0.49	0.50	0	1
Antecedents of transfer opportunity recognition								
Number of publications (log)	1.85	1.56	0	6.30				
Work experience outside academia	1.36	1.45	0	4				
Average impact factor	0.91	0.79	0	4.80				
Share of publications with industry	0.03	0.12	0	1				
Exclusion restriction								
Organizational transfer orientation	0.45	0.18	0	1				
Internal funding (=1)	0.49	0.50	0	1				
Variables for channel choice								
Basic research					2.65	0.71	1	4
Applied research					3.08	0.75	1	4
Risk willingness					6.75	2.07	1	11
Role models: S-I Collaboration					0.46	0.25	0	1
Role models: IPR					0.10	0.14	0	1
Role models: Spin-off					0.08	0.09	0	1
Control variables								
Professor (=1)	0.18	0.39	0	1	0.22	0.41	0	1
Female (=1)	0.37	0.48	0	1	0.31	0.46	0	1
Discipline: Computer Science and Mathematics	0.11	0.31	0	1	0.14	0.35	0	1
Discipline: Engineering	0.16	0.37	0	1	0.24	0.43	0	1
Discipline: Humanities	0.10	0.29	0	1	0.05	0.22	0	1
Discipline: Life Sciences	0.15	0.36	0	1	0.12	0.33	0	1
Discipline: Medicine	0.10	0.30	0	1	0.09	0.28	0	1
Discipline: Physics and Chemistry	0.20	0.40	0	1	0.22	0.41	0	1
Discipline: Social Sciences	0.19	0.39	0	1	0.13	0.34	0	1
Organizational focus: Basic	0.15	0.36	0	1	0.13	0.34	0	1
Organizational focus: Between basic and applied	0.64	0.48	0	1	0.58	0.49	0	1
Organizational focus: Applied	0.20	0.40	0	1	0.29	0.45	0	1
N	1,149				504			

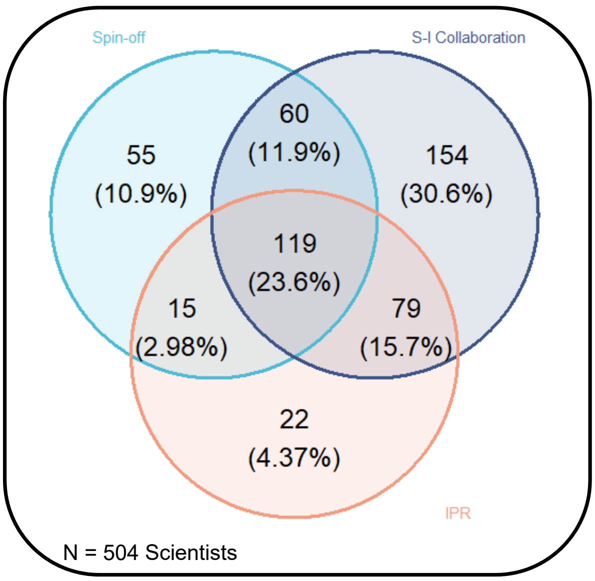

Figure 2.1: Venn diagram of the scientists' transfer channels choice (N=504).

mainly for the *S-I Collaboration* and *IPR* channel. Therefore, accounting for selection is essential to obtain unbiased estimates. Furthermore, there is a significant negative relationship between the choice of *S-I Collaboration* and *Spin-off*, indicating an opposing relationship between those two channels.

Our regression results regarding hypotheses 1a and 1b in the selection equation in column (1) show a positive and significant correlation between the *Number of publications* and the probability to recognize a transfer opportunity *(TOR (=1))*. The same holds for the *Work experience outside academia*. The results support hypotheses 1a and 1b stating a positive influence of prior academic and prior non-academic knowledge on transfer opportunity recognition. The coefficient for the *Average impact factor*, our proxy for scientific quality, is negative and significant. This goes against our hypothesis 2 that proposed a positive relationship with the TOR. The *Share of publications with industry* has no significant influence on the TOR and therefore does not support hypothesis 3 on the relevance of relations to industrial actors. Besides the core variables for our hypotheses, the exclusion restriction, *Organizational transfer orientation* and *Internal funding*, both show the expected and necessary correlation with *TOR (=1)*.[10] Furthermore, among the control variables, those in the disciplines *Humanities* and *Social Sciences* have a significantly lower probability to recognize a transfer opportunity compared to the baseline category *Computer Science and Mathematics*.

The results for the factors that influence the choice of a transfer channel can be obtained from columns 2-4 for the three channels. With respect to *Basic research*, the coefficient is only positive and significant for the choice of the spin-off channel and insignificant for the others. We, therefore, find no support for hypothesis 4a but for 4b. For *Applied research*, a positive and significant coefficient for the IPR channel is obtained and insignificant ones obtained for the other two channels. Respectively, there is no support for hypothesis 4c but for 4d. Concerning the scientists' *Risk willingness*, there is a positive and significant coefficient for choosing the spin-off channel. This provides support in favor of hypothesis 5. For

[10]We tested whether our two variables for the exclusion restriction are valid by running our model with these variables included in the outcome equations, too. They turned out to be not significant for any of the outcomes, indicating the exclusion restriction served its purpose (see Table 2.12 in the Online Appendix).

Table 2.2: Results of Seemingly Unrelated Regressions (SUR) with Selection.

	Selection	Outcomes		
	(1) TOR (=1)	(2) S-I Collaboration (=1)	(3) IPR (=1)	(4) Spin-off (=1)
Antecedents of transfer opportunity recognition				
Number of publications	0.234***			
	(0.036)			
Work experience outside academia	0.079**			
	(0.037)			
Average impact factor	-0.215***			
	(0.075)			
Share of publications with industry	0.417			
	(0.373)			
Exclusion restrictions				
Organizational transfer orientation	2.068***			
	(0.321)			
Internal funding (=1)	-0.241***			
	(0.091)			
Factors of channel choice				
Basic research		-0.094	0.089	0.216**
		(0.086)	(0.083)	(0.083)
Applied research		0.133	0.262***	0.057
		(0.089)	(0.079)	(0.085)
Risk willingness		-0.001	-0.011	0.098***
		(0.030)	(0.027)	(0.029)
Role models: S-I Collaboration		-0.599*		
		(0.356)		
Role models: IPR			1.497***	
			(0.574)	
Role models: Spin-off				1.328**
				(0.616)
Control variables				
Professor (=1)	0.140	0.270	0.037	0.018
	(0.123)	(0.167)	(0.151)	(0.151)
Female (=1)	-0.018	0.285**	-0.213	-0.326**
	(0.086)	(0.140)	(0.132)	(0.130)
Discipline: Engineering	-0.015	0.174	-0.006	-0.044
	(0.159)	(0.244)	(0.193)	(0.203)
Discipline: Humanities	-0.392**	-0.869**	0.386	1.022**
	(0.199)	(0.400)	(0.332)	(0.419)
Discipline: Life Sciences	-0.259	-0.264	0.404	0.380
	(0.175)	(0.284)	(0.248)	(0.282)
Discipline: Medicine	-0.173	-0.344	0.399	0.117
	(0.188)	(0.287)	(0.244)	(0.270)
Discipline: Physics and Chemistry	-0.076	-0.122	0.413**	0.183
	(0.162)	(0.225)	(0.196)	(0.209)
Discipline: Social Sciences	-0.309*	-0.184	0.139	0.085
	(0.161)	(0.276)	(0.250)	(0.277)
Organizational focus: Basic	-0.014	-0.184	-0.010	-0.381*
	(0.131)	(0.207)	(0.193)	(0.208)
Organizational focus: Applied	0.139	-0.040	-0.131	0.077
	(0.130)	(0.188)	(0.153)	(0.168)
Constant	-1.201***	1.468***	-0.927**	-1.710***
	(0.223)	(0.424)	(0.448)	(0.418)
	$\varepsilon_{Selection}$	$\varepsilon_{Collaboration}$	ε_{IPR}	$\varepsilon_{Spin-off}$
$\varepsilon_{Collaboration}$	-0.626***			
	(0.168)			
ε_{IPR}	-0.505**	0.198		
	(0.243)	(0.121)		
$\varepsilon_{Spin-off}$	0.212	-0.435***	0.151	
	(0.282)	(0.100)	(0.141)	
N	1,149			
Pseudo Log-Likelihood	-1520.9598			
Wald Chi^2	271.32			

Note: Robust standard errors in parentheses. Significance levels at *** p<0.01, ** p<0.05, * p<0.1.

the channel-specific *Role models*, a negative and significant coefficient is obtained for the S-I collaboration channel, while for the other two channels, the coefficient is positive and significant. With these results, we find only partial support for our hypothesis 6. With respect to the control variables, some interesting relationships exist. *Female* scientists are more likely to choose the S-I collaboration channel but less likely to choose the spin-off channel. Furthermore, scientists from the *Humanities* are less likely to recognize opportunities for S-I Collaborations but more likely to see such opportunities for spin-offs compared to the reference category *Computer Science and Mathematics*. Scientists from *Physics and Chemistry* are more likely to choose the protection of IPR compared to the baseline. Scientists employed in organizations focusing predominantly on basic research have a lower probability to choose the Spin-off channel.

2.4.3 Robustness tests

We conduct three robustness tests to our main specification. First, we use an alternative estimation procedure to check whether the results are driven by the choice of multiple channels. Second, we perform a subsample analysis and exclude scientists from the Humanities and Social Sciences which can have substantially different transfer activities. Third, since the *Work experience outside academia* and the *Share of publications with industry* show very low values, we transform these continuous variables to dummy variables to check whether it is the instance or the magnitude that characterizes the underlying mechanisms. All results are presented in the Appendix.

First, we model the initiation of KTT separately for the three transfer channels by estimating a Heckprobit two-stage model for each channel. Each of the three models consists of a selection and an outcome. The transfer opportunity recognition always represents the selection, while the channel under consideration constitutes the outcome of the model. While the Heckprobit models do not account for the possibility of multiple outcomes, i.e. using more than one channel to follow up on a recognized opportunity, they do correct for selection bias. Also, they produce robust coefficients when focusing on a specific channel (Miranda & Rabe-Hesketh, 2006). Results are very similar to our main model estimated with the SUR method, regarding both antecedents of transfer opportunity recognition and the factors of channel choice (Table 2.4). This indicates that the selection of multiple channels does not influence the results.

Second, we re-estimate the SUR model excluding scientists from social sciences and the humanities (Table 2.5). The reason is to assess potential differences in industrial applicability of knowledge within the academic disciplines. Scientists in these disciplines are predominantly engaged in transfer activities through consultancy, contract research or training (Olmos-Peñuela et al., 2014) – transfer channels that are not considered in our more commercially oriented view of transfer and for which no transfer opportunity by the scientist is the initiating step. The results are very similar to our main model. The only essential difference is that the coefficient for *Role models* for the spin-off channel is not significant any longer.

Third, we convert the *Work experience outside academia* and *Share of publications with industry* to binary variables to check whether having conducted such activities is relevant at all, irrespective of their intensity. The results from the SUR model (Table 2.6) do not differ substantially from the main specification. The binary operationalization of the *Work experience outside academia* is again positive and significant, but the *Share of publications with industry* turns positive and significant at the 10% level as well. This gives some small indication that relational capital and ties to industry also influence the recognition of transfer opportunities, in line with our third hypothesis.

2.5 Discussion and conclusion

The transfer of knowledge and technology from academia into industrial application is usually understood as a process (Fabiano et al., 2020; Maresova et al., 2019). While most research focuses on the end of the process (e.g. Abreu & Grinevich, 2013; Audretsch et al., 2012; Battistella et al., 2016; Bonaccorsi et al., 2014; de Fuentes & Dutrénit, 2012; D'Este et al., 2019), we focus on the initiation of transfer activities at the very beginning of the process. We conceptualize the initiation as a simultaneous recognition of a transfer opportunity and the respective choice of a transfer channel to seize the recognized opportunity. We base our reasoning on opportunity recognition in entrepreneurship (e.g. Ardichvili & Cardozo, 2000; Ardichvili et al., 2003; Baron & Ensley, 2006; George, Parida, et al., 2016; Shane, 2003) and generalize it for transfer activities by scientists who can seize their opportunity via different transfer channels (S-I collaboration, IPR, and Spin-off) (Abreu & Grinevich, 2013; Fabiano et al., 2020; Haeussler & Colyvas, 2011). We hypothesize on several antecedents to recognize a transfer opportunity as well as the factors that influence the choice of a transfer channel. For the recognition of a transfer opportunity, we build on the concept of scientific and technical human capital by Bozeman et al. (2001) and hypothesize that prior academic and prior non-academic knowledge, scientific quality and relationships to industry actors are relevant. For the channel choice, we hypothesize that scientists' research orientation, their willingness to take risks and the presence of role models shape their choice for a transfer channel. To test our hypotheses, we conduct a novel, representative survey of scientists in the German state of Thuringia. We apply seemingly unrelated regressions (SUR) (Roodman, 2011) to simultaneously estimate the antecedents of transfer opportunity recognition as well as the factors of channel choice for three transfer channels. SUR allows us to take account the selection into having a transfer opportunity recognition as well as the possibility to choose multiple channels.

On a descriptive level, we observe that less than half of the scientists recognize a transfer opportunity in the last five years. This indicates that a substantial share of scientists deems their generated knowledge not relevant or applicable for application outside academia (Amara et al., 2019). Related research shows that many scientists have little awareness and low intention to engage in transfer activities with industry (Huyghe & Knockaert, 2015; Neves & Brito, 2020). Among the scientists who have recognized an opportunity, the highest frequency is in S-I collaboration with more than 80%, while IPR or spin-off creation are chosen by slightly less than 50% each. Furthermore, more than 50% of the scientists recognize opportunities for more than one channel and about a quarter for all the channels. This finding is in line with results from D'Este and Patel (2007) and Iorio et al. (2017). Similar frequencies of channels choice are reported in surveys by Llopis et al. (2018) and D'Este et al. (2019), but they assess the implementation of transfer activities at the end of the process. However, their proportions of scientists who implemented a transfer activity is substantially smaller than the ones who recognize a transfer opportunity in our data, highlighting the difference between examining KTT at the beginning or at the end of the process, since many transfer opportunities do not succeed along the process (Cantner et al., 2023).

Our regression results for the transfer opportunity recognition show that prior academic and prior non-academic knowledge are highly relevant for the recognition of an opportunity. While previous findings already highlighted the importance of research productivity for successful transfer activities (Bekkers & Bodas Freitas, 2008; Garcia et al., 2020; Haeussler & Colyvas, 2011), our results show that the generated scientific knowledge is a prerequisite to recognize opportunities in the first place. Furthermore, our results show that it is not only the scientific knowledge a scientist generated and possesses but also that knowledge gained from activities and experiences in other domains than academia which increase the probability to recognize transfer opportunities, similar to related findings about entrepreneurial opportunity recognition (Cliff et al., 2006; Corner & Ho, 2010). Contrary to the amount of knowledge a scientist possesses, scientific quality has a negative impact on the recognition of transfer opportunities. Going against our hypothesis, the result shows that qualitatively excellent scientists are less likely to recognize a transfer opportunity, which is, however, in line with the ambiguity of the relationship between scientific quality and transfer activities in general, as discussed, for example, by Perkmann et al. (2021). Explanations for this relationship can be that qualitatively excellent scientists are so strongly embedded in their academic domain and the respective norms and logics that they are hardly or not at all receptive to transfer activities (Sauermann & Stephan, 2013). Furthermore, the measurement of scientific quality is skewed towards basic research and attributes a lower value to applied or transfer-relevant research (Waltman et al., 2013). With respect to the influence of previous scientific engagement with industry actors on the recognition of a transfer opportunity, we find ambiguous results. While we find no effect for the magnitude of the interaction, our robustness test gives some indication that having done such interaction or not can matter. Nevertheless, we do not find strong support for such a relationship, which is contrary to previous studies focusing on the implementation of transfer activities (Landry et al., 2007; 2010). It indicates that relational capital to industry might be of higher relevance in the later phases of the transfer process, as shown by Hayter (2016a), but not at its initiation.

Regarding the factors influencing the choice of the transfer channel, our results show that the scientist's research orientation is relevant in some cases. A stronger orientation toward basic research increases the probability of a scientist to pursue the opportunity through the spin-off channel. This indicates that such kind of knowledge needs to be commercialized with a long-term perspective, meaning that the development can take years until it is ready for the market (Agarwal & Bayus, 2002; Müller, 2010; Vohora et al., 2004). Examples are recent spin-offs in pharmaceuticals such as BioNTech, which was founded in 2008 and just recently launched a product (Senior, 2020). However, contrary to our hypothesis, we do not observe that scientists with an orientation towards basic research choose S-I collaboration to realize the opportunity. Scientists who are more oriented towards basic research are therefore less concerned with practically relevant questions, which could make it difficult for them to formulate a transfer idea into a collaborative project with industrial partners (Bartunek & Rynes, 2014; Stokes, 1997). Additionally, they most closely embody the image of a traditional scientist who sees a clearly separating boundary between academia and industry and therefore might fundamentally avoid collaborating with industry actors (Lam, 2010; Merton, 1968). With respect to the orientation towards applied research, the results show that it increases the probability to choose the IPR channel as hypothesized. However, we do not find this relationship with the spin-off channel and, thus, do not find support for our hypothesis. One reason for this could be that transfer opportunities from application-oriented researchers more often have a clear technological character, which scientists want to protect as IPR before it is used later in the transfer process as the basis for a spin-off (Leitner et al., 2021; Vohora et al., 2004; Wood, 2011).

We furthermore hypothesized that the channels have different risks associated with them and our results support such a relationship. We find a strong relationship between an individual's risk willingness and the choice of the spin-off channel. Since a scientist must be willing to accept high opportunity costs, e.g. change in tasks, foregone salary and personal financial investment to engage in founding a firm (Arza, 2010; Muscio et al., 2016), only risk-taking scientists choose this channel. For the other two channels which have no substantial costs but potential rewards, the risk willingness does not matter. Besides a scientist's personal characteristics, also the environment and especially role models influence the choice of transfer channel. Role models for IPR and spin-off channels show a positive influence on the choice of the respective channel. The latter results are in line with findings for non-academic entrepreneurship (Ozgen & Baron, 2007; Scherer et al., 1989). With respect to IPR, role models can signal the benefits of such activities, potentially in terms of reputation or financial rewards. However, the role models for the S-I collaboration channel show a negative effect. While this finding seems puzzling, there are arguments for negative role models and certain attributes or behavior which shall be rejected (Gibson, 2004). Since S-I collaboration can be perceived as a "necessary evil" to finance research on the costs of freedom of science and delay or even suppression of scientific publication (see, e.g. Ankrah et al., 2013; Gerbin & Drnovsek, 2020; Geuna & Nesta, 2006). Nevertheless, the result contradicts our initial hypothesis.

Besides our main findings, the results reveal additional interesting insights. First, the control variables show that gender disparities are striking. While there is no difference in the likelihood to recognize an opportunity, female scientists are more likely to choose S-I collaboration and less likely to choose the spin-off channel, in line with previous findings (Abreu & Grinevich, 2017; D'Este et al., 2019). Second, disciplinary differences, in terms of a lower likelihood for Humanities and Social Sciences to recognize a transfer opportunity, exist. However, for Humanities, if an opportunity emerges, the S-I collaboration channel will be chosen with a lower likelihood, while the spin-off channel has a much higher likelihood. The high relevance of academic entrepreneurship in the humanities has been discussed already, e.g., by Pilegaard et al. (2010). Third, the interrelationship between the channel choices reveals that there is a negative correlation between choosing the S-I collaboration channel and the spin-off channel. This indicates that scientists consider the two channels as diametrical, which has been indicated already by Barbieri et al. (2018). An underlying reason could be the intention to exploit knowledge personally and to not share it with potential competitors from the industry.

We contribute with our findings to the understanding of the very beginning, the initiation, of the KTT process from an academic perspective. We provide a conceptualization of the transfer initiation phase with a scientist's simultaneous recognition of a transfer opportunity and the channel choice. We generalize the concept of opportunity recognition, from the entrepreneurship literature to the context of academia to industry transfer, and refine the overall research on the KTT process with a focus on the transfer initiation phase. Analyzing the initiation of the transfer process allows us to capture the whole recognized transfer potential, which then enables us to understand the preconditions required to recognize transfer opportunities, irrespective of their further development along the transfer process. This perspective complements the output-oriented literature that focuses on the results from the transfer process and reveals differences in the relevance of influential factors. Our result that heterogeneity in prior knowledge, in our case academic and non-academic prior knowledge, is decisive to recognize an opportunity and can be associated with the importance of knowledge recombination across knowledge domains and its high relevance to start the KTT process. Contributing to research on conflicting logis in academia, we show that researchers who produce high-impact knowledge are less likely to recognize an opportunity, indicating that the conflicting logics are relevant already at the beginning of the transfer process. With respect to the factors that influence the transfer channel choice, the insight that different kinds of research orientation favor different transfer channels gives a finer-grained picture of the underlying mechanisms of transfer channel choices. Our results with respect to the role models show that the social context is already relevant at the beginning of the transfer process, paving the way for a potential pursuit of the transfer opportunity. Peer effects can influence channel choices, but this can happen in both directions. Lastly, our results on risk willingness contribute to the growing literature on personality characteristics and transfer activity. From a methodological point of view, we suggest new instruments to account for potential selection bias in recognizing transfer opportunities as well as accounting for the choice of multiple transfer channels.

Our findings can also be used to derive implications for policy makers and research management to foster transfer activities. First, since heterogeneous knowledge is relevant to recognize opportunities, the possibility for scientists to work with or in industry should be eased and fostered. Industry-related experience would lead to a better understanding of industrial needs and commercial potential. Second, our results show that especially scientists with high-quality knowledge do not recognize transfer opportunities. Programs that raise their awareness or better incentive structures in the academic reward system could help them realize transfer potential. Third, transfer managers and policymakers should consider in their support that scientists can have different research orientations and provide tailor-made programs for different kinds of research activity. Fourth, role models are a decisive factor and prominent examples can be used to raise awareness and serve as best-practice examples or even mentorship on how to transfer via a specific channel. Lastly, the high risk involved in spin-off attempts should be better cushioned, enabling more ideas with commercial potential to find their way into economic application. To lower the risk of foregone academic rewards, one approach could be to reduce time constraints for spin-off projects and grant scientists an entrepreneurial leave term to realize their idea. Similarly, spin-off activities should be acknowledged for academic qualification, too.

Our analysis is subject to several limitations, serving as starting points for further research. First, for the transfer opportunity recognition, we cannot disentangle whether the opportunity was triggered by a push from academia, by a pull from industry or whether it was a mix of both (D'Este et al., 2019; Nemet, 2009; Walsh, 1984). Understanding the triggering event can provide additional insights into opportunity recognition. Second, we cannot elaborate on scientists' willingness to pursue the recognized opportunity. Scientists may be fundamentally unwilling to engage in such activities but may still see transfer potential in their research and vice versa. Third, since we focus on the initiation of the transfer process, we cannot make any statements about whether scientists change the transfer channel in the course of the pursuit or whether a follow-up opportunity develops from a pursuit (Hayter et al., 2020). Lastly, the transfer opportunities we observed are not assessed based on their quality or feasibility. We cannot include an assessment regarding the commercializability of the opportunity in the analysis and how this affects the further course of the transfer process.

Besides these limitations, further research on the initiation of the transfer process should investigate the quality and frequency of recognized transfer opportunities and whether a higher intensity leads to a larger probability of high-quality opportunities. Furthermore, our results show that risk willingness is decisive for the channel choice, but other personality traits could influence opportunity recognition and channel choice as well. Understanding the influence of personality characteristics in more detail would make further contributions to the psychological foundations of science commercialization (Hmieleski & Powell, 2018). In more general terms, our conceptualization of the transfer initiation can be applied to other transfer channels, including informal transfer channels (Grimpe & Hussinger, 2013; Schaeffer et al., 2020) and other aims of transfer, such as societal engagement (Benneworth & Cunha, 2015; Bornmann, 2013; Fini et al., 2018). For such extensions, other factors can be relevant for the recognition of opportunities and the respective choice of channels.

2.6 Appendix

2.6.1 Variable construction

Table 2.3: List of variables and their construction.

Variable	Construction	Data type
Dependent variables		
TOR (=1)	Aggregation of the three variables for channel choice	Binary
S-I Collaboration	Survey item: *Development of an idea for a cooperation with company participation, i.e. identification of a research question or problem for which a cooperation between universities/research institutes and companies could be helpful*	Binary
IPR (=1)	Survey item: *Identification of an idea or invention that can be attributed to potential commercial exploitation or can be legally protected*	Binary
Spin-off (=1)	Survey item: *Development of an idea to found a firm, e.g. discussion of the idea with others, assessment of the economic potential or application of creative techniques?*	Binary
Antecedents of transfer opportunity recognition		
Number of publications	Data collected from Web of Science and Scopus	Numerical
Work experience outside academia	Survey item: *How many years of work experience outside the public science sector have you gained overall?* (5 categories (in years): 0: =0; 1: < 1; 2: >1 ... <3; 3: >3 ... <10 ; 4: >10)	Numerical
Average impact factor	Average of the scientist's journals' Source Normalized Impact per Paper	Numerical
Share of publications with industry	Share of scientist's publications in co-authorship with at least one firm	Numerical
Organizational transfer orientation	Share of respondents with a TOR from same organization as focal respondent	Numerical
Internal funding	Survey item: *How is your current position financed?*	Binary

Variable	**Construction**	**Data type**
Factors of channel choice		
Basic research	Survey item: *Please assess the extent to which you contribute with your research to scientific progress in your discipline and thus shift the research frontier in your discipline further.* (4-point Likert-scale: ”Not at all” to ”To a large extent”)	Numerical
Applied research	Survey item: *Please assess the extent to which your research is targeted towards practical application.* (4-point Likert-scale: ”Not at all” to ”To a large extent”)	Numerical
Risk willingness	Survey item: *How do you see yourself: Are you generally a person who is fully prepared to take risks or are you trying to avoid risks?* as used by SOEP-IS Group (2014, p. 36) (11-point Likert scale)	Numerical
Role models: S-I collaboration	Share of respondents from same faculty/organizational unit as focal respondent with at least one successful S-I collaboration (Survey item: *Realisation or participation in a research cooperation with company participation.*	Numerical
Role models: IPR	Share of respondents from same faculty/organizational unit as focal respondent with at least one successful IPR (Survey item: *Selling or licensing of an idea or invention e.g. selling a patent to a company.*	Numerical
Role models: Spin-off	Share of respondents from same faculty/organizational unit as focal respondent with at least one successful academic spin-off (Survey item: *Completed foundation of a firm, i.e. the launch of business activities.*	Numerical
Control variables		
Professor (=1)	Survey item: *Which of the following options describes your current position best?*	Binary
Female (=1)	Survey item: *Please indicate your gender.*	Binary
Organizational focus	Distinction of organizations between 1: Basic, 2: Between basic and applied, 3: Applied, following (Bundesministerium für Bildung und Forschung, 2014)	Categorical
Discipline	Data collected from participants' webpages.	Categorical

2.6.2 Robustness tests

Table 2.4: Heckprobit estimation of each channel choice separately.

	S-I Collaboration (=1)		IPR (=1)		Spin-off (=1)	
	(1) Selection (TOR)	(2) Outcome	(3) Selection (TOR)	(4) Outcome	(5) Selection (TOR)	(6) Outcome
Antecedents of transfer opportunity recognition						
Number of publications	0.221***		0.231***		0.222***	
	(0.038)		(0.037)		(0.039)	
Work experience outside academia	0.093***		0.096***		0.107***	
	(0.031)		(0.032)		(0.030)	
Average impact factor	-0.217***		-0.230***		-0.226***	
	(0.074)		(0.072)		(0.076)	
Share of publications with industry	0.507		0.531		0.564	
	(0.353)		(0.356)		(0.373)	
Exclusion restrictions						
Organizational transfer orientation	2.066***		2.061***		2.025***	
	(0.308)		(0.308)		(0.313)	
Internal funding (=1)	-0.271***		-0.237***		-0.257***	
	(0.085)		(0.091)		(0.090)	
Factors of channel choice						
Basic research		-0.096		0.092		0.213**
		(0.088)		(0.079)		(0.084)
Applied research		0.127		0.254***		0.060
		(0.083)		(0.084)		(0.084)
Risk willingness		-0.010		-0.012		0.097***
		(0.030)		(0.027)		(0.029)
Role models: Collaboration		-0.612*				
		(0.367)				
Role models: IPR				1.407***		
				(0.523)		
Role models: Spin-off						1.623**
						(0.640)
Control variables						
Professor (=1)	0.170	0.250	0.132	0.022	0.159	0.001
	(0.124)	(0.166)	(0.125)	(0.148)	(0.126)	(0.150)
Female (=1)	-0.024	0.269*	-0.014	-0.210	-0.018	-0.329**
	(0.086)	(0.138)	(0.086)	(0.130)	(0.086)	(0.130)
Discipline: Engineering	-0.021	0.151	-0.024	-0.005	-0.031	-0.023
	(0.159)	(0.247)	(0.158)	(0.193)	(0.159)	(0.204)
Discipline: Humanities	-0.412**	-0.813**	-0.414**	0.366	-0.433**	1.040***
	(0.200)	(0.399)	(0.200)	(0.318)	(0.201)	(0.395)
Discipline: Life Sciences	-0.255	-0.256	-0.255	0.397	-0.254	0.414
	(0.174)	(0.280)	(0.175)	(0.245)	(0.175)	(0.272)
Discipline: Medicine	-0.148	-0.307	-0.163	0.397	-0.166	0.163
	(0.185)	(0.292)	(0.185)	(0.245)	(0.187)	(0.270)
Discipline: Physics and Chemistry	-0.063	-0.098	-0.049	0.412**	-0.044	0.210
	(0.161)	(0.226)	(0.160)	(0.196)	(0.161)	(0.211)
Discipline: Social Sciences	-0.313*	-0.191	-0.310*	0.136	-0.324**	0.122
	(0.160)	(0.277)	(0.161)	(0.246)	(0.161)	(0.268)
Organizational focus: basic	-0.007	-0.191	-0.009	-0.011	-0.012	-0.383*
	(0.131)	(0.201)	(0.131)	(0.194)	(0.131)	(0.208)
Organizational focus: applied	0.112	-0.038	0.119	-0.120	0.110	0.070
	(0.123)	(0.188)	(0.123)	(0.152)	(0.124)	(0.165)
Constant	-1.183***	1.599***	-1.206***	-0.896**	-1.181***	-1.732***
	(0.219)	(0.422)	(0.219)	(0.437)	(0.221)	(0.435)
ε_C	-0.710***		-0.506**		0.193	
	(0.198)		(0.211)		(0.265)	
N	1,149		1,149		1,149	
Pseudo Log-Likelihood	-893.0884		-997.1153		-1002.761	
Wald Chi^2	20.13		25.15		47.64	

Note: Robust standard errors in parentheses. Significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: SUR estimation of a sub sample excluding scientists from Social Sciences and Humanities.

	Selection	Outcomes		
	(1) TOR (=1)	(2) S-I Collaboration (=1)	(3) IPR (=1)	(4) Spin-off (=1)
Antecedents of transfer opportunity recognition				
Number of publications	0.256***			
	(0.045)			
Work experience outside academia	0.109***			
	(0.040)			
Average impact factor	-0.273***			
	(0.089)			
Share of publications with industry	0.428			
	(0.405)			
Exclusion restrictions				
Organizational transfer orientation	2.451***			
	(0.394)			
Internal funding	-0.330***			
	(0.122)			
Factors of channel choice				
Basic research		-0.032	0.048	0.207**
		(0.105)	(0.092)	(0.095)
Applied research		-0.013	0.213**	0.134
		(0.097)	(0.098)	(0.097)
Risk willingness		-0.016	-0.030	0.075**
		(0.034)	(0.031)	(0.032)
Role models: S-I Collaboration		-0.763*		
		(0.438)		
Role models: IPR			1.781***	
			(0.643)	
Role models: Spin-off				1.146
				(0.731)
Control variables				
Professor (=1)	0.185	0.193	0.074	0.186
	(0.165)	(0.191)	(0.177)	(0.168)
Female (=1)	-0.027	0.304*	-0.325**	-0.327**
	(0.104)	(0.164)	(0.154)	(0.146)
Discipline: Engineering	-0.027	0.136	-0.027	-0.044
	(0.164)	(0.246)	(0.201)	(0.208)
Discipline: Life Sciences	-0.151	-0.345	0.369	0.501*
	(0.186)	(0.293)	(0.268)	(0.289)
Discipline: Medicine	-0.073	-0.408	0.356	0.133
	(0.202)	(0.286)	(0.260)	(0.277)
Discipline: Physics and Chemistry	0.016	-0.194	0.391*	0.255
	(0.172)	(0.228)	(0.207)	(0.214)
Organizational focus: Basic	-0.090	-0.238	-0.059	-0.502**
	(0.142)	(0.216)	(0.214)	(0.225)
Organizational focus: Applied	0.104	0.105	-0.065	0.014
	(0.156)	(0.221)	(0.181)	(0.194)
Constant	-1.404***	1.997***	-0.682	-1.733***
	(0.254)	(0.498)	(0.535)	(0.527)
	$\varepsilon_{Selection}$	$\varepsilon_{Collaboration}$	ε_{IPR}	$\varepsilon_{Spin-off}$
$\varepsilon_{Collaboration}$	-0.697***			
	(0.202)			
ε_{IPR}	-0.297	0.146		
	(0.345)	(0.135)		
$\varepsilon_{Spin-off}$	0.124	-0.324***	0.222*	
	(0.350)	(0.122)	(0.116)	
N	822			
Pseudo Log-Likelihood	-1172.66			
Wald Chi^2	207.33			

Note: Robust standard errors in parentheses. Significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6: SUR estimation with dummy variables for *Work experience outside academia* and *Publications with industry*

	Selection	Outcomes		
	(1) TOR (=1)	(2) S-I Collaboration (=1)	(3) IPR (=1)	(4) Spin-off (=1)
Antecedents of transfer opportunity recognition				
Number of publications	0.198***			
	(0.040)			
Work experience outside academia (=1)	0.221**			
	(0.096)			
Average impact factor	-0.204***			
	(0.073)			
Publications with industry (=1)	0.227*			
	(0.124)			
Exclusion restrictions				
Organizational transfer orientation	2.070***			
	(0.323)			
Internal funding (=1)	-0.241***			
	(0.090)			
Factors of channel choice				
Basic research		-0.091	0.092	0.214**
		(0.089)	(0.079)	(0.085)
Applied research		0.136	0.268***	0.056
		(0.085)	(0.083)	(0.083)
Risk willingness		-0.001	-0.011	0.097***
		(0.030)	(0.027)	(0.029)
Role models: S-I Collaboration		-0.601*		
		(0.352)		
Role models: IPR			1.525***	
			(0.553)	
Role models: Spin-off				1.311**
				(0.614)
Control variables				
Professor (=1)	0.156	0.270	0.042	0.025
	(0.123)	(0.166)	(0.150)	(0.149)
Female (=1)	-0.018	0.282**	-0.219*	-0.325**
	(0.085)	(0.139)	(0.131)	(0.129)
Discipline: Engineering	-0.017	0.183	-0.002	-0.050
	(0.159)	(0.243)	(0.194)	(0.202)
Discipline: Humanities	-0.381*	-0.845**	0.378	0.966**
	(0.199)	(0.389)	(0.328)	(0.402)
Discipline: Life Sciences	-0.257	-0.251	0.403	0.354
	(0.176)	(0.281)	(0.249)	(0.276)
Discipline: Medicine	-0.175	-0.331	0.399	0.096
	(0.187)	(0.285)	(0.245)	(0.265)
Discipline: Physics and Chemistry	-0.076	-0.113	0.416**	0.172
	(0.162)	(0.224)	(0.198)	(0.208)
Discipline: Social Sciences	-0.310*	-0.173	0.126	0.053
	(0.161)	(0.273)	(0.245)	(0.262)
Organizational focus: Basic	0.001	-0.176	-0.005	-0.378*
	(0.131)	(0.205)	(0.194)	(0.207)
Organizational focus: Applied	0.154	-0.047	-0.129	0.092
	(0.126)	(0.186)	(0.154)	(0.162)
Constant	-1.205***	1.452***	-0.969**	-1.728***
	(0.224)	(0.419)	(0.434)	(0.404)
	$\varepsilon_{Selection}$	$\varepsilon_{Collaboration}$	ε_{IPR}	$\varepsilon_{Spin-off}$
$\varepsilon_{Collaboration}$	-0.647***			
	(0.162)			
ε_{IPR}	-0.483**	0.195*		
	(0.223)	(0.115)		
$\varepsilon_{Spin-off}$	0.269	-0.451***	0.139	
	(0.243)	(0.092)	(0.131)	
N	1,149			
Pseudo Log-Likelihood	-1519.3906			
Wald Chi^2	263.97			

Note: Robust standard errors in parentheses. Significance levels at *** p<0.01, ** p<0.05, * p<0.1.

2.7 Supplementary material

2.7.1 Non-response analysis and sample representativeness

Table 2.7: Non-response analysis.

Variable	Approached (%)	Sample (%)	Sample - Approached
Professor (=1)	16.49	18.28	1.79
Female (=1)	37.56	36.73	-0.83
Basic	16.06	15.23	-0.83
Between basic and applied	63.85	63.97	0.12
Applied	20.09	20.80	0.71
Computer Science & Mathematics	10.11	10.53	0.42
Engineering	14.04	16.36	2.32**
Humanities	12.78	9.66	-3.12***
Life Science	13.50	14.97	1.47
Medicine	15.65	9.75	-5.9***
Physics & Chemistry	18.87	19.67	0.8
Social Sciences	15.05	19.06	4.01***
N	7,785	1,149	

Note: Group comparison based on Wilcoxon rank-sum tests as non-parametric alternative to two-sided t-test;
Significance at *p<0.1; **p<0.05; ***p<0.01

Table 2.8: Representativeness

Variable	Germany (Universities) (%)	Sample (Universities) (%)
Professor (=1)	18.63	20.99
Female (=1)	40.20	37.27

Note: The comparison is only between the respondents affiliated to universities and universities of applied science, not to research organizations; Data for the overall population of scientists at universities in Germany is taken from Statistisches Bundesamt (2020)

2.7.2 Research organizations in Thuringia

Table 2.9: List of approached organizations and their research focus.

Number	Organization	Organizational focus
	Universities and universities of applied sciences	
1	Bauhaus-Universität Weimar	between basic and applied
2	Duale Hochschule Gera-Eisenach	applied
3	Ernst-Abbe-Hochschule Jena	applied
4	Fachhochschule Erfurt	applied
5	Friedrich-Schiller-Universität Jena	between basic and applied
6	Hochschule für Musik FRANZ LISZT Weimar	applied
7	Hochschule Nordhausen	applied
8	Hochschule Schmalkalden	applied
9	SRH Hochschule für Gesundheit	applied
10	Technische Universität Ilmenau	between basic and applied
11	Universität Erfurt	between basic and applied
	Research institutes	
12	Forschungsinstitut für Mikrosensorik	applied
13	Forschungszentrum für Medizintechnik und Biotechnologie	applied
14	Fraunhofer-Institut für Angewandte Optik und Feinmechanik	applied
15	Fraunhofer-Institut für Digitale Medientechnologie	applied
16	Fraunhofer-Institut für Keramische Technologien und Systeme	applied
17	Fraunhofer-Institut für Optronik, Systemtechnik und Bildauswertung Institutsteil Angewandte Systemtechnik	applied
18	Friedrich-Loeffler-Institut für bakterielle Infektionen und Zoonosen	applied
19	Friedrich-Loeffler-Institut für molekulare Pathogenese	applied
20	Gesellschaft für Fertigungstechnik und Entwicklung	applied
21	Günter-Köhler-Institut für Fügetechnik und Werkstoffprüfung	applied
22	Helmholtz-Institut Jena	basic
23	Innovent	applied
24	Institut für Angewandte Bauforschung	applied
25	Institut für Bioprozess- und Analysenmesstechnik Heiligenstadt	applied
26	Institut für Datenwissenschaften	applied
27	Institut für Mikroelektronik- und Mechatronik-Systeme	applied
28	Leibniz-Institut für Alternsforschung - Fritz-Lipmann-Institut e.V.	basic
29	Leibniz-Institut für Naturstoff-Forschung und Infektionsbiologie Hans-Knöll-Institut	basic
30	Leibniz-Institut für Photonische Technologien	basic
31	Materialforschungs- und -prüfanstalt	applied
32	Max-Planck-Institut für Biogeochemie	basic
33	Max-Planck-Institut für chemische Ökologie	basic
34	Max-Planck-Institut für Menschheitsgeschichte	basic
35	Textilforschungsinstitut Thüringen-Vogtland	applied
36	Thüringer Landessternwarte Tautenburg	basic
37	Thüringisches Institut für Textil- u. Kunststoff-Forschung	applied

2.7.3 Correlation tables

Table 2.10: Pearson correlation coefficients all scientists (N=1,149).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	TOR (=1)																		
2	Number of publications (log)	0.15*																	
3	Average impact factor	-0.01	0.62*																
4	Work experience outside academia	0.12*	-0.17*	-0.21*															
5	Share of publications with industry	0.13*	0.08*	0.06*	0.05														
6	Organizational transfer orientation	0.33*	-0.04	-0.08*	0.10*	0.22*													
7	Internal funding (=1)	-0.06*	0.17*	0.04	0.07*	-0.04	-0.08*												
8	Professor (=1)	0.08*	0.29*	0.07*	0.19*	0.00	-0.02	0.37*											
9	Female (=1)	-0.11*	-0.18*	-0.07*	-0.11*	-0.06*	-0.11*	-0.05	-0.12*										
10	Discipline: Computer Science and Mathematics	0.11*	0.01	-0.02	0.00	0.06*	0.21*	-0.04	-0.01	-0.14*									
11	Discipline: Engineering	0.18*	-0.14*	-0.15*	0.15*	0.16*	0.44*	-0.03	0.03	-0.08*	-0.15*								
12	Discipline: Humanities	-0.13*	-0.16*	-0.13*	0.11*	-0.05	-0.25*	-0.04	0.01	0.09*	-0.11*	-0.14*							
13	Discipline: Life Sciences	-0.06*	0.09*	0.15*	-0.13*	-0.01	-0.10*	-0.03	-0.06*	0.06*	-0.14*	-0.19*	-0.14*						
14	Discipline: Medicine	-0.04	0.16*	0.12*	0.00	-0.03	-0.18*	0.10*	0.00	0.12*	-0.11*	-0.15*	-0.11*	-0.14*					
15	Discipline: Physics and Chemistry	0.05	0.22*	0.16*	-0.17*	-0.06	-0.03	-0.15*	-0.09*	-0.07*	-0.17*	-0.22*	-0.16*	-0.21*	-0.16*				
16	Discipline: Social Sciences	-0.13*	-0.18*	-0.13*	0.07*	-0.07*	-0.13*	0.20*	0.12*	0.04	-0.17*	-0.21*	-0.16*	-0.20*	-0.16*	-0.24*			
17	Organizational focus: basic	-0.05	0.18*	0.26*	-0.16*	-0.02	-0.15*	-0.12*	-0.13*	0.01	-0.15*	-0.19*	0.05	0.35*	-0.14*	0.25*	-0.21*		
18	Organizational focus: Between basic and applied	-0.11*	-0.01	-0.06*	-0.10*	-0.10*	-0.28*	0.07*	-0.05	0.04	0.16*	-0.17*	-0.03	-0.19*	0.18*	-0.12*	0.23*	-0.57*	
19	Organizational focus: applied	0.18*	-0.15*	-0.16*	0.26*	0.13*	0.47*	0.02	0.18*	-0.05	-0.05	0.37*	-0.01	-0.08*	-0.09*	-0.08*	-0.08*	-0.22*	-0.68*

Note: N=1149. Significance level at * p<0.05.

Table 2.11: Pearson correlation coefficients for scientists with recognized transfer opportunity (N=504).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Spin-off (=1)																				
2	S-I Collaboration (=1)	-0.25*																			
3	IPR (=1)	0.14*	0.06																		
4	Applied research	0.04	0.13*	0.16*																	
5	Basic research	0.14*	-0.06	0.08	0.07																
6	Risk willingness	0.17*	-0.01	0.01	0.08	0.17*															
7	Role models Spin-off	0.07	-0.01	0.03	0.02	0.00	-0.02														
8	Role models S-I Collaboration	-0.06	0.12*	0.18*	0.30*	-0.06	-0.03	0.05													
9	Role models IPR	-0.04	0.05	0.22*	0.18*	0.04	-0.01	0.13*	0.49*												
10	Professor (=1)	0.04	0.09*	0.01	0.00	0.09*	0.11*	0.01	-0.10*	-0.09*											
11	Female (=1)	-0.08	0.03	-0.09*	0.00	0.00	-0.09*	0.03	-0.10*	-0.01	-0.07										
12	Discipline: Computer Science and Mathematics	0.00	0.06	0.00	0.12*	0.03	0.00	0.24*	0.17*	0.02	-0.04	-0.13*									
13	Discipline: Engineering	-0.06	0.13*	0.01	0.22*	-0.07	0.02	0.00	0.41*	0.24*	-0.02	-0.04	-0.23*								
14	Discipline: Humanities	0.13*	-0.19*	-0.06	-0.04	0.09*	-0.01	-0.05	-0.30*	-0.16*	-0.02	0.16*	-0.10*	-0.13*							
15	Discipline: Life Sciences	0.02	-0.07	0.00	-0.15*	0.01	0.05	-0.07	-0.12*	-0.09*	0.00	0.07	-0.16*	-0.21*	-0.09*						
16	Discipline: Medicine	-0.02	-0.02	0.00	-0.08	-0.04	0.01	-0.11*	-0.12*	-0.10*	0.08	0.10*	-0.13*	-0.17*	-0.07	-0.12*					
17	Discipline: Physics and Chemistry	0.00	-0.01	0.13*	-0.10*	0.07	-0.02	0.01	0.11*	0.16*	-0.10*	-0.07	-0.22*	-0.30*	-0.12*	-0.20*	-0.16*				
18	Discipline: Social Sciences	-0.01	-0.01	-0.12*	-0.04	-0.06	-0.05	-0.08	-0.41*	-0.25*	0.13*	0.02	-0.16*	-0.22*	-0.09*	-0.15*	-0.12*	-0.21*			
19	Organizational focus: Basic	-0.02	-0.13*	0.02	-0.20*	0.11*	0.02	-0.01	-0.16*	-0.02	-0.11*	-0.01	-0.16*	-0.22*	0.09*	0.40*	-0.12*	0.20*	-0.15*		
20	Organizational focus: Between basic and applied	0.02	0.02	-0.09*	-0.16*	0.03	0.03	-0.01	-0.33*	-0.29*	-0.06	0.01	0.23*	-0.17*	-0.06	-0.23*	0.19*	-0.11*	0.21*	-0.46*	
21	Organizational focus: Applied	0.00	0.08	0.09	0.32*	-0.11*	-0.05	0.02	0.49*	0.33*	0.15*	0.00	-0.14*	0.35*	-0.01	-0.05	-0.11*	-0.03	-0.12*	-0.25*	-0.75*

Note: N=504. Significance level at * p<0.05.

2.7.4 Including the exclusion restrictions in the outcome equations

Table 2.12: SUR estimation with exclusion restriction in the outcome equations.

	Selection	Outcomes		
	(1) TOR (=1)	(2) S-I Collaboration (=1)	(3) IPR (=1)	(4) Spin-off (=1)
Antecedents of transfer opportunity recognition				
Number of publications	0.236***			
	(0.037)			
Work experience outside academia	0.080			
	(0.052)			
Average impact factor	-0.215**			
	(0.087)			
Share of publications with industry	0.399			
	(0.444)			
Exclusion restrictions				
Organizational transfer orientation	1.998***	1.069	0.113	0.199
	(0.326)	(0.836)	(0.642)	(0.654)
Internal funding (=1)	-0.273***	-0.032	0.147	-0.211
	(0.090)	(0.151)	(0.127)	(0.129)
Factors of channel choice				
Basic research		-0.092	0.095	0.209**
		(0.096)	(0.080)	(0.085)
Applied research		0.142	0.263***	0.044
		(0.092)	(0.084)	(0.082)
Risk willingness		0.005	-0.009	0.096***
		(0.032)	(0.026)	(0.029)
Role models: S-I Collaboration		-1.152**		
		(0.450)		
Role models: IPR			1.432***	
			(0.522)	
Role models: Spin-off				1.331**
				(0.642)
Control variables				
Professor (=1)	0.149	0.355	-0.039	0.145
	(0.127)	(0.235)	(0.179)	(0.182)
Female (=1)	-0.017	0.286*	-0.203	-0.336***
	(0.087)	(0.148)	(0.137)	(0.128)
Discipline: Engineering	-0.016	0.192	-0.015	-0.036
	(0.159)	(0.253)	(0.193)	(0.203)
Discipline: Humanities	-0.410**	-0.986*	0.410	1.005**
	(0.201)	(0.505)	(0.327)	(0.447)
Discipline: Life Sciences	-0.265	-0.297	0.415*	0.365
	(0.176)	(0.320)	(0.247)	(0.294)
Discipline: Medicine	-0.180	-0.271	0.394	0.173
	(0.187)	(0.300)	(0.254)	(0.265)
Discipline: Physics and Chemistry	-0.079	-0.080	0.432**	0.173
	(0.168)	(0.236)	(0.205)	(0.208)
Discipline: Social Sciences	-0.308*	-0.263	0.142	0.105
	(0.161)	(0.333)	(0.252)	(0.289)
Organizational focus: Basic	-0.018	-0.212	-0.018	-0.362*
	(0.131)	(0.216)	(0.192)	(0.207)
Organizational focus: Applied	0.151	-0.102	-0.158	0.061
	(0.133)	(0.209)	(0.167)	(0.173)
Constant	-1.158***	1.057	-1.034	-1.758***
	(0.240)	(0.672)	(0.750)	(0.610)
	$\varepsilon_{Selection}$	$\varepsilon_{Collaboration}$	ε_{IPR}	$\varepsilon_{Spin-off}$
$\varepsilon_{Collaboration}$	-0.456			
	(0.461)			
ε_{IPR}	-0.538*	0.158		
	(0.324)	(0.215)		
$\varepsilon_{Spin-off}$	0.322	-0.462***	0.110	–
	(0.282)	(0.124)	(0.232)	
N		1,149		
Pseudo Log-Likelihood		-1516.893		
Wald Chi^2		262.97		

Note: Robust standard errors in parentheses. Significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

A procedural perspective on academic spin-off creation: The changing relative importance of the academic and the commercial sphere

3.1 Introduction

Academic spin-offs (ASOs) are an important mechanism for transferring scientific and technological knowledge from academia to practical application in the economy and society (Meoli & Vismara, 2016; Rasmussen et al., 2006; Shane, 2004). These ASOs can have a substantial economic and societal impact by introducing new business models, creating jobs, contributing to the formation and growth of new industries, and addressing grand societal challenges (Fini et al., 2018; Rasmussen et al., 2020; Vincett, 2010). However, despite the increasing number of ASOs in recent decades (Mathisen & Rasmussen, 2019), the rate of ASO projects that have failed or been abandoned at some point in the venture creation process remains high, leaving a large stock of knowledge and commercial opportunities unexploited (e.g., Braunerhjelm, 2007; Fini et al., 2017).

Extensive research has been conducted to understand the ASO creation process, focusing on its phases and the barriers encountered along the way. It has been shown that in this dynamic and multi-phase process, founders need to accomplish a specific set of activities in each development phase before progressing to the next (Ndonzuau et al., 2002; Rasmussen, 2011; van Geenhuizen & Soetanto, 2009; Vohora et al., 2004; Wood, 2011). Academic entrepreneurs must overcome "critical junctures", defined as complex problems that "occur at a point along a new high-tech venture's expansion path, preventing it from achieving the transition from one development phase to the next" (Vohora et al., 2004, p. 159). These critical junctures arise because different phases of spin-off development require distinct configurations of resources, capabilities, network ties, and support. Qualitative studies document how ASOs develop through the creation process depending on the academic entrepreneurs' access to specific resources and social networks in different process phases (Fernández-Alles et al., 2015; Hayter, 2016a; 2016b). Additionally, first quantitative analyses focus on specific phases of the ASO creation process. For instance, (Krabel & Mueller, 2009) explored the drivers of individual academic scientists' decision to pursue ASO creation, i.e., becoming nascent entrepreneurs, while Landry et al. (2006) investigated the individual and organizational assets that increase the likelihood of ASO formation. However, a quantitative assessment of the entire ASO creation process, its different phases, and the transitions between these phases is still missing. Such an analysis would provide insights into the relevant determinants in each phase and can have implications, beyond scholarly advancement, for practitioners and policymakers (Fini et al., 2018; Sandström et al., 2018).

Prior studies on the determinants of success in the ASO creation process highlight the importance of scientists' embeddedness in both the academic and commercial spheres (Dasgupta & David, 1994; Rasmussen, 2011; Stephan & Levin, 1996). These two spheres represent distinct sets of competencies, activities, and social behaviors. Individuals embedded in a sphere share and appreciate specific attitudes, norms, and logics. They determine social individual behavior from which deviation is only tolerated to a certain degree (Merton, 1968). Thus, the two spheres encompass the different characteristics that describe the scientists and their contexts, serving as meta constructs to describe the two settings in which scientists must be embedded during the ASO creation process. Embeddedness refers to the relationship between the institutional and social structures of a sphere and an individual's behavior within that sphere (Beckert, 2003; Granovetter, 1992; Le Breton-Miller & Miller, 2009; Zukin & DiMaggio, 1990). Specifically, "embeddedness involves: understanding the nature of the structure [i.e. sphere], enacting or reenacting this structure which forges new ties, and maintaining both the link and the structure" (Jack & Anderson, 2002, p. 468). In the context of the ASO creation process, the central issue is that scientists are initially embedded in the academic sphere, where Mertonian norms prevail and knowledge is considered a public good. However, they must also engage with the commercial sphere, which operates under substantially different attitudes, norms, and logics, such as rent-seeking and secrecy. Throughout the process of new venture creation, scientists face tensions between these two spheres due to their opposing logics (Ambos et al., 2008). To successfully create a new venture, scientists must navigate and overcome these tensions (Rasmussen, 2011). While the importance of the two spheres and the challenge of reconciling their differences between the two spheres have been widely acknowledged, empirical insights into the importance and how this importance changes throughout the process are absent so far.

In this study, we aim to bridge this gap by empirically testing the changing relative importance of the academic and commercial spheres along the ASO creation process. To achieve this objective, we adopt a procedural perspective on ASO creation and investigate how scientists' embeddedness in both spheres influences their transition from one process phase to the next. We begin by conceptualizing the ASO creation as a sequential process divided into subsequent phases, drawing on similar approaches in the existing literature (Ndonzuau et al., 2002; Rasmussen, 2011; van Geenhuizen & Soetanto, 2009; Vohora et al., 2004; Wood, 2011). To successfully transition from one phase to the next and eventually establish a new firm, scientists must overcome critical junctures that act as barriers between these process phases. We recognize that venturing scientists are initially embedded in the academic sphere, but need to adapt to the commercial sphere. Building on previous research on institutional logics theory (Fini et al., 2010; Perkmann et al., 2019) and the relevance of both spheres in the ASO creation process (Clarysse

& Moray, 2004; Fisher et al., 2016; Rasmussen, 2011), we hypothesize that the relative importance of the academic sphere decreases as the process unfolds, while the relative importance of the commercial sphere increases.

To test our hypotheses, we utilize novel survey data collected from a representative sample of 1,149 scientists employed at universities and public research institutes in the German federal state of Thuringia. The survey elicits information about the scientists' past involvement in various phases of ASO creation and their embeddedness in the different spheres. Our cross-sectional dataset enables us to reconstruct each scientist's involvement in the respective phases of the ASO creation process. We estimate the likelihood of individual scientists advancing to the subsequent phase for each phase transition. By applying dominance analysis, we can determine the changing relative importance of scientists' embeddedness in the two spheres throughout the ASO creation process. This method decomposes the overall goodness-of-fit measure of a regression model into the contributions of each predictor variable, allowing us to assess their relative importance. Additionally, we employ different approaches to examine how the relative importance of each sphere changes between phases.

Our results provide support for our hypotheses, showing that the relative importance of the academic sphere decreases throughout the ASO creation process, while the commercial sphere becomes increasingly important. However, we find an exception during the transition into the final phase of venture creation, where the commercial sphere turns out to be less important. These findings partially support the conceptual suggestions by Rasmussen (2011). Furthermore, when comparing the relative importance of the two spheres, our results reveal that the commercial sphere consistently has a higher importance than the academic sphere for transitioning from one phase to the next, even from the early stages of the process, challenging existing perceptions. These results remain stable when subjected to several robustness checks, including alternative estimation approaches, control variables, and operationalizations of the spin-off creation process. Overall, our findings highlight the differential influences of the academic and commercial spheres in different phases of the ASO creation process. Scientists, who are initially embedded in the academic sphere, must adapt to the logics prevalent in the commercial sphere to successfully accomplish spin-off creation.

Our study contributes to the academic entrepreneurship literature in several ways. Firstly, we adopt a micro-level perspective by analyzing the ASO creation process from the viewpoint of individual scientists, focusing on their engagement in spin-off creation. Previous research has remained predominantly at the spin-off project level, neglecting the individual characteristics and tensions. We start from the premise that academic entrepreneurship is an individual endeavor where the scientist as the main actor has to bring his idea to the market (Guerrero & Urbano, 2014; Kleinhempel et al., 2022). Secondly, by starting with a population of scientists working in research organizations, we are able to trace the selection process of ASO throughout the entire ASO creation process, from recognizing a business opportunity based on scientific research to venture creation (Aldrich & Martinez, 2001; Ndonzuau et al., 2002). Thus, we provide quantitative assessment of scientists' discontinuation of their entrepreneurial pursuit along the ASO creation process. Thirdly, we integrate the academic entrepreneurship process theory (Rasmussen, 2011; Vohora et al., 2004; Wood & McKinley, 2010) with the multiple institutional logics theory (Fini et al., 2010; Perkmann et al., 2019). This integration allows for a better understanding of the importance of scientists' embeddedness in both spheres for development until the firm is established and to understand the tensions between the spheres that arise from differences in attitudes, norms and logics faced by scientists during ASO creation. By exploring the impact of scientists' embeddedness in the academic and commercial spheres on their progression along the ASO creation process, we contribute to a better understanding of the complex relationships in the process. Lastly, by employing dominance analysis to determine the changing relative importance of scientists' embeddedness in the two spheres, we can compare the importance of these spheres throughout the ASO creation process. This analytical method enables us to move beyond assessing the effect sizes of individual variables and instead examine the combined influence of multiple variables on the phenomena under investigation, i.e., the two spheres (Azen & Budescu, 2003; Azen & Traxel, 2009; Budescu, 1993).

In the following Section 3.2, we discuss the peculiarities and differences between the academic and the commercial spheres, propose a conceptualization of the ASO creation process, and present our hypotheses linking both spheres to the individual process phases. Section 3.3 provides a description of our data and empirical approach. Our analysis is presented in Section 3.4. Finally, in Section 3.5, we discuss the results and provide concluding remarks.

3.2 Theoretical background

3.2.1 Academic and commercial sphere

Academic scientists primarily engage in the generation and diffusion of knowledge, but some of them recognize an opportunity to commercialize the findings. Such an economic opportunity can be exploited via different transfer channels, such as patenting, licensing, or creating a new venture (Bekkers & Bodas Freitas, 2008; D'Este et al., 2019; Ding & Choi, 2011; Wood, 2009). Commercialization activities require scientists to move from the familiar academic sphere into the less familiar commercial sphere. In particular, academic spin-offs (ASO) – firms founded by scientists based on their research outcomes – directly transfer these outcomes into economic application (Karnani, 2012; Steffensen et al., 2000). The entrepreneurial scientists either leave academia altogether to work solely on their spin-off or stay in both the academic and the commercial spheres, sometimes referred to as an entrepreneurial hybrid (Lam, 2010; Nicolaou & Birley, 2003). The latter case is particularly interesting because these scientists need to simultaneously engage with two spheres where opposing logics prevail (Murray, 2010; Rasmussen, 2011; Samsom & Gurdon, 1993; Shinn & Lamy, 2006). The differences between the two spheres and the way to cope with these differences might create tensions or even failures in the ASO creation process (Gurdon & Samsom, 2010).

Significant challenges in founding an ASO refer to reaching out from the known academic sphere to a commercial one and adapting and acting within this commercial sphere (Dasgupta & David, 1994; Rasmussen, 2011; Stephan & Levin, 1996). In this process, difficulties arise because the two spheres have opposing logics which we summarize in Table 3.1. These logics comprise different norms constituting scientists' roles and functions, different understandings and usages of knowledge. Also, the logics contain different reward systems incentivizing a behavior compliant with the respective norms and different motivational factors to perform their roles and functions (Clarysse et al., 2023; Hayter, 2011; Jain et al., 2009; Lam, 2010). Furthermore, in both spheres, competition exists but for different outcomes: academic and commercial success. Specific competencies are required to fulfill their roles and functions and to withstand the competition within each sphere. Overcoming these differences between the two logics is a prerequisite for establishing the ASO. Along this process, scientists must learn, change and adapt to successfully establish a firm. In the following, we discuss the two spheres in more detail and the process of dealing with their idiosyncrasies.

According to Merton (1973), in the *academic sphere*, the ethos of science can be characterized by four norms: communism, disinterestedness, universalism, and organized skepticism. Ziman (1984) added originality as a fifth norm.[1] These norms guarantee the freedom of research, create an open science mentality and treat knowledge as a public good to ensure the progress of science (Baldini et al., 2007; Nelson, 1959b; Rosenberg, 1974). Embedded in these norms, scientists are both intrinsically and extrinsically motivated to conduct research. They are intrinsically motivated by the quest for fundamental understanding, the freedom of research, and the enjoyment of puzzle-solving (Lam, 2011; Merton, 1968). Extrinsically, they are motivated by community recognition via publications and citations (Lam, 2011). Another extrinsic motivation is financial rewards, which is the least relevant (Lam, 2011). The academic reward system grants peer recognition and reputation to scientists based on their scientific contributions (Dasgupta & David, 1994), leading to a predominant publication orientation and a "publish-or-perish" culture (Ndonzuau et al., 2002). The reward system introduces competition between scientists in terms of quantity and quality of research outputs and competition for scarce inputs they need for their research (van Rijnsoever et al., 2008). To successfully compete in this sphere, specific competencies,

[1] Communism of science refers to unbiased research, knowledge generation, and sharing since it is considered a public good. Disinterestedness of science describes the independent work of scientists only for the contribution to the knowledge stock as an end in itself. Thus, they behave with integrity without any profit-driven motives. Universalism of science characterizes the verifiability of research and its results' independence of the investigator. Organized skepticism describes the scientists' approach of critical reflection when theorizing and conceptualizing. Originality entails the ambition to always search for the unknown to discover novel research results.

such as analytical thinking, methodological and technical skills, and the ability to communicate research results, are needed (Bartunek & Rynes, 2014; de Grande et al., 2014). Overall, the academic sphere is characterized by the underlying impetus of the production and the advancement of knowledge in aiming for the progress of science (Nelson, 1959b; Rosenberg, 1974). An economic rationale plays hardly any role.

Table 3.1: Comparison of the academic and commercial sphere

	Academic sphere	**Commercial sphere**
Norms	Ethos of science defined by the norms communism, disinterestedness, universalism, organized skepticism, and originality (Merton, 1973; Ziman, 1984)	Market competition and rent-seeking under bureaucratic control, secrecy and restrictions on disclosure (Sauermann & Stephan, 2013)
Relation to knowledge	Knowledge production, diffusion, and scientific progress (Nelson, 1959b; Rosenberg, 1974)	Appropriation of knowledge for commercial exploitation (Levin et al., 1987)
Motivation	Intrinsic: quest for fundamental understanding, puzzle solving (Lam, 2011; Stokes, 1997) Extrinsic: reputation, peer recognition and financial returns (Lam, 2011)	Intrinsic: passion for business ideas, self-realization (Cardon et al., 2005) Extrinsic: financial gain and growth intentions (Cassar, 2007; Lam, 2011)
Reward system	Career progress and peer recognition via publications, citations, and rankings (Dasgupta & David, 1994)	Maximization of profit and market share
Competition	For journal publications, funding, and research inputs (van Rijnsoever et al., 2008)	For markets, market share, and knowledge (Dosi & Nelson, 2010)
Competencies	Analytical thinking, methodological skills, technical skills, etc. (de Grande et al., 2014)	Ability to evaluate commercial potential, acquire resources, to lead a team, and show a vision (Baldini et al., 2007; Shane, 2004)

Source: Own elaboration

The *commercial sphere* stands opposite the academic sphere, where fundamentally different logics and norms apply (see Table 3.1). The norms of this sphere revolve around market competition and rent-seeking, both of which encourage behavior that leads to knowledge generation and application under cost-benefit considerations. This behavior is embedded in bureaucratic control, secrecy, and restrictions on disclosure (Hayter, 2011; Sauermann & Stephan, 2013). Knowledge is understood as a private good. Its exploitation and attainment aims at creating a competitive advantage (Dasgupta & David, 1994; Levin et al., 1987; Stephan & Levin, 1996). The focus is on application-oriented knowledge to solve problems for practical purposes (Bartunek & Rynes, 2014; Stokes, 1997). Especially entrepreneurs exploit such knowledge when they work on a business opportunity (Schumpeter, 1911). They are intrinsically motivated by, for instance, the passionate identification with their business, often describing it as their "baby", or self-realization (Cardon et al., 2005; Huyghe et al., 2016). Extrinsically, entrepreneurs are motivated by, e.g., financial gains and growth ambitions (Cassar, 2007; Hossinger et al., 2021). The reward system recognizes entrepreneurial success via profits and market shares. In this sphere, entrepreneurship-specific knowledge, skills, and competencies are required to found and run a company (Criaco et al., 2014; Stuetzer et al., 2012; Ucbasaran et al., 2008). Also, the ability to evaluate the commercial potential, acquire and manage resources, lead (larger) teams, and show vision for sustainable returns are required (Baldini et al., 2007; Shane, 2004).

Scientists are socialized in the academic sphere, and commercializing research results contradicts their norms. As a result of this socialization process, they usually acquire a "taste for science" (Roach & Sauermann, 2010), lowering their appeal to working within the commercial sphere (Fritsch, 2012). Entrepreneurial activity contradicts the open-science mentality, which considers knowledge a public good (Krabel & Mueller, 2009). However, for a successful application of research results in the commercial sphere, scientists need to adapt to the logics of the commercial sphere while fulfilling their academic role (Rasmussen, 2011). The transition from the academic to the commercial sphere can be understood as a process. It is challenging, risky, and the actors are confronted with tensions (Ambos et al., 2008; Neves & Franco, 2018; Samsom & Gurdon, 1993). Along this process, the scientists also transition into their role identity and become academic entrepreneurs (Hayter et al., 2022; Jain et al., 2009).

3.2.2 The two spheres in the academic spin-off creation process

The process of creating an ASO consists of distinct phases, with specific activities and challenges to overcome in each phase (Clarysse & Moray, 2004; Hossinger et al., 2020; Kleinhempel et al., 2022; Ndonzuau et al., 2002; Neves & Franco, 2018; Vohora et al., 2004). It is important to acknowledge that this process involves a degree of trial and error. Therefore, the development of ASO projects is seen as a quasi-linear process with feedback loops within each phase (van Geenhuizen & Soetanto, 2009; Vohora et al., 2004). Based on this understanding, we conceptualize the ASO creation process as comprising four consecutive phases (see Table S3 in Electronic Supplementary Material) for similar conceptualizations in the academic entrepreneurship literature). As shown in the upper half of Figure 3.1, venturing scientists must navigate three transitions: from the initial research phase to the opportunity framing phase (Transition 1); from the opportunity framing phase to the pre-spin-off phase (Transition 2); and finally, from the pre-spin-off phase to the spin-off phase (Transition 3). In each phase, scientists need to accomplish specific objectives to progress to the next phase, and at each transition, some scientists may drop out of the ASO process. We argue that these dropouts are driven by the individual scientists' embeddedness in the academic and commercial spheres, as well as the changing relevance of these spheres along the ASO process (as depicted in the lower part of Figure 3.1). In the following, we discuss the different phases and the importance of embeddedness in both spheres for successful transitions, drawing on and expanding upon prior research by Fini and Toschi (2016), Fisher et al. (2016), Rasmussen et al. (2011), among others.

The *research phase* is the initial stage of the ASO creation process, where venturing scientists focus on conducting scientific research within their respective fields of expertise. They dedicate their efforts to purely academic activities, such as knowledge generation and publication, driven by the pursuit of academic reputation and in adherence to the norms and rules of the academic sphere (Lam, 2011; Merton, 1973; Vohora et al., 2004). Engaging in research activities serves as an essential prerequisite for scientists to identify potential business opportunities (Aldawod, 2022; Huegel et al.,

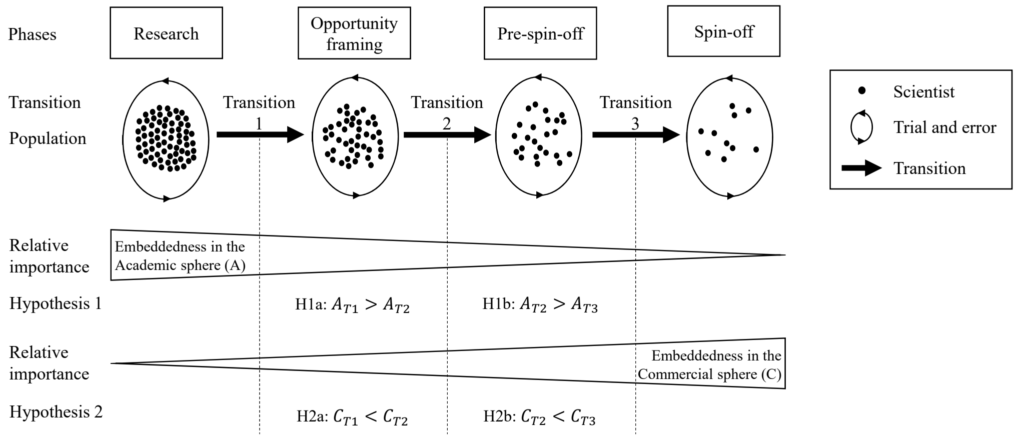

Figure 3.1: Conceptualization of the transition process and the changing relative importance of the two spheres

2023). Studies have demonstrated that scientists who produce more research output and possess a more diverse knowledge base are better equipped to recognize the commercial potential of their work (see, e.g., Louis et al., 1989).

Following the research phase, scientists enter the *opportunity framing phase* (Transition 1). At this stage, the academic sphere holds greater importance than the commercial sphere, as scientists draw upon their academic embeddedness to validate the commercial potential of their research (Ramos-Rodríguez et al., 2010; Rasmussen et al., 2011). The academic sphere provides a supportive environment where they can leverage their research-oriented norms, access resources, and collaborate with peers to identify entrepreneurial prospects and refine research outcomes into viable business opportunities (Fernández-Alles et al., 2015; Rasmussen et al., 2011). On the other hand, the commercial sphere's relevance is relatively lower in this phase. The commercialization process is in its early stage, and scientists prioritize understanding the potential applications of their research. Interaction with the commercial sphere may involve initial market research or consultation with industry experts, but the emphasis is primarily on nurturing and developing the scientific foundation upon which the spin-off venture will be built (Ndonzuau et al., 2002; Rasmussen et al., 2011). The opportunity framing phase concludes with the commitment to the spin-off project and the initiation of necessary preparatory steps (Vohora et al., 2004). However, not all venturing scientists show their commitment at this stage. Factors such as a lack of entrepreneurial self-efficacy (Huyghe & Knockaert, 2015), insufficient entrepreneurial competencies (González-López et al., 2021), concerns regarding time commitment and risk, or a reluctance to depart from the open science mentality may contribute to scientists' decision not to pursue the spin-off project and abandon the ASO process (Erikson et al., 2015; Krabel & Mueller, 2009; Nelson, 2016).

Once scientists commit to their spin-off project, they transition from the opportunity framing phase to the *pre-spin-off phase* (Transition 2). This transition involves translating the identified business opportunity into a concrete business idea and preparing for the establishment of the spin-off (Vohora et al., 2004). In this context, the commercial sphere becomes more important, while the significance of the academic sphere relatively diminishes. The increasing importance of the commercial sphere arises from the need to align the business idea with market demands and considerations. Scientists must understand customer needs, identify suitable markets, and develop a compelling value proposition (Ndonzuau et al., 2002). The commercial sphere operates under different norms and logics, emphasizing market competition, profitability, and the creation of competitive advantage. Scientists need to adapt to these norms and engage with commercial actors, such as industry professionals, investors, and potential customers, to enhance their business idea and receive market validation (Audretsch et al., 2011; Dohse et al., 2021; Fernández-Alles et al., 2015; Hayter, 2016b; Huynh et al., 2017). Furthermore, transitioning to the pre-spin-off phase requires scientists to develop entrepreneurial competencies and perform activities that are specific to the commercial sphere, such as writing a business plan, conducting market analyses, and assessing financial viability (Ndonzuau et al., 2002; Vohora et al., 2004). By contrast, the embeddedness in the academic sphere at this stage holds less relevance, and in some cases, it can even be detrimental to the progress of the ASO process. For instance, uncertainty surrounding the commercial viability of the spin-off project may hinder scientists from establishing a firm (Mathisen & Rasmussen, 2019; Raposo et al., 2008). Moreover, academic career development goals and responsibilities in teaching and administration may leave insufficient time for pre-spin-off activities (Gilsing et al., 2011; Jacobson et al., 2004; Sá et al., 2011). Consequently, these scientists encounter difficulties in fully adapting to the commercial logics, thereby further exacerbating tensions between the academic and commercial spheres (Gümüsay & Bohné, 2018; Gurdon & Samsom, 2010). However, if scientists successfully navigate these conflicting logics, they can transition to the next phase.

In summary, the academic sphere's greater importance during the transition from the research phase to the opportunity framing phase can be attributed to its role in providing the foundation for recognizing a business opportunity based on research activities. Conversely, during the transition from the opportunity framing phase to the pre-spin-off phase, the focus shifts towards leveraging the commercial sphere to frame the business opportunity into a concrete idea, develop a market entry plan, and secure the necessary resources for establishing the spin-off project. Accordingly, we suggest the following hypotheses:

H1a: Scientists' embeddedness in the academic sphere is more important for recognizing a business opportunity based on research activities (Transition 1) than for engaging in pre-spin-off activities based on a framed business opportunity (Transition 2).

H2a: Scientists' embeddedness in the commercial sphere is less important for recognizing a business opportunity based on research activities (Transition 1) than for engaging in pre-spin-off activities based on a framed business opportunity (Transition 2).

The ASO creation process culminates in the *spin-off phase*, wherein research outcomes are eventually transformed into a commercial venture (Fernández-Alles et al., 2015). During the transition towards the spin-off phase (Transition 3), the importance of the commercial sphere further increases while the academic sphere ceases to be relevant (Rasmussen, 2011; Rasmussen & Wright, 2015). As the spin-off project moves closer to commercialization, the focus fully shifts from scientific research and academic networks to the practicalities of running a business. The commercial sphere becomes more pertinent as scientists-turned-entrepreneurs need to acquire resources, secure funding, develop marketing strategies, build customer relationships, and establish a competitive position in the market (Delmar & Shane, 2006; Neves

& Franco, 2018). The success of the spin-off venture hinges on effectively navigating the market landscape (Huynh et al., 2017). This requires business-oriented expertise, market knowledge, and the ability to adapt to market dynamics (Berbegal-Mirabent et al., 2015; Neves & Franco, 2018). As such, scientists' embeddedness in the commercial sphere is vital as it provides the necessary tools and frameworks for entrepreneurial success. Additionally, while valuable in the early stages, the academic sphere's norms and practices may not align optimally with the practical aspects of setting up and running a business (Perkmann et al., 2019; Rasmussen et al., 2011; Sauermann & Stephan, 2013).

To conclude, as the venturing scientists progress towards the spin-off phase and enter the business realm, the commercial sphere assumes substantial importance, as it encompasses the practical aspects of executing the business plan, securing entrepreneurial resources, and competing in the market. Meanwhile, the norms and logics of the academic sphere no longer apply. Thus, we hypothesize:

H1b: Scientists' embeddedness in the academic sphere is more important for engaging in pre-spin-off activities based on a framed business opportunity (Transition 2) than for founding a firm based on a business plan (Transition 3).

H2b: Scientists' embeddedness in the commercial sphere is less important for engaging in pre-spin-off activities based on a framed business opportunity (Transition 2) than for founding a firm based on a business plan (Transition 3).

3.3 Data and method

3.3.1 Data

We conducted a novel online survey of scientists in the German Federal State of Thuringia to understand the academic spin-off creation process. Thuringia resembles the heterogeneity in the German research landscape well. There are four universities in Thuringia, including one technical university and one university with a university hospital. Furthermore, seven universities of applied sciences, including one music college, and 25 research institutes are present. The research institutes cover the whole range from basic science-oriented institutes of the Max Planck Society, the Helmholtz Association and the Leibnitz Association to the applied science institutes, including the Fraunhofer Society, as well as other public and private research organizations (see Table S4 in Electronic Supplementary Material). This variety of organizations assures coverage of different disciplines and different modes of research.

We collected publicly available contact information and characteristics of the scientists from their institutional web pages. We identified 7,785 scientists who we invited to participate in our web-based survey in December 2019 and January 2020. We received 1,409 responses (18.1% response rate) of which we had to exclude 260 observations due to incomplete answers and conduct our analysis with 1,149 observations. The difference between the sample of respondents and the initial population is marginal and non-response bias unlikely.[2] A comparison with the overall population of scientists at universities in Germany (Statistisches Bundesamt, 2020) shows that our sample is representative in terms of academic rank and gender (Table S2 in Electronic Supplementary Material).

Our survey consists of a set of novel questions on the academic spin-off creation process. To ensure the reliability of our survey, we discussed the items with other scientists and practitioners from technology transfer offices and conducted a pre-test with a random sample of scientists from a comparable German state, as suggested by Sue and Ritter (2007). In our survey, we elicited scientists' general socio-demographic characteristics as well as their engagement in knowledge and technology transfer. We included a list of questions on their spin-off creation activities in the last five years. Respondents were asked separately about their activities in the four different phases of the spin-off creation process (see Figure 3.1). Table

[2]We compared the key characteristics position, gender, organizational focus and academic discipline (Armstrong & Overton, 1977) in Table S1 in Electronic Supplementary Material. There are some statistically significant differences concerning the disciplines. There is especially an under-representation of scientists from medicine in our respondents. We believe that our initial data collection included many medical doctors with an affiliation to the university hospital but who are not involved in research anymore.

3.5 provides the exact wording of the survey questions. These questions are derived from process schemes from the literature conceptualizing academic entrepreneurship (see Table S3 in Electronic Supplementary Material). Due to the nature of the survey questions, scientists might have referred to both single or team entrepreneurship.

The retrospective survey of their sequential activities allows us to overcome the cross-sectional nature of the survey and to reconstruct the spin-off creation process with its successive phases. Furthermore, asking about the different phases individually allows us to not only consider successful spin-off creations, as is usually the case in studies tracking scientists along the academic spin-off creation process (e.g., Fernández-Alles et al., 2015; Fini et al., 2009; Hayter, 2016b), but also spin-off attempts, which stopped at different phases along the process. We can therefore for each scientist reconstruct the process until they either established a venture or abandoned the venture creation process for whatever reason. For our empirical analysis, we create sub-samples of active scientists per phase, as portrayed in our research design (Figure 3.1) and data (Table 3.2). Our study considers only the scientists who, in addition to their spin-off project, continued in academia, neglecting spin-offs where the entrepreneur left academia. This specific subgroup of scientists who are sometimes called "hybrid entrepreneurs" (Lam, 2010; Nicolaou & Birley, 2003) is of our interest because they need to act in both the academic and the commercial spheres.

In addition to the survey data, we collected data on the respondents' publication record from Web of Science (WoS) and Scopus.[3] Furthermore, we collected the publications' source normalized impact factor (SNIP) as provided in the journal record of Scopus.

[3] Our primary source for publication data is WoS. If there is no publication record in WoS for a surveyed scientist, we queried Scopus which has a larger coverage for some disciplines esp. for social sciences and humanities (Martín-Martín et al., 2021). If, again, there are no publications in Scopus listed, we treated such cases as zero, which is plausible especially for PhD students. In doing so, we probably underestimate the influence of publications.

3.3.2 Variables

Dependent variables

To measure a scientist's successful transition along the four phases of the academic spin-off creation process (Research phase, Opportunity framing, Pre-spin-off phase and Spin-off phase), we construct three dummy variables for each successful phase transition. A transition from one phase to the next is regarded as successful in our data if scientists stated that they undertook activities relevant to the subsequent phase. First, we treat all our respondents as part of the Research phase, since they are all scientists conducting research. If respondents reported any development of an idea to found a firm, they made Transition 1 into the Opportunity framing phase. Second, those who reported any activities to prepare the firm foundation managed Transition 2 and, thus, reached the Pre-spin-off phase. Third, respondents completed Transition 3 into the Spin-off phase if they reported the foundation of an academic spin-off. From this information, we construct three dummy variables which take the value 1 if respondents successfully transitioned into the next process phase and 0 otherwise.

Independent variables

We use two sets of variables to operationalize the scientists' embeddedness in the academic and commercial spheres. These sets of variables capture the specific characteristics of each sphere, as described in Section 3.2. For a comprehensive overview of the variables, see Table 3.5 in the Appendix.

Academic sphere: We use six variables to proxy scientists' embeddedness in and exposure to the academic sphere. First, we create a dummy variable indicating if the scientist is a *Professor* or not.[4] The academic rank of a professor in Germany, especially, is a clear indicator of the embeddedness in the academic sphere. Previous research shows that the deep embeddedness of professors in the academic sphere has a negative relationship with spin-off creation (e.g., Aldridge et al., 2014; Fritsch & Krabel, 2012). Second, we use

[4]We treat junior professors as well as directors or heads of departments in research institutes equal to full professors.

Time devoted to research as an indicator of the extent to which scientists value research activity and how they respond to the incentives provided by the academic reward system. Survey participants were asked to state the share of weekly working hours spent on research activities. Third, the scientist's overall *Number of publications* reflects the scientists' reputation as well as their embeddedness in the scientific community. Furthermore, scientific publications serve as a knowledge pool from which commercializable ideas can be identified. Prior research suggests a positive relationship between publication output, research reputation, and the propensity to be involved in spin-off activities (e.g., Aschhoff & Grimpe, 2014; D'Este et al., 2019; Ding & Choi, 2011; Zucker et al., 1998). We log-transform the scientists' number of publications to account for its skewed distribution. Fourth, we use the *Average impact factor* to measure the quality of scientists' research output. Similar to quantity, a higher quality increases the embeddedness in the academic sphere due to reputation and potentially increases access to resources. We construct the variable by averaging the SNIP for each scientist's journal publication to account for differences across disciplines. Lastly, we include two variables to measure scientists' research orientation within the last five years. Following Amara et al. (2019), respondents were asked to indicate the extent to which they conduct *Basic research*, characterized by contributions to fundamental understanding and the extent to which *Applied research* is conducted, characterized by the consideration of the use of her/his research results. Both variables were assessed on a 4-point Likert scale, ranging from "not at all" to "a lot". Higher scores indicate stronger embeddedness in the academic system since they aim to generate research output that concentrates on less understood research problems and new academic practices (Amara et al., 2019).

Commercial sphere: We use four variables to operationalize the scientists' embeddedness in the commercial sphere. First, the *Share of publications with industry* measures scientists' endowment with both commercialization-specific human capital and network ties with actors from the commercial sphere (D'Este, Mahdi, et al., 2012; Fritsch & Krabel, 2012; Krabel & Mueller, 2009). We calculate the variable as the number of publications with at least one co-author with industry affiliation over the total number of publications. Second, scientists can benefit in the same way from previous *Work experience outside academia*. Non-academic work experience can increase awareness of differences between the academic and the commercial sphere, and scientists who previously worked in the industry are more likely to engage in commercial activities and adapt to the commercial sphere (Gulbrandsen & Thune, 2017). Third, the *Time devoted to knowledge and technology transfer (KTT)* indicates how much time scientists spend per week engaging with the commercial sphere. The more time scientists spend on transfer activities, the more likely they are to be familiar with the commercial sphere and to better understand the rules and norms of the commercial sphere. Lastly, we asked the survey participants about their *Disclosed intellectual property (IP)*, the number of ideas or inventions disclosed to the employer that may have commercial potential or be legally protected since 2015. The generation of IP that could potentially be patented indicates scientists' interest in research commercialization and their understanding of the relevance of IP in the commercial environment. Patenting has been found to relate positively to spin-off intentions (Goethner et al., 2012; Prodan & Drnovsek, 2010), nascent academic entrepreneurship (Dohse et al., 2021), and successful firm foundations by academics (Ding & Choi, 2011; Krabel & Mueller, 2009; Landry et al., 2006).

Control variables

In our empirical analysis, we control for several factors that influence the successful creation of academic spin-offs. First, we control for whether the scientist is *Female* or not, since a strong gender gap has been identified in the literature (Guzman & Kacperczyk, 2019). Second, we measure the *Risk willingness* of the survey participants on an 11-point Likert scale according to SOEP-IS Group (2014). Scientists' attitude towards risk is highly influential for the persistence in continuing with the spin-off creation process (Fini & Toschi, 2016; Fritsch & Krabel, 2012; Stephan & El-Ganainy, 2007). Third, we control for organizational heterogeneity in the mode of knowledge generation, which influences the general embeddedness of scientists in a sphere (e.g., Bercovitz & Feldman, 2008). We create a categorical variable to account for the *Organizational focus* that distinguishes the research focus of the scientists' organization in three groups: *basic*, *between basic and applied*, and *applied*. We rely on a broad categorization put forward by the German Ministry for Science and Education (Bundesministerium für Bildung und Forschung, 2014).[5] Lastly, we control for differences in spin-off activities across disciplines (see, e.g., Abreu & Grinevich, 2013). Therefore, we distinguish seven broader disciplines: *Engineering*, *Humanities*, *Life Sciences*, *Medicine*, *Physics*, *Chemistry*, *Social Sciences*, and *Computer Science and Mathematics*.

3.3.3 Empirical approach

We apply dominance analysis to test our hypotheses on the relative importance of the two spheres along the academic spin-off creation process. Dominance analysis computes the relative importance of predictors among each other and decomposes the overall goodness-of-fit measure of a regression into the predictors' individual contribution (Azen & Budescu, 2003; Azen & Traxel, 2009; Budescu, 1993). Furthermore, dominance analysis allows to combine different predictors into sets of predictors. Thereby, it is irrelevant how large the sets of predictors are since the predictors are neither weighted nor adjusted. This allows us to assess how much a set of predictors, e.g., related to the academic sphere or the commercial sphere, contributes relatively to the transition to the next phase of the spin-off creation process. Compared to other approaches such as standardized regression coefficients, dominance analysis has the advantage of accounting for correlation among the predictors (Azen & Traxel, 2009).

To conduct dominance analysis, we first run each transition regression to estimate which individual factors of the two spheres influence the progression to the next phase of the ASO creation process. Since each transition is measured by a binary outcome variable Y, we use logistic regression for each of the transitions $T = \{1, 2, 3\}$ and the respective individual scientists i. The estimation results allow us to determine the relative importance of

[5] Research institutes of the Leibniz Association, the Max Planck Society and similar are allocated to basic research; universities are located between basic and applied research; and universities of applied sciences as well as institutes such as the ones from the Fraunhofer Society and similar are allocated to applied research (see Table S4 in Electronic Supplementary Material).

the spheres for each transition in the second step. The logistic estimation takes the following stylized form:

$$log(\frac{Y_{iT}}{1 - Y_{iT}}) = \alpha + \beta \mathbf{A}_i + \gamma \mathbf{C}_i + \delta \mathbf{Z}_i + \epsilon_i \tag{3.1}$$

where $\mathbf{A_i}$ is the set of variables for the academic sphere and $\mathbf{C_i}$ is the set of variables for the commercial sphere. $\mathbf{Z_i}$ is the set of control variables and ϵ_i is an error term. We estimate the regression for each of the transitions T separately.

We use the McFadden (1974) R^2 as our goodness-of-fit measure for the dominance analysis. The McFadden (1974) R^2 is frequently used in logistic regressions and fulfills the criteria to be used in a dominance analysis (Azen & Traxel, 2009).[6] The calculation of relative dominance is an iterative process. Starting with one predictor, the gain in importance is measured by adding another predictor and so forth. This results in a set of regressions where each predictor is compared against every other predictor, and all combinations of predictors are compared against all other combinations. The general dominance is the average of all the gains the predictor has across the different iterations (see Azen & Traxel, 2009, for a detailed example). In our case, we do not conduct the dominance analysis on each predictor but on sets of predictors, the academic and the commercial spheres, as well as the control variables. For each of these three sets, we calculate the general dominance, where the sum of the general dominance is equal to the overall goodness-of-fit measure of the estimation. As suggested in Azen and Traxel (2009), we furthermore apply bootstrapping to generate a distribution of relative dominance values.[7] To empirically test our hypotheses, we conduct two-sided t-tests to compare the mean of the bootstrapped distributions for each sphere across the different transitions.

[6] Azen and Traxel (2009) propose four criteria that a goodness-of-fit measure should fulfill to be suitable for dominance analysis. Besides the McFadden R^2, the Nagelkerke R^2, and the Estrella R^2 can be used, but Azen and Traxel (2009) show analytically that they result in the same direction of dominance, just with a different level of magnitude. Our results are robust towards the different goodness-of-fit measures.

[7] However, Azen and Traxel (2009) note that bootstrapping generates larger standard errors than sampling from the full population but is still considered reliable.

We conduct three robustness tests concerning our econometric approach, our control variables, and our operationalization of the spin-off creation process. First, we use a different operationalization of the transition process, in which the population of scientists does not change between the phases. Second, we use a linear probability estimation and apply the dominance analysis for the ordinary least squares regressions (Azen & Budescu, 2003; Budescu, 1993). Third, we conduct another set of linear probability regression, including organizational fixed effects to control for differences between organizations and replace the organizational focus.

3.4 Results

3.4.1 Descriptive results

The descriptive statistics in Table 3.2 and the correlations for each of the three transitions in Tables S5, S6, and S7 in the Electronic Supplementary Material provide a first indication of the transition process and the changes in the relative importance of the two spheres. We report descriptive statistics for the three transitions separately, since they show a distinctive pattern. Concerning the successful transitions along the process, we see a continuously diminished number of scientists in the process. Only 22% (249 out of 1,149) recognized a business opportunity necessary for Transition 1. The next step, developing the opportunity further to reach the pre-spin-off phase (Transition 2), was successful for 58% (145 out of 249). Making it to venture creation (Transition 3), e.g., after acquiring the necessary resources, was achieved only by 44% (64 out of 145), which is 5.6% of the initial sample.[8] Such low success rates are frequently reported in the literature (e.g., Abreu & Grinevich, 2013; D'Este et al., 2019; Haeussler & Colyvas, 2011; Muscio et al., 2022).

For the independent variables constituting the academic sphere, scientists' discontinuation of entrepreneurial pursuit at each phase of the process reveals a selection on specific characteristics in the sample population. For nearly all

[8]Descriptive statistics for the 64 successful academic entrepreneurs are provided in Table 3.6.

six variables, we see a clear trend in the means. The share of *Professors* in the sample increases, but the mean *Time devoted to research* decreases along the transitions. Only for the *Number of publications* is there initially an increase but then a decrease in the mean along the process. For publications' *Average impact factor*, we also see a decreasing trend. The two variables describing the extent of the scientists' *Basic research* and *Applied research* show an increase, reflecting an ideal type of scientist in search of both new insights and applications (Amara et al., 2019; Stokes, 1997). When comparing these developments with the scientists who found a firm, these trends are confirmed (see Table 3.6).

A similar development can be observed for the variables of the commercial sphere. The means of all four variables *Share of publications with industry*, *Time devoted to KTT*, *Disclosed IP*, and *Work experience outside academia* increase from transition to transition in the remaining samples. When we compare the trends with the scientists who found a firm, the development is continued only for *Time devoted to KTT* and *Work experience outside academia* (see Table 3.6).

In addition, the control variables show a similar pattern. We find a decreasing trend in *female* scientists and an increase in *risk willingness*. There is also a selection on organizations that have a focus on applied research along the process. Trends among the disciplines are also observable, e.g., the number of scientists from life science or medicine decline in the population along the process. Overall, the development of the sample characteristics indicates that selection on these criteria takes place, indicating their relative importance for the different spheres.

3.4.2 Regression results and dominance analysis

In the following, we discuss the results of our empirical analysis. To test our hypotheses on the changing relative importance of the academic and commercial spheres along the ASO creation process, we first report logistic regression results for each transition and the respective dominance analysis in Table 3.3. We estimate one model for each of the three transitions (Model 1-3). For each model, we conduct dominance analysis to decompose the overall McFadden R^2 goodness-of-fit measure into a R^2_A for the academic sphere

Table 3.2: Descriptive statistics for the three transitions

	Mean			Standard Deviation			Minimum			Maximum		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
Dependent variables												
Transition 1 (=1)	0.22			0.41			0			1		
Transition 2 (=1)		0.58			0.49			0			1	
Transition 3 (=1)			0.44			0.50			0			1
Academic sphere												
Professor (=1)	0.18	0.24	0.30	0.39	0.43	0.46	0	0	0	1	1	1
Time devoted to research	52.37	49.73	46.13	27.11	23.89	24.63	0	0	0	100	100	100
Number of publications	21.86	28.95	25.68	50.89	69.88	70.53	0	0	0	532	532	532
Average impact factor	0.91	0.84	0.74	0.79	0.74	0.66	0	0	0	4.80	4.80	2.40
Basic research	2.54	2.75	2.78	0.71	0.73	0.73	1	1	1	4	4	4
Applied research	2.75	3.11	3.26	0.86	0.74	0.68	1	1	2	4	4	4
Commercial sphere												
Share of publications with industry	0.03	0.05	0.06	0.12	0.15	0.18	0	0	0	1	1	1
Time devoted to KTT	8.22	11.59	14.75	11.95	13.63	15.41	0	0	0	100	100	100
Disclosed IP	0.40	0.90	1.22	1.42	1.82	2.23	0	0	0	16	16	16
Work experience outside academia	1.37	1.72	2.08	1.45	1.52	1.45	0	0	0	4	4	4
Control variables												
Female (=1)	0.37	0.27	0.26	0.48	0.45	0.44	0	0	0	1	1	1
Risk willingness	6.52	7.12	7.39	2.18	2.06	2.01	1	1	3	11	11	11
Organizational focus: between basic and applied	0.64	0.59	0.54	0.48	0.49	0.50	0	0	0	1	1	1
Organizational focus: basic	0.15	0.12	0.10	0.36	0.33	0.30	0	0	0	1	1	1
Organizational focus: applied	0.21	0.29	0.36	0.41	0.45	0.48	0	0	0	1	1	1
Discipline: Computer Science and Mathematics	0.11	0.14	0.15	0.31	0.35	0.36	0	0	0	1	1	1
Discipline: Engineering	0.16	0.21	0.24	0.37	0.41	0.43	0	0	0	1	1	1
Discipline: Humanities	0.10	0.08	0.08	0.30	0.27	0.27	0	0	0	1	1	1
Discipline: Life Sciences	0.15	0.13	0.09	0.36	0.34	0.29	0	0	0	1	1	1
Discipline: Medicine	0.10	0.08	0.07	0.30	0.27	0.25	0	0	0	1	1	1
Discipline: Physics and Chemistry	0.19	0.23	0.22	0.40	0.42	0.42	0	0	0	1	1	1
Discipline: Social Sciences	0.19	0.13	0.15	0.39	0.34	0.36	0	0	0	1	1	1

Note: T: Transition; There are 1,149 observations for T1, 249 observations for T2 and 145 observations for T3

and a R^2_C for the commercial sphere (and R^2_Z for the control variables). We report the absolute values as well as the relative share of each sphere in the overall McFadden R^2, which is our measure of interest. By using these relative shares, we are able to compare between the different models, i.e., phases, because the constituting variables do not change. Hence, we avoid to assess differences in the spheres' importance due to the overall model fit. In a second step, we bootstrap the dominance analysis and present the distribution of the relative R^2_A and R^2_C values in Figure 3.2.[9] Lastly, we conduct two-sided t-tests on the difference in means of the bootstrapped relative R^2_A and R^2_C values for the transitions (see Table 3.4).

[9] Azen and Traxel (2009) and Tonidandel and LeBreton (2011) suggest that in the case of relative importance analyses, samples of a dominance analysis should be replicated in sufficient numbers to extend the results by confidence intervals. Therefore, we calculate 5,000 bootstrap samples for each model and provide sample statistics.

Table 3.3: Logit regression results and dominance analysis

	(1) Transition 1 *Research* to *Opportunity framing*	(2) Transition 2 *Opportunity framing* to *Pre-spin-off*	(3) Transition 3 *Pre-spin-off* to *Spin-off*
Academic sphere			
Professor (=1)	0.045 (0.237)	1.111** (0.475)	0.563 (0.584)
Time devoted to research	-0.003 (0.004)	0.002 (0.008)	0.002 (0.011)
Number of publications	-0.011 (0.078)	-0.238* (0.139)	-0.367* (0.192)
Average impact factor	-0.173 (0.150)	-0.248 (0.242)	0.389 (0.415)
Basic research	0.408*** (0.126)	0.097 (0.225)	-0.017 (0.302)
Applied research	0.376*** (0.099)	0.064 (0.222)	0.015 (0.310)
Joint R^2_A	**0.046 (35.2%)**	**0.057 (29.6%)**	**0.022 (15.8%)**
Commercial sphere			
Share of publications with industry	0.830 (0.878)	1.276 (1.165)	-1.542 (1.589)
Time devoted to KTT	0.005 (0.006)	0.053*** (0.020)	0.028* (0.015)
Disclosed IP	0.942*** (0.193)	0.718** (0.293)	0.168 (0.323)
Work experience outside academia	0.097* (0.058)	0.232** (0.118)	-0.037 (0.148)
Joint R^2_C	**0.056 (42.5%)**	**0.098 (51.0%)**	**0.021 (15.4%)**
Control variables			
Female (=1)	-0.349** (0.178)	0.043 (0.348)	-1.025** (0.501)
Risk willingness	0.101*** (0.038)	0.102 (0.077)	0.145 (0.104)
Organ. focus: basic	-0.260 (0.279)	0.709 (0.477)	0.538 (0.735)
Organ. focus: applied	0.072 (0.223)	0.304 (0.408)	-0.614 (0.499)
Discipline: Engineering	-0.453 (0.306)	-0.154 (0.545)	-0.796 (0.658)
Discipline: Humanities	-0.486 (0.353)	-0.518 (0.665)	0.435 (0.879)
Discipline: Life Sciences	0.007 (0.322)	-0.831 (0.607)	-0.078 (0.823)
Discipline: Medicine	-0.244 (0.341)	-0.026 (0.703)	-0.259 (0.964)
Discipline: Physics and Chemistry	-0.014 (0.297)	-0.106 (0.518)	-0.653 (0.647)
Discipline: Social Science	-0.492* (0.293)	0.127 (0.612)	0.721 (0.731)
Joint R^2_Z	**0.029 (22.3%)**	**0.037 (19.4%)**	**0.096 (68.8%)**
Constant	-3.866** (0.513)	-1.726* (1.037)	-0.928 (1.450)
N	1,149	249	145
Log Likelihood	-522.020	-136.658	-85.699
Akaike Inf. Crit.	1,086.039	315.316	213.399
McFadden R^2	0.131	0.192	0.139

Note: A: Academic sphere, C: Commercial sphere, Z: Controls.
Robust standard errors in parentheses;
Significance at *p<0.1; **p<0.05; ***p<0.01

Table 3.4: Differences in bootstrapped relative dominance based on logit estimates for the three transitions

	T1 mean	T2 mean	T3 mean	difference mean T2-T1	difference mean T3-T2
Academic sphere R^2_A	34.6% (0.09)	29.7% (0.10)	22.5% (0.13)	-4.9%***	-7.2%***
Commercial sphere R^2_C	40.1% (0.09)	43.4% (0.12)	17.0% (0.12)	3.3%***	-26.4%***

Note: 5000 bootstrapped replications; Standard errors in parentheses;
Differences in means tested by two-sided t-tests; T: Transition;
Significance at *p<0.1; **p<0.05; ***p<0.01

Relative importance of the academic sphere

Central to our analysis is the decomposition of the overall McFadden R^2 goodness-of-fit measure into the Joint R^2_A for the academic sphere and the Joint R^2_C for the commercial sphere for the three models. The overall McFadden R^2 for the three models is 0.131, 0.192, and 0.139 respectively. The values are in line with related literature (e.g., Caliendo et al., 2014; 2020; Davidsson & Honig, 2003) and depict a reasonable model fit according to McFadden (1979). The values are also large enough to allow for a meaningful decomposition. In Model 1 and Model 2 the two spheres account for 77.7% and 80.6% of the overall model fit but in Model 3 only for 31.2%.

For Hypothesis 1a, we compare Model 1 with Model 2 and the respective contribution of the academic sphere (Table 3.3). For the first Transition 1 in Model 1, the overall McFadden R^2 is 0.131. The dominance analysis decomposes this overall R^2 into the Joint R^2_A of 0.046 for the academic sphere, which is a relative contribution of 35.2% to the overall model fit. Among the individual variables that constitute scientists' embeddedness in the academic spheres, only the research foci towards *Basic research* and *Applied research* show significant coefficients. Neither the scientists' position nor their publication output matter for Transition 1. With respect to the bootstrapped sample (Figure 3.2 and Table 3.4), the Joint R^2_A from the estimation is very close to the bootstrapped median and the average of 34.6%. In Model 2 for Transition 2, the overall McFadden R^2 is higher with 0.192, as is the absolute Joint R^2_A with 0.057 compared to Model 1. In relative terms, the R^2_A accounts for only 29.6% in Model 2 and is lower compared to the first model. With respect to the individual variables for the embeddedness in Model 2, being a *Professor* has a significant influence on a successful transition. We also observe a negative but weakly significant coefficient of the *Number of* *publications*. Since the variable acts as a proxy for the relationship between the embeddedness and the transition success, here higher embeddedness reduces the success.[10] The bootstrapped dominance analysis shows again a similar median as well as a similar average of 29.7% to the Joint R_A^2 of 29.6%. Our Hypothesis 1a postulates lower relative importance of the academic sphere for Transition 2 compared to the Transition 1. The negative difference of the Joint R_A^2 for the dominance analyses of the two models supports such a relationship. Also, the bootstrapped distribution supports this relationship, but the distribution for Transition 2 has a higher dispersion than for Transition 1. Furthermore, the t-test on the difference between R_A^2 from Transition 1 and Transition 2 is statistically significant at the 1% level (Table 3.4). Overall, we find support for Hypothesis 1a, which suggests a higher relative importance of the academic sphere for the Transition 1 from the research phase to the opportunity framing phase than for Transition 2 from the opportunity framing phase to the pre-spin-off phase.

For Hypothesis 1b, we compare Model 2 with Model 3 and the respective contribution of the academic sphere (Table 3.3). In Model 3, Transition 3, the overall McFadden R^2 is 0.139. The Joint R_A^2 is comparably small, 0.022 in absolute terms and 15.8% in relative terms. Among the individual variables, the *Number of publications* has again a significant but negative coefficient.[11] The other variables show no significant coefficients. The bootstrapped distribution of the relative R_A^2 shows slightly deviating results, with a higher median and an average of 22.5%. Our Hypothesis 1b states that the relative importance of the academic sphere for Transition 3 is lower compared to Transition 2. The negative difference of the Joint R_A^2 for the dominance analyses of Model 2 and Model 3 supports such a relationship, especially if the influence of the *Number of publications* is accounted for. Also, the

[10] Since goodness-of-fit measures do not distinguish between the direction of a coefficient, but we are interested in the influence of higher embeddedness, we estimated an additional Model 2a without the *Number of publications* to remove the negative contribution of the variable to the overall measure of embeddedness. The Joint R_A^2 without this variable is slightly lower with 27.6% of the overall model fit (see Table S8 in Electronic Supplementary Material).

[11] Similar to the previous transition estimation, we estimated an additional Model 3a without the *Number of publications* to remove the negative contribution of the variable to the overall measure of embeddedness. The Joint R_A^2 without this variable accounts now for only 2.4% of the overall model fit (see Table S8 in Electronic Supplementary Material).

bootstrapped distribution of the relative R_A^2 supports this relationship and a t-test on the difference between R_A^2 from Transition 2 and Transition 3 is statistically significant at the 1% level (Table 3.4). Overall, we find support for Hypothesis 1b, which implies a higher relative importance of the academic sphere for Transition 2 from the opportunity framing phase to the pre-spin-off phase than for Transition 3 from the pre-spin-off phase to the spin-off phase.

Relative importance of the commercial sphere

For Hypothesis 2a, we compare Model 1 with Model 2 and the respective contribution of the commercial sphere (Table 3.3). In Model 1, the commercial sphere R_C^2 contributes 0.056 to the overall McFadden R^2 of 0.131, which is 42.5% in relative terms. Among the different variables for the embeddedness in the commercial sphere, the *Disclosed IP* and *Work experience outside academia* have positive and significant coefficients. The other two variables are insignificant. Bootstrapping shows a slightly lower median (Figure 3.2) and an average of 40.1% for the relative importance of R_C^2 (Table 3.4). In Model 2 (Table 3.3), the R_C^2 is 0.098 in absolute terms and 51.0% in relative terms. The significant variables from Model 1 are again significant in Model 2. Additionally, *Time devoted to KTT* has a significant coefficient for Transition 2 to the pre-spin-off phase. Similar to Model 1, the bootstrapped distribution shows in the median (Figure 3.2) and on average a smaller R_C^2 (43.4%) (Table 3.4). The relative R_C^2 51.0% from the initial estimation is above the third quartile of the bootstrapped distribution, showing some considerable deviation. Hypothesis 2a postulates a higher relative importance of the academic sphere for Transition 2 compared to Transition 1. The positive difference of the Joint R_C^2 for the dominance analyses of Model 1 and Model 2 supports such a relationship. The bootstrapped distribution supports this relationship as well but on a slightly lower relative level. The t-test on the difference between R_C^2 from Transition 1 and Transition 2 is statistically significant at the 1% level (Table 3.4). Overall, we find support for Hypothesis 2a, which suggests a lower relative importance of the commercial sphere for Transition 1 from the research phase to the opportunity framing phase than for Transition 2 from the opportunity framing phase to the pre-spin-off phase.

For Hypothesis 2b, we compare Model 2 with Model 3 and the respective contribution of the commercial sphere (Table 3.3). The commercial sphere in Model 3 has only an absolute R^2_C of 0.021 and a relative one of 15.4%, indicating a very low contribution to a successful firm foundation. Among the individual variables, only the *Time devoted to KTT* has a significant coefficient. The bootstrapped distribution of the relative R^2_C is in its median and mean of 17.0% very similar (Figure 3.2 and Table 3.4). Our Hypothesis 2b states that the relative importance of the commercial sphere for Transition 3 is higher compared to Transition 2. The large negative difference of the Joint R^2_C for the dominance analyses of Model 2 and Model 3 indicates a rejection of such a relationship. The bootstrapped distribution of the relative R^2_C does not support the hypothesized relationship, either. The t-test on the negative difference between R^2_C from Transitions 2 and Transition 3 is statistically significant at the 1% level. Overall, we do not find support for Hypothesis 2b on a lower relative importance of the commercial sphere for Transition 2 from the opportunity framing phase to the pre-spin-off phase than for Transition 3 from the pre-spin-off phase to the spin-off phase.

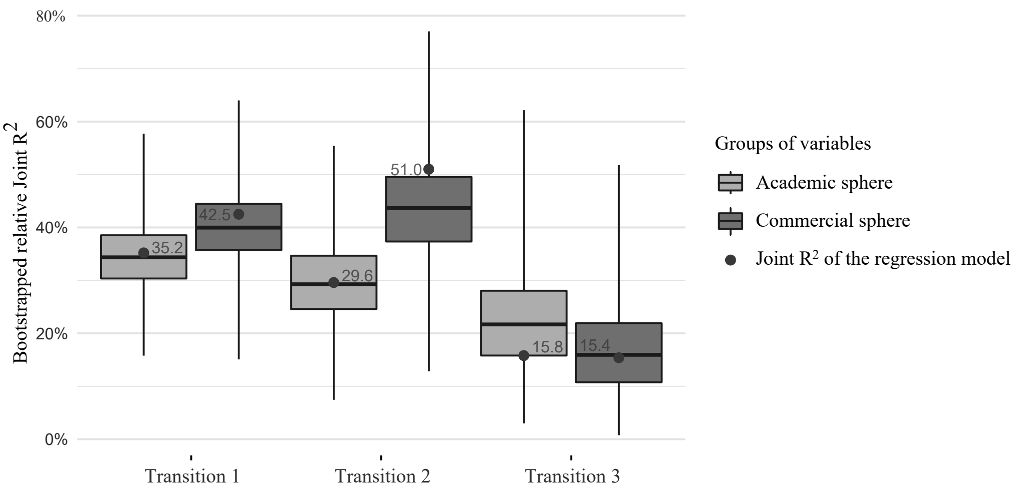

Figure 3.2: Dominance analysis on logit estimates for the three transitions based on 5,000 replications

Control variables

The results concerning our control variables show a relative R_Z^2 around 20% for Transition 1 and Transition 2. For Transition 3 in Model 3, it increases to almost 70%. Among the control variables, we observe a significant negative association between female scientists and the recognition of a business opportunity (Transition 1) as well as successful spin-off creation (Transition 3). Furthermore, the risk willingness influences the success of Transition 1 only. The organizational focus does not matter. Also, we hardly find any differences between the disciplines. Only in Transition 1 do scientists from social sciences have a significantly higher likelihood to make a successful transition than the reference group, scientists from Computer Science and Mathematics.

3.4.3 Robustness tests

We conduct three robustness tests. First, we use a different operationalization of the spin-off creation process. Second, we apply linear probability models as an alternative estimation approach. Third, we add organizational fixed effects to account for different organizational characteristics and support. Results are presented in the Appendix.

In the first robustness test, we estimate Model 2 and 3 with the overall number of scientists and do not reduce the sample for Transitions 2 and Transition 3. This maintains the variation in the independent variables constant across the models (Tables 3.7, 3.8, Figure 3.3). The results are qualitatively similar to the initial analysis. We again see a decrease of the academic sphere's relative importance along the spin-off creation process, while at the same time the contribution of the commercial sphere increases in Transition 2 and declines again for Transition 3. However, the decline in Transition 3 is not as pronounced as in the initial analysis, and the relative contribution is nearly as large as in Transition 1 (39.6%). Moreover, a few individual covariates show different effects than in the initial analysis. For instance, for Transition 2, the variable *Professor* is no longer significant, but the research foci towards *Basic research* and *Applied research* show significant coefficients. Overall, the results provide robustness to our results of the main analysis.

In the second test, we estimate Models 1-3 with OLS as linear probability models and conduct the dominance analysis based on the R^2 (Tables 3.9, 3.10 and Figure 3.4). The results for the academic sphere show the same tendency as in the main specification, but there is only a slight decrease in the relative importance between Transition 1 and Transition 2 (30.9% vs 30.3%). The t-test on the small negative difference between R^2_A from Transition 1 and Transition 2 is statistically significant at the 1% level. For the commercial sphere, the results for the first two transitions are also very similar. The relative importance for Transition 1 increases to 48.9% compared to the main specification and is slightly larger than the relative importance of 48.3% for Transition 2. This negative difference is even more pronounced in the bootstrapped sample average and confirmed by the t-test. Overall, we find additional evidence in favor of our Hypotheses 1a and 1b, but no support for Hypothesis 2a because the relative importance in Transition 1 is substantially larger in this estimation. Also, we find again no support for H 2b.

The third test accounts for differences between the individual universities and research institutes, such as the general support via technology transfer offices (TTO), or other factors that can influence the success of scientists from a specific organization. We estimate linear probability models including organizational fixed-effects and drop the control variables for organizational focus (see Tables 3.11, 3.12 and Figure 3.5). The results show the same development as in the previous robustness test in Table 3.9. Thereby, the absolute R^2 is substantially larger, but nearly entirely attributed to R^2_Z, which includes the organizational fixed effects. This indicates that heterogeneity on the organizational level, such as the TTO support, contributes substantially to the success of the individual spin-off creation process. Again, we find evidence in favor of our Hypotheses 1a and 1b, but no support for Hypotheses 2a and 2b.

Overall, our robustness checks provide additional support for our Hypotheses 1a and 1b and some additional support for H 2a.

3.5 Discussion and conclusions

Entrepreneurial scientists are embedded in the academic sphere but have to engage with the commercial sphere to accomplish venture creation. In this study, we examine how the relative importance of these two spheres changes for different phases in the academic spin-off (ASO) creation process and its impact on scientists' transition along this process. The differences between the academic and the commercial spheres arise from their inherent logics, which reflect fundamentally different views on knowledge production and exploitation. These differences create tensions that academic entrepreneurs have to overcome (Ambos et al., 2008; Murray, 2010; Rasmussen, 2011; Samsom & Gurdon, 1993). Building on previous conceptualizations of the ASO creation process (e.g., Fernández-Alles et al., 2015; Ndonzuau et al., 2002; Rasmussen, 2011; Roberts & Malonet, 1996; Vanaelst et al., 2006; Vohora et al., 2004), we divide the ASO creation process into four consecutive phases: the research phase, the opportunity framing phase, the pre-spin-off phase, and the spin-off phase. In this process, scientists experience phase transitions influenced to varying degrees by the opposing spheres. In particular, we hypothesize a decreasing relative importance of embeddedness in the academic sphere and an increasing relative importance of embeddedness in the commercial sphere as the process unfolds.

To test our hypotheses, we conduct a novel, representative survey of scientists in the German state of Thuringia. Through this survey, we elicit the scientists' entrepreneurial activity and reconstruct the spin-off creation process, including its phase-specific successes or failures. Utilizing this micro-data, we empirically analyze the changing relative importance of the spheres throughout the entire process. This approach overcomes the limitations of previous studies that either analyzed small samples using qualitative methods (e.g., Clarysse & Moray, 2004; Hayter, 2016a; 2016b; Vohora et al., 2004), focused on specific process stages (e.g., Krabel & Mueller, 2009), or only considered successful spin-offs (e.g., Landry et al., 2006). Methodologically, we apply dominance analysis (Azen & Budescu, 2003; Azen & Traxel, 2009; Budescu, 1993) to measure the influence of the two spheres on scientists' success in transitioning to the next phase. More technically, dominance analysis decomposes the goodness-of-fit measure of an estimation into the relative contributions of a set of variables that capture a sphere and explain past phase transitions. This approach allows us to overcome the limitations of individual predictors and describe the complex construct of embeddedness in a sphere. Our empirical results provide the first quantitative analysis of scientists' transition across all phases of the ASO creation process, including the associated selection process.

Findings The descriptive results show a strong selection of scientists throughout the ASO creation process, a widespread phenomenon in venturing processes (e.g., Aldrich & Martinez, 2001; Ndonzuau et al., 2002). Especially for the first transition between the research phase and the opportunity framing phase, not even a quarter of scientists recognized an opportunity for venture creation in the last five years. In the next phases, there is a considerably diminished number of scientists as well. In the end, 5.6% of the scientists found a firm, which is similar in magnitude to other studies (Abreu & Grinevich, 2013; D'Este et al., 2019). Within the process, we can observe on the descriptive level that the variables constituting the embeddedness in the spheres reflect the selection taking place. For most of the variables of the academic sphere, a decline in their means can be observed. This already implies at the descriptive level that, on average, scientists are less embedded in the academic sphere the further they progress in the process. For the variables constituting the commercial sphere, the opposite development is observable. This highlights that the individuals with higher embeddedness, on average, progress further in the venture creation process. Furthermore, certain characteristics of the scientists become prominent. Besides a substantial gender gap in our data regarding recognized business opportunities, there is even a considerably lower share of women who establish a firm in the end, which is observed frequently in entrepreneurship research (Dohse et al., 2021; Guzman & Kacperczyk, 2019). One reason for that could be lower access to venture capital, which seems to be a structural problem for women in Germany (Lins & Lutz, 2016) but also in other countries (Lauto et al., 2022). Another personal characteristic is risk willingness, which is highest among scientists reaching firm foundation. This is in line with the argument that the academic entrepreneur acts against all odds in a Schumpeterian manner (Cantner et al., 2017).

Our estimations and dominance analyses show for the academic sphere a declining relative importance along the ASO creation process, in line with our hypotheses. At the beginning of the process, research activities and the academic environment serve as sources of business ideas. This holds true especially for business ideas derived from basic research despite high uncertainty with respect to their feasibility and economic potential (Aghion et al., 2008; Lacetera, 2009). Scientists with a high research orientation towards both basic and applied research are especially prone to recognize and frame an entrepreneurial opportunity. This result is consistent with the idea of the Pasteur-like scientist who generates new research results and who simultaneously is interested in their practical application (Amara et al., 2019; Stokes, 1997). In the later phases, the relative importance of the academic sphere subsequently declines, in line with the conceptual model by Rasmussen (2011) and others. At the end of the process, the academic sphere plays hardly any role and can even reduce the likelihood to found a firm. Our estimates show that the higher the publication output of a scientist, the lower the likelihood to set up a firm in the last phase. This finding is contrary to previous findings that indicate a strong positive relationship between these two variables. However, most of these cases refer to Pasteur-like star scientists (e.g., Aschhoff & Grimpe, 2014; D'Este et al., 2019; Ding & Choi, 2011; Zucker et al., 1998).

For the commercial sphere, the dominance analysis shows first an increase in relative importance but then a decrease towards the end of the process. This is only partly consistent with our hypotheses, which propose increasing relative importance of the commercial sphere throughout the whole process. In particular, for the first transition the relative importance of the commercial sphere is already quite high, and recognizing an opportunity correlates highly with disclosing intellectual property. Such a relationship between patenting and intentions to found a firm is well established (Goethner et al., 2012; Prodan & Drnovsek, 2010). Along with a positive influence of previous work experience (see, for instance, Gulbrandsen & Thune, 2017), exposure to the commercial sphere seems to give scientists a positive mindset toward economic activity and lets them pursue such a direction. The relative importance of the commercial sphere increases further along in the process, and the actual time to conduct such activities also becomes relevant for scientists to substantially invest in the founding activity. However, at the end of the process, the relative importance drastically declines. Reasons for this decrease could be related to a higher influence of contextual factors, such as market conditions, available venture capital, technological feasibility, or policy support (Autio et al., 2014; Rizzo, 2015; Wright et al., 2006). We explore the influence of contextual factors in more detail. The scientist's organization accounts for a substantial variation in the transition success, as adding organizational fixed effects in our robustness tests shows. This might be explained via the scope and performance of institutional support, e.g., via activities that are socialized within the organization such as courses and events on entrepreneurial education (Bercovitz & Feldman, 2008; Prodan & Drnovsek, 2010; Stuart & Ding, 2006) or via TTOs (O'Shea et al., 2005; Rasmussen & Borch, 2010). Especially TTOs and incubators are important providers of such dedicated support, consisting of business idea development, provision of infrastructure, and boundary spanning (Clarysse et al., 2005; Huyghe et al., 2014).[12] Nevertheless, we find no support in our data that the commercial sphere has a higher relative importance at the end of the process than in earlier phases.

Besides the provided empirical evidence for the changing relative importance of the two spheres, we also observe interesting differences in their magnitude. At the beginning of the process, when scientists frame a commercial opportunity from their research activity, the commercial sphere already has higher relative importance than the academic sphere. Such an observation contrasts established theories which initially ascribe a lower relative importance to the commercial sphere than to the academic sphere (Rasmussen, 2011). Our finding corresponds to related literature on entrepreneurial opportunity recognition, which already provides evidence for positive associations between business-related competencies as well as commercial experiences and the recognition of entrepreneurial opportunities (Ardichvili & Cardozo, 2000; Ardichvili et al., 2003; George, Parida, et al., 2016; Shepherd & DeTienne, 2005; Ucbasaran et al., 2009). Integrating the empirical finding

[12]However, in general, there is a controversial debate about the performance of TTOs and evidence regarding their impact on venture creation is ambiguous (see, e.g., Bourelos et al., 2012; Brettel et al., 2013; Chapple et al., 2005; Horner et al., 2019). Hayter (2016a), for instance, points out that TTOs often rather strengthen the academic nature of spin-offs than bridge between the two spheres.

on the generally higher relative importance of the commercial sphere in the conceptualization of the spin-off creation process can provide starting points for evidence-based updating of existent conceptualization and further development of the ASO creation theory.

Our results allow us to derive characteristics on the level of the individual scientist as well. The results indicate that due to scientists' engagement with both spheres, especially early on in the process, they have to adapt their role and identity. Jain et al. (2009) show in their qualitative study on scientists' commercialization activity that they develop a hybrid-role identity to successfully handle both logics. To develop such hybridity, scientists need to be ambidextrous to deal with the tension of the opposing spheres. Mom et al. (2009) characterize ambidextrous individuals by their ability to deal with tensions, their adaptability to different roles and their refinement and renewal of their knowledge, skills and expertise. Even though we do not directly test for the scientists' ambidexterity, selection among the scientists' characteristics along the transfer process hints to such an underlying mechanism. In that sense, our findings are similar to the findings by Ambos et al. (2008) who show that ambidextrous scientists can balance the demands from both spheres and successfully commercialize research results.

Contributions and implications We make several contributions to the literature on academic entrepreneurship and theory development. Conceptually, we provide a holistic perspective on the ASO creation process, spanning from scientists' research activity to the establishment of a venture. To achieve this, we synthesize existing approaches to understand the ASO process and develop a quasi-linear process with four phases and three transitions, drawing on the concept of "critical junctures" introduced by Vohora et al. (2004). Our focus is on individual scientists, offering a micro-level perspective on their engagement in spin-off creation. Previous research has remained predominantly at the spin-off project level, neglecting individual characteristics and tensions. However, we start from the premise that academic entrepreneurship is an individual endeavor, where scientists, as the main actors, must bring their ideas to the market and navigate the accompanying tensions in the process, whether independently or in a team (Guerrero &

Urbano, 2014; Kleinhempel et al., 2022). To understand the tensions and conflicts in the process, we link the academic entrepreneurship process theory (Rasmussen, 2011; Vohora et al., 2004; Wood & McKinley, 2010) with the multiple institutional logics theory (Fini et al., 2010; Perkmann et al., 2019). By connecting these two streams of literature, we enhance our understanding of the influence of scientists' embeddedness in both spheres on successful firm foundations. We derive empirically testable hypotheses to explore the tensions between the spheres arising from differences in attitudes, norms, and logics that scientists encounter during ASO creation. By examining how scientists' embeddedness in the academic and commercial spheres influences their progression throughout the ASO creation process, we contribute to a better understanding of the intricate relationships in the process.

Empirically, by starting with a population of scientists working in research organizations, we are able to trace the ASO selection process from recognizing a business opportunity based on scientific research to venture creation (Aldrich & Martinez, 2001; Ndonzuau et al., 2002). Thus, we provide a quantitative assessment of scientists' discontinuation of their entrepreneurial pursuits throughout the ASO creation process. Our theoretical conceptualization of the process explains this phenomenon, and our results provide the first quantitative evidence of the contrasting influences of the academic and commercial spheres on the complete ASO creation process, substantiating prior research. Our findings affirm the diminishing relative importance of the academic sphere as the process unfolds and demonstrate that researchers have to overcome the norms and logics prevalent in this sphere to progress. Simultaneously, the relevance of the commercial sphere grows, necessitating scientists' embeddedness in this sphere for successful venture creation. Nonetheless, we identify some contradictions at the end of the process, where the relative importance of this sphere declines. This suggests either non-linearity in the relative importance throughout the process or external forces that lie beyond individual scientists, such as the market environment. Our related finding, that the commercial sphere's relative importance exceeds that of the academic sphere already at the beginning of the process, challenges traditional lines of thought that prioritize the academic sphere in the early stages. However, research on entrepreneurial opportunity recognition points to the relevance of market knowledge in identifying entrepreneurial opportunities (Shane, 2000), which aligns with our findings and underscores the significance of embeddedness in the commercial sphere.

Our central finding of the changing relevance of the academic and commercial spheres along the ASO creation process has important policy implications that can guide interventions aimed at fostering academic entrepreneurship. Our study reveals that the relative importance of the commercial sphere is already higher than the academic sphere at the beginning of the ASO creation process. Policymakers can leverage this finding by facilitating scientists' exposure to the commercial sphere. This can be achieved by implementing entrepreneurship education initiatives and encouraging scientists to gain industry experience (Belitski & Heron, 2017; Bienkowska et al., 2016; Thomas et al., 2020). Additionally, academic institutions can incentivize scientists' engagement with the commercial sector by reducing administrative burdens and recognizing their entrepreneurial activity alongside their academic qualifications (Davey et al., 2016). By bringing scientists and industry actors together, policy initiatives can promote mutual understanding, trust, and collaboration between the two spheres (Hayter, 2016a; Rasmussen et al., 2006), thereby increasing the likelihood of successful ASO creation. Another key policy implication is the provision of tailored support for scientists at different stages of the ASO creation process. Our study identifies distinct phases and highlights the changing relevance of the academic and commercial spheres across these phases. Policymakers can develop targeted support programs that address the specific needs and challenges faced by scientists during each phase. This can include early-stage funding, access to lab facilities, mentorship programs, market validation support, industry partnerships, and regulatory guidance, among others (Sandström et al., 2018). By providing such tailored support, policymakers can effectively assist scientists in navigating the ASO creation process and increase the likelihood of successful outcomes. Finally, our findings indicate that female scientists may encounter specific challenges, particularly at the end of the spin-off creation process. Policymakers should develop targeted support mechanisms to address these disparities and provide equal opportunities for all scientists to participate and succeed in entrepreneurial endeavors (Abreu & Grinevich, 2017).

Limitations and further research Our study has several limitations that merit careful consideration. The cross-sectional nature of our data does not allow for a causal identification of the relative importance of the two spheres. Moreover, we collected retrospective data to reconstruct the spin-off creation process. This requires that participants recall past activities and experiences accurately. For future research, longitudinal study designs to observe entrepreneurial scientists over time would be advisable. Furthermore, our survey specifically targeted scientists who are still affiliated with research organizations, ensuring their embeddedness in the academic sphere. However, this means we did not survey ASO founders who have already left academia, potentially introducing bias in assessing the relative contributions of the two spheres. Another important limitation of this study is the fact that our analysis focuses on individual scientists, overlooking the distinction between single and team entrepreneurship. Team structures are known to play an important factor in the venture creation process (Visintin & Pittino, 2014). Additionally, we lack information on the established ASOs and their characteristics, such as the industry they are operating in or their business idea, which could have an influence on the embedding in the two spheres.

While our study provides the first empirical assessment of the changing relative importance of scientists' embeddedness in two opposing spheres during the ASO creation process, avenues for further research are manifold. Scholars could validate our findings using a broader empirical basis, including longitudinal data or samples from different countries. Furthermore, it could be valuable to consider the interaction between the two spheres, both conceptually and empirically, rather than studying them in isolation. Further research should also explore the ambidexterity of scientists and investigate whether it is endogenous to the process. Moreover, the influence of the two spheres extends beyond ASO creation, impacting other transfer channels, such as science-industry collaboration or licensing of intellectual property. Examining these transfer channels can provide additional insights. Such investigations should also encompass transfer channels that go beyond the professional management of research commercialization, such as open science strategies (Hayter et al., 2020). Finally, applying this research approach to other contexts where the balancing multiple spheres and their logics are crucial for the venturing process, such as social entrepreneurship, holds promise for future entrepreneurship research. In such contexts, reconciling commercial logics with social-oriented logics becomes essential.

3.6 Appendix

3.6.1 Variable construction

Table 3.5: List of variables and their construction

Variable	**Construction**	**Data type**
Dependent variables		
Transition 1 (=1)	Survey item: *Development of an idea to found a firm, e.g. discussion of the idea with others, assessment of the economic potential or application of creative techniques?*	Binary
Transition 2 (=1)	Survey item: *Foundation preparation, e.g. development of a prototype, preparation of a business plan or acquisition of resources?*	Binary
Transition 3 (=1)	Survey item: *Completed foundation of a firm, i.e. the launch of business activities?*	Binary
Academic variables:		
Professor (=1)	Survey item: *Which of the following options describes your current position best?*	Binary
Time devoted to research	Survey item: *How was your scientific working time distributed on average during the last 5 years [regarding research]?* (0% to 100%)	Numeric
Number of publications	Data collected from Web of Science and Scopus (logarithmized)	Numeric
Average impact factor	Average of the scientist's journals' Source Normalized Impact per Paper	Numeric
Basic research	Survey item: *Please assess the extent to which you contribute with your research to scientific progress in your discipline and thus shift the research frontier in your discipline further.* (4-point Likert-scale: "Not at all" to "To a large extent")	Numerical
Applied research	Survey item: *Please assess the extent to which your research is targeted towards practical application.* (4-point Likert-scale: "Not at all" to "To a large extent")	Numerical

Variable	Construction	Data type
Commercial variables:		
Share of publications with industry	Share of scientist's publications in co-authorship with at least one firm (0% to 100%)	Numerical
Time devoted to KTT	Survey item: *How was your scientific working time distributed on average during the last 5 years [knowledge and technology transfer]?* (0% to 100%)	Numerical
Disclosed IP	Survey item: *Disclosure of an idea or invention (that can be attributed to potential commercial exploitation or can be legally protected) to the employer (Number since 2015).* (logarithmized)	Numerical
Work experience outside academia	Survey item: *How many years of work experience outside the public science sector have you gained overall?* (5 categories (in years): 0: =0; 1: < 1; 2: >1 ... <3; 3: >3 ... <10 ; 4: >10)	Numerical
Control variables:		
Female (=1)	Survey item: *Please indicate your gender.*	Binary
Risk willingness	Survey item: *How do you see yourself: Are you generally a person who is fully prepared to take risks or are you trying to avoid risks?* as used by SOEP-IS Group (2014, p. 36) (11-point Likert scale)	Numerical
Organizational focus	Distinction of organizations between 1: Basic, 2: Between basic and applied, 3: Applied, following Bundesministerium für Bildung und Forschung (2014)	Categorical
Discipline	Data collected from the participants' webpages	Categorical

3.6.2 Descriptive statistics for the actual founders

Table 3.6: Descriptive statistics of the variables for the actual founders (T3=1)

	Founders (T3=1)			
	mean	sd	min	max
Academic sphere				
Professor (=1)	0.33	0.47	0	1
Time devoted to research	45.36	26.05	0	100
Number of publications	14.73	31.09	0	207
Average impact factor	0.73	0.70	0	2.40
Basic research	2.81	0.75	1	4
Applied research	3.28	0.72	2	4
Commercial sphere				
Share of publications with industry	0.04	0.13	0	0.80
Time devoted to KTT	16.83	17.46	0	100
Disclosed IP	1.09	1.63	0	7
Work experience outside academia	2.11	1.39	0	4
Control variables				
Female (=1)	0.20	0.41	0	1
Risk willingness	7.78	1.96	3	11
Organizational focus: between basic and applied	0.60	0.50	0	1
Organizational focus: basic	0.12	0.33	0	1
Organzational focus: applied	0.28	0.45	0	1
Discipline: Computer & Mathematics	0.17	0.38	0	1
Discipline: Engineering	0.17	0.38	0	1
Discipline: Humanities	0.09	0.29	0	1
Discipline: Life Sciences	0.11	0.31	0	1
Discipline: Medicine	0.05	0.21	0	1
Discipline: Physics & Chemistry	0.19	0.39	0	1
Discipline: Social Sciences	0.22	0.42	0	1

Note: T3 founders refer to the 64 scientists who founded a firm

3.6.3 Robustness tests

Table 3.7: Logit regression results and dominance analysis for the three transitions with complete sample at each transition

	(1) Transition 1 *Research* to *Opportunity framing*	(2) Transition 2 *Opportunity framing* to *Pre-spin-off*	(3) Transition 3 *Pre-spin-off* to *Spin-off*
Academic sphere			
Professor (=1)	0.045 (0.237)	0.382 (0.291)	0.641 (0.399)
Time devoted to research	-0.003 (0.004)	-0.003 (0.005)	-0.003 (0.007)
Number of publications	-0.011 (0.078)	-0.113 (0.100)	-0.311** (0.140)
Average impact factor	-0.173 (0.150)	-0.261 (0.191)	-0.078 (0.265)
Basic research	0.408*** (0.126)	0.378** (0.155)	0.281 (0.232)
Applied research	0.376*** (0.099)	0.379*** (0.131)	0.369* (0.204)
Joint R^2_A	**0.046 (35.2%)**	**0.061 (30.9%)**	**0.057 (28.1%)**
Commercial sphere			
Share of publications with industry	0.830 (0.878)	1.041 (1.061)	0.032 (1.150)
Time devoted to KTT	0.005 (0.006)	0.019*** (0.007)	0.028*** (0.009)
Disclosed IP	0.942*** (0.193)	1.055*** (0.210)	1.012*** (0.271)
Work experience outside academia	0.097* (0.058)	0.203*** (0.073)	0.127 (0.092)
Joint R^2_C	**0.056 (42.5%)**	**0.096 (48.1%)**	**0.080 (39.6%)**
Control variables			
Female (=1)	-0.349** (0.178)	-0.276 (0.224)	-0.740** (0.349)
Risk willingness	0.101*** (0.038)	0.159*** (0.051)	0.265*** (0.073)
Organ. focus: basic	-0.260 (0.279)	-0.125 (0.375)	0.166 (0.520)
Organ. focus: applied	0.072 (0.223)	0.149 (0.285)	-0.340 (0.428)
Discipline: Engineering	-0.453 (0.306)	-0.633 (0.406)	-1.172* (0.632)
Discipline: Humanities	-0.486 (0.353)	-0.794* (0.444)	-0.574 (0.594)
Discipline: Life Sciences	0.007 (0.322)	-0.357 (0.441)	-0.235 (0.570)
Discipline: Medicine	-0.244 (0.341)	-0.253 (0.446)	-0.600 (0.666)
Discipline: Physics and Chemistry	-0.014 (0.297)	0.019 (0.378)	-0.333 (0.504)
Discipline: Social Science	-0.492* (0.293)	-0.356 (0.362)	0.039 (0.452)
Joint R^2_Z	**0.029 (22.3%)**	**0.042 (21.0%)**	**0.066 (32.3%)**
Constant	-3.866*** (0.513)	-5.157*** (0.689)	-6.200*** (1.043)
N	1,149	1,149	1,149
Log Likelihood	-522.020	-348.961	-196.862
Akaike Inf. Crit.	1,086.039	739.923	435.723
McFadden R^2	0.131	0.199	0.203

Note: A: Academic sphere, C: Commercial sphere, Z: Controls;
Robust standard errors in parentheses;
Significance at *p<0.1; **p<0.05; ***p<0.01

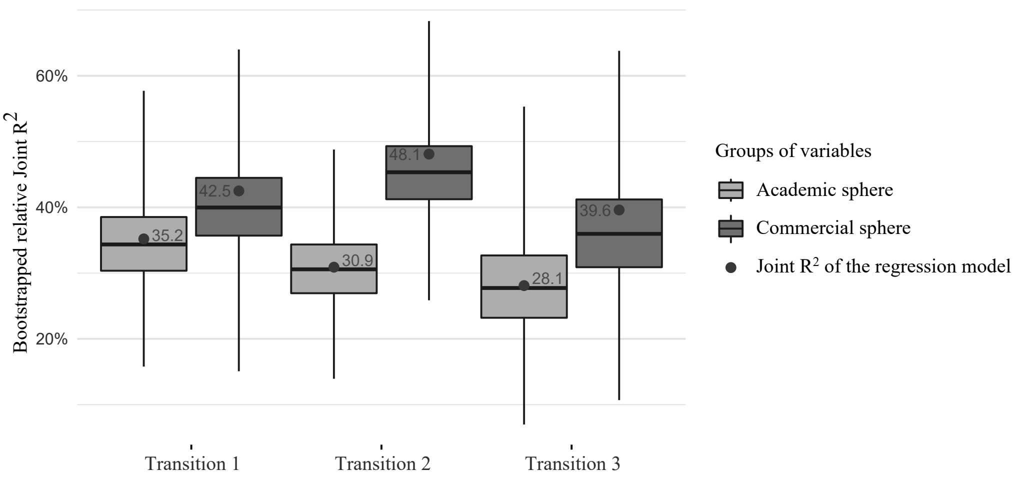

Figure 3.3: Dominance analysis on logit estimates for the three transitions with the complete sample based on 5,000 replications

Table 3.8: Differences in bootstrapped relative dominance based on logit estimates for the three transitions with the complete sample

	T1 mean	T2 mean	T3 mean	difference mean T2-T1	difference mean T3-T2
Academic sphere R^2_A	34.6% (0.09)	30.7% (0.08)	28.1% (0.10)	-3.9***	-2.6***
Commercial sphere R^2_C	40.1% (0.09)	45.3% (0.08)	36.1% (0.11)	5.2***	-9.2***

Note: 5000 bootstrapped replications; Standard errors in parentheses;
Differences in means tested by two-sided t-tests ;
Significance at *p<0.1; **p<0.05; ***p<0.01

Table 3.9: OLS regression results and dominance analysis for the three transitions

	(1) Transition 1 *Research* to *Opportunity framing*	(2) Transition 2 *Opportunity framing* to *Pre-spin-off*	(3) Transition 3 *Pre-spin-off* to *Spin-off*
Academic sphere			
Professor (=1)	0.014 (0.037)	0.177** (0.085)	0.124 (0.115)
Time devoted to research	-0.0004 (0.0005)	0.0001 (0.002)	0.001 (0.002)
Number of publications	-0.004 (0.012)	-0.039 (0.024)	-0.077** (0.037)
Average impact factor	-0.023 (0.019)	-0.044 (0.044)	0.087 (0.083)
Basic research	0.060*** (0.019)	0.005 (0.043)	-0.003 (0.063)
Applied research	0.050*** (0.014)	0.029 (0.045)	0.001 (0.064)
Joint R^2_A	**0.044 (30.9%)**	**0.066 (30.3%)**	**0.028 (15.8%)**
Commercial sphere			
Share of publications with industry	0.150 (0.157)	0.231 (0.212)	-0.335 (0.312)
Time devoted to KTT	0.001 (0.001)	0.006** (0.003)	0.006** (0.003)
Disclosed IP	0.199*** (0.037)	0.129*** (0.047)	0.035 (0.063)
Work experience outside academia	0.016* (0.009)	0.049** (0.022)	-0.006 (0.030)
Joint R^2_C	**0.070 (48.9%)**	**0.106 (48.3%)**	**0.027 (15.5%)**
Control variables			
Female (=1)	-0.048** (0.024)	0.004 (0.065)	-0.204** (0.092)
Risk willingness	0.014*** (0.005)	0.023 (0.014)	0.030 (0.021)
Organ. focus: basic	-0.041 (0.038)	0.121 (0.091)	0.113 (0.153)
Organ. focus: applied	0.012 (0.036)	0.053 (0.073)	-0.129 (0.098)
Discipline: Engineering	-0.081 (0.052)	-0.038 (0.103)	-0.171 (0.133)
Discipline: Humanities	-0.077 (0.054)	-0.094 (0.128)	0.091 (0.188)
Discipline: Life Sciences	-0.006 (0.051)	-0.161 (0.117)	-0.008 (0.177)
Discipline: Medicine	-0.047 (0.052)	-0.019 (0.142)	-0.052 (0.187)
Discipline: Physics & Chemistry	-0.008 (0.050)	-0.013 (0.100)	-0.146 (0.132)
Discipline: Social Science	-0.081* (0.046)	0.027 (0.111)	0.154 (0.144)
Joint R^2_Z	**0.029 (20.2%)**	**0.047 (21.4%)**	**0.122 (68.7%)**
Constant	-0.127* (0.067)	0.169 (0.205)	0.294 (0.289)
N	1,149	249	145
Residual Std. Error	0.385 (df = 1128)	0.455 (df = 228)	0.487 (df = 124)
R^2	0.143	0.219	0.177

Note: A: Academic sphere, C: Commercial sphere, Z: Controls;
Robust standard errors in parentheses;
Significance at *p<0.1; **p<0.05; ***p<0.01

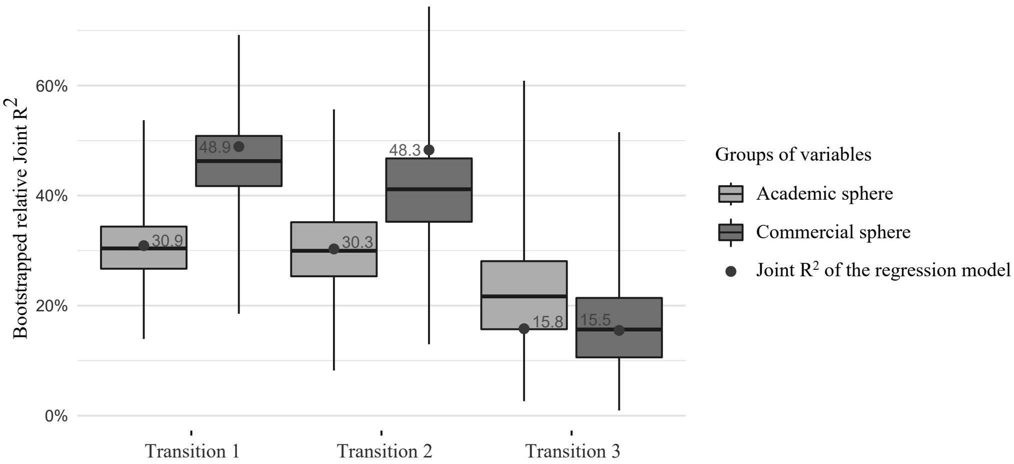

Figure 3.4: Dominance analysis on OLS estimates for the three transitions based on 5,000 replications

Table 3.10: Differences in bootstrapped relative dominance based on OLS estimates for the three transitions

	T1 mean	T2 mean	T3 mean	difference mean T2-T1	difference mean T3-T2
Academic sphere R^2_A	30.7% (0.08)	30.3% (0.10)	22.5% (0.13)	-0.4***	-7.8***
Commercial sphere R^2_C	46.2% (0.10)	41.1% (0.12)	16.6% (0.11)	-5.1***	-24.5***

Note: 5000 bootstrapped replications. Standard errors in parentheses.
Differences in means tested by two-sided t-tests;
Significance at *p<0.1; **p<0.05; ***p<0.01

Table 3.11: OLS regression results and dominance analysis for the three transitions with organizational fixed effects

	(1) Transition 1 *Research* to *Opportunity framing*	(2) Transition 2 *Opportunity framing* to *Pre-spin-off*	(3) Transition 3 *Pre-spin-off* to *Spin-off*
Academic sphere			
Professor (=1)	0.016 (0.038)	0.222** (0.086)	0.087 (0.134)
Time devoted to research	-0.0005 (0.0005)	0.001 (0.002)	0.001 (0.002)
Number of publications	-0.003 (0.012)	-0.031 (0.025)	-0.072* (0.036)
Average impact factor	-0.033* (0.018)	-0.051 (0.043)	0.103 (0.085)
Basic research	0.064*** (0.019)	-0.012 (0.042)	0.016 (0.066)
Applied research	0.050*** (0.014)	0.041 (0.046)	-0.028 (0.076)
Joint R^2_A	**0.045 (23.5%)**	**0.068 (20.6%)**	**0.026 (7.7%)**
Commercial sphere			
Share of publications with industry	0.188 (0.149)	0.027 (0.190)	-0.457 (0.353)
Time devoted to KTT	0.002* (0.001)	0.008*** (0.003)	0.008*** (0.003)
Disclosed IP	0.188*** (0.039)	0.180*** (0.051)	0.064 (0.073)
Work experience outside academia	0.013 (0.009)	0.040* (0.024)	0.010 (0.034)
Joint R^2_C	**0.065 (34.3%)**	**0.106 (32.0%)**	**0.034 (10.2%)**
Control variables			
Female (=1)	-0.054** (0.024)	0.023 (0.065)	-0.196* (0.102)
Risk willingness	0.015*** (0.005)	0.027** (0.014)	0.031 (0.021)
Discipline: Engineering	-0.093 (0.059)	-0.139 (0.141)	-0.170 (0.184)
Discipline: Humanities	-0.115 (0.071)	-0.225 (0.190)	0.021 (0.330)
Discipline: Life Sciences	0.032 (0.068)	0.018 (0.208)	-0.234 (0.283)
Discipline: Medicine	0.016 (0.069)	-0.141 (0.210)	-0.015 (0.304)
Discipline: Physics & Chemistry	0.078 (0.069)	-0.056 (0.195)	-0.160 (0.271)
Discipline: Social Science	-0.057 (0.056)	-0.036 (0.137)	0.014 (0.197)
Organ. fixed effects	Yes	Yes	Yes
Joint R^2_Z	**0.080 (42.2%)**	**0.158 (47.4%)**	**0.272 (82.1%)**
Constant	-0.194** (0.078)	0.109 (0.262)	0.220 (0.365)
N	1,149	249	145
Residual Std. Error	0.380 (df = 1095)	0.451 (df = 199)	0.491 (df = 99)
R^2	0.190	0.332	0.332

Note: A: Academic sphere, C: Commercial sphere, Z: Controls.
Robust standard errors in parentheses
Significance at *p<0.1; **p<0.05; ***p<0.01

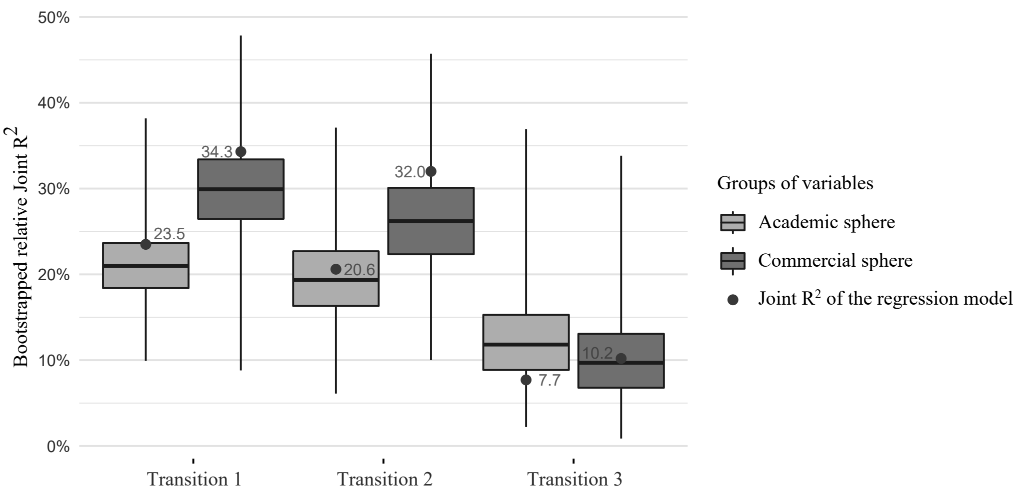

Figure 3.5: Dominance analysis on OLS estimates for the three transitions with organizational fixed effects based on 5,000 replications

Table 3.12: Differences in bootstrapped relative dominance based on OLS estimates with for the three transitions with organizational fixed effects

	T1 mean	T2 mean	T3 mean	difference mean T2-T1	difference mean T3-T2
Academic sphere R_A^2	21.2% (0.06)	19.6% (0.07)	12.3% (0.07)	-1.6***	-7.3***
Commercial sphere R_C^2	30.0% (0.07)	26.3% (0.08)	10.3% (0.07)	-3.7***	-16.0***

Note: 5000 bootstrapped replications. Standard errors in parentheses.
Differences in means tested by two-sided t-tests
Significance at *p<0.1; **p<0.05; ***p<0.01

3.7 Supplementary material

3.7.1 Non-response analysis and sample representativeness

Table 3.13: Non-response analysis

Variable	Approached (%)	Sample (%)	Sample - Approached
Professor (=1)	16.49	18.28	1.79
Female (=1)	37.56	36.73	-0.83
Basic	16.06	15.23	-0.83
Between basic and applied	63.85	63.97	0.12
Applied	20.09	20.80	0.71
Computer Science & Mathematics	10.11	10.53	0.42
Engineering	14.04	16.36	2.32**
Humanities	12.78	9.66	-3.12***
Life Science	13.50	14.97	1.47
Medicine	15.65	9.75	-5.9***
Physics & Chemistry	18.87	19.67	0.8
Social Sciences	15.05	19.06	4.01***
N	7,785	1,149	

Note: Group comparison based on Wilcoxon rank-sum tests as non-parametric alternative to two-sided t-test;
Significance at *p<0.1; **p<0.05; ***p<0.01

Table 3.14: Representativeness

Variable	Germany (Universities) (%)	Sample (Universities) (%)
Professor (=1)	18.63	20.99
Female (=1)	40.20	37.27

Note: The comparison is only between the respondents affiliated to universities and universities of applied science, not to research organizations; Data for the overall population of scientists at universities in Germany is taken from Statistisches Bundesamt (2020)

3.7.2 Process schemes

Table 3.15: Overview of process schemes on academic entrepreneurship

	Research	**T1**	Opportunity framing	**T2**	Pre-Spin-off	**T3**	Spin-off
Roberts and Malonet (1996)	Research & Development				Invention		New venture creation & Product development
Ndonzuau et al. (2002)			Generating business ideas		Finalizing new venture projects		Launch
Vohora et al. (2004)	Research		Opportunity framing		Pre-organization		
Clarysse and Moray (2004)			Idea		Pre-start-up		Start-up
Vanaelst et al. (2006)			Opportunity screening		Gestation		Spin-off's proof of viability
Mustar et al. (2008)			Pre-seed		Seed & Pre-start-up		Post-creation
Rasmussen (2011)	Research		Opportunity framing		Proof of viability		
Fernández-Alles et al. (2015)					Creation and initial development		Consolidation

Note: T: Transition; Source: Own elaboration

3.7.3 Research organizations in Thuringia

Table 3.16: List of approached organizations and their research focus

Number	Organization	Organizational focus
Universities and universities of applied sciences		
1	Bauhaus-Universität Weimar	between basic and applied
2	Duale Hochschule Gera-Eisenach	applied
3	Ernst-Abbe-Hochschule Jena	applied
4	Fachhochschule Erfurt	applied
5	Friedrich-Schiller-Universität Jena	between basic and applied
6	Hochschule für Musik FRANZ LISZT Weimar	applied
7	Hochschule Nordhausen	applied
8	Hochschule Schmalkalden	applied
9	SRH Hochschule für Gesundheit	applied
10	Technische Universität Ilmenau	between basic and applied
11	Universität Erfurt	between basic and applied
Research institutes		
12	Forschungsinstitut für Mikrosensorik	applied
13	Forschungszentrum für Medizintechnik und Biotechnologie	applied
14	Fraunhofer-Institut für Angewandte Optik und Feinmechanik	applied
15	Fraunhofer-Institut für Digitale Medientechnologie	applied
16	Fraunhofer-Institut für Keramische Technologien und Systeme	applied
17	Fraunhofer-Institut für Optronik, Systemtechnik und Bildauswertung Institutsteil Angewandte Systemtechnik	applied
18	Friedrich-Loeffler-Institut für bakterielle Infektionen und Zoonosen	applied
19	Friedrich-Loeffler-Institut für molekulare Pathogenese	applied
20	Gesellschaft für Fertigungstechnik und Entwicklung	applied
21	Günter-Köhler-Institut für Fügetechnik und Werkstoffprüfung	applied
22	Helmholtz-Institut Jena	basic
23	Innovent	applied
24	Institut für Angewandte Bauforschung	applied
25	Institut für Bioprozess- und Analysenmesstechnik Heiligenstadt	applied
26	Institut für Datenwissenschaften	applied
27	Institut für Mikroelektronik- und Mechatronik-Systeme	applied

Number	Organization	Organizational focus
28	Leibniz-Institut für Alternsforschung - Fritz-Lipmann-Institut e.V.	basic
29	Leibniz-Institut für Naturstoff-Forschung und Infektionsbiologie Hans-Knöll-Institut	basic
30	Leibniz-Institut für Photonische Technologien	basic
31	Materialforschungs- und -prüfanstalt	applied
32	Max-Planck-Institut für Biogeochemie	basic
33	Max-Planck-Institut für chemische Ökologie	basic
34	Max-Planck-Institut für Menschheits-geschichte	basic
35	Textilforschungsinstitut Thüringen-Vogtland	applied
36	Thüringer Landessternwarte Tautenburg	basic
37	Thüringisches Institut für Textil- u. Kunststoff-Forschung	applied

3.7.4 Correlation tables

Table 3.17: Pearson correlation coefficients between the variables of transition 1 (N=1,149)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
	Dependent variable																						
1	Transition 1 (=1)																						
	Academic sphere																						
2	Professor (=1)	0.08***																					
3	Time devoted to research	-0.05*	-0.35***																				
4	Number of publications	0.07**	0.32***	-0.06**																			
5	Average impact factor	-0.04	0.07**	0.14***	0.28***																		
6	Basic research	0.15***	0.11***	0.20***	0.15***	0.14***																	
7	Applied research	0.22***	0.05*	-0.07**	-0.04	-0.15***	0.15***																
	Commercial sphere																						
8	Share of publications with industry	0.08***	0.00	0.01	0.01	0.06**	-0.03	0.13***															
9	Time devoted to KTT	0.15***	0.02	-0.25***	-0.03	-0.03	0.09***	0.31***	0.07**														
10	Disclosed IP	0.19***	0.13***	-0.05*	0.18***	0.04	0.12***	0.19***	0.09***	0.20***													
11	Work experience outside academia	0.13***	0.20***	-0.25***	-0.05*	-0.22***	-0.01	0.23***	0.05*	0.12***	0.04												
	Control variables																						
12	Female (=1)	-0.10***	-0.12***	0.03	-0.12***	-0.07**	-0.03	-0.03	-0.07**	0.00	-0.07**	-0.11***											
13	Risk willingness	0.14***	0.10***	0.02	0.06**	0.00	0.23***	0.13***	0.03	0.04	0.07**	0.19***	-0.04										
14	Organizational focus: between basic and applied	-0.05*	-0.04	-0.03	0.00	-0.05*	-0.03	-0.12***	-0.10***	-0.14***	-0.12***	-0.11***	0.03	-0.04									
15	Organizational focus: basic	-0.05	-0.14***	0.27***	0.12***	0.26***	0.14***	-0.15***	-0.01	-0.01	-0.03	-0.16***	0.01	0.04	-0.56***								
16	Organizational focus: applied	0.11***	0.18***	-0.20***	-0.11***	-0.17***	-0.08***	0.28***	0.13***	0.18***	0.17***	0.26***	-0.04	0.01	-0.68***	-0.22***							
17	Discipline: Computer Science and Mathematics	0.07**	-0.01	0.01	-0.04	-0.02	0.02	0.10***	0.06**	-0.01	0.00	0.00	-0.14***	0.00	0.16***	-0.15***	-0.06*						
18	Discipline: Engineering	0.07**	0.03	-0.09***	-0.11***	-0.15***	-0.03	0.24***	0.17***	0.15***	0.18***	0.14***	-0.08***	0.03	-0.17***	-0.19***	0.37***	-0.15***					
19	Discipline: Humanities	-0.03	0.01	-0.04	-0.10***	-0.13***	0.09***	-0.08**	-0.05*	0.03	-0.05*	0.12***	0.10***	0.04	-0.04	0.05*	0.00	-0.11***	-0.14***				
20	Discipline: Life Sciences	-0.03	-0.07**	0.15***	0.04	0.15***	0.01	-0.13***	-0.01	-0.05*	-0.06**	-0.13***	0.06**	-0.01	-0.19***	0.34***	-0.08***	-0.14***	-0.19***	-0.14***			
21	Discipline: Medicine	-0.03	0.00	-0.04	0.17***	0.12***	-0.06**	0.00	-0.03	-0.05*	-0.04	-0.01	0.11***	-0.01	0.18***	-0.14***	-0.09***	-0.11***	-0.15***	-0.11***	-0.14***		
22	Discipline: Physics and Chemistry	0.03	-0.09***	0.18***	0.16***	0.16***	0.07**	-0.08***	-0.05*	0.03	0.07**	-0.17***	-0.07**	0.00	-0.12***	0.25***	-0.08***	-0.17***	-0.22***	-0.16***	-0.21***	-0.16***	
23	Discipline: Social Sciences	-0.08***	0.13***	-0.17***	-0.12***	-0.13***	-0.09***	-0.06*	-0.07**	-0.09***	-0.12***	0.07**	0.04	-0.04	0.22***	-0.21***	-0.08***	-0.17***	-0.21***	-0.16***	-0.20***	-0.16***	-0.24***

Note: Significance at *p<0.1; **p<0.05; ***p<0.01

Table 3.18: Pearson correlation coefficients between the variables of transition 2 (N=249)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Dependent variable																						
1 Transition 2 (=1)																						
Academic sphere																						
2 Professor (=1)	0.17***																					
3 Time devoted to research	-0.18***	-0.39***																				
4 Number of publications	-0.06	0.30***	-0.03																			
5 Average impact factor	-0.16**	0.15**	0.07	0.28***																		
6 Basic research	0.05	0.09	0.10	0.10	0.13**																	
7 Applied research	0.24***	0.10*	-0.09	-0.10	-0.13**	0.10																
Commercial sphere																						
8 Share of publications with industry	0.07	-0.01	0.02	-0.03	0.14**	-0.08	0.06															
9 Time devoted to KTT	0.27***	0.03	-0.36***	0.00	0.00	0.13**	0.31***	0.01														
10 Disclosed IP	0.21***	0.19***	-0.13**	0.12*	0.07	0.15**	0.20***	0.09	0.28***													
11 Work experience outside academia	0.28***	0.21***	-0.25***	0.04	-0.31***	0.01	0.26***	0.05	0.12*	-0.03												
Control variables																						
12 Female (=1)	-0.03	-0.05	0.00	-0.03	-0.07	0.06	-0.01	-0.10	-0.04	-0.03	-0.04											
13 Risk willingness	0.15**	0.12*	0.04	0.03	-0.04	0.16***	0.11*	0.03	0.02	0.03	0.19***	-0.02										
14 Organizational focus: between basic and applied	-0.11*	-0.10	0.07	0.04	-0.08	0.09	-0.14**	-0.13**	-0.16***	-0.11*	-0.08	-0.04	0.05									
15 Organizational focus: basic	-0.09	-0.15**	0.22***	0.12*	0.25***	0.06	-0.22***	0.08	-0.06	-0.07	-0.18***	0.08	0.01	-0.44***								
16 Organizational focus: applied	0.18***	0.22***	-0.23***	-0.13**	-0.09	-0.13**	0.31***	0.08	0.22***	0.17***	0.22***	-0.01	-0.06	-0.77***	-0.24***							
17 Discipline: Computer Science and Mathematics	0.02	0.04	0.09	-0.06	-0.01	0.05	0.17***	-0.03	-0.02	-0.02	0.01	-0.12*	0.01	0.16**	-0.15**	-0.06						
18 Discipline: Engineering	0.08	-0.09	-0.06	-0.13**	-0.11*	-0.05	0.20***	0.09	0.12*	0.21***	0.07	-0.08	-0.03	-0.11*	-0.19***	0.25***	-0.21***					
19 Discipline: Humanities	-0.02	-0.06	0.01	-0.08	-0.02	0.14**	-0.12**	0.00	0.00	-0.03	0.06	0.18***	0.02	-0.08	0.21***	-0.06	-0.12*	-0.15**				
20 Discipline: Life Sciences	-0.14**	0.04	0.10	0.03	0.14**	-0.03	-0.12*	0.11*	-0.12*	-0.12*	-0.08	0.09	0.05	-0.22***	0.34***	-0.01	-0.16**	-0.20***	-0.11*			
21 Discipline: Medicine	-0.05	0.11*	-0.11*	0.24***	0.07	-0.06	-0.10*	-0.06	-0.11*	-0.02	-0.01	0.05	-0.01	0.13**	-0.11*	-0.06	-0.12*	-0.15**	-0.09	-0.11*		
22 Discipline: Physics and Chemistry	0.00	-0.05	0.07	0.14**	0.15**	0.06	-0.05	-0.07	0.10	0.07	-0.13**	-0.09	-0.01	-0.03	0.10	-0.04	-0.22***	-0.28***	-0.16**	-0.20***	-0.16**	
23 Discipline: Social Sciences	0.07	0.06	-0.12*	-0.11*	-0.22***	-0.09	-0.04	-0.05	-0.04	-0.14**	0.11*	0.05	-0.02	0.18***	-0.14**	-0.09	-0.16**	-0.20***	-0.12*	-0.15**	-0.12*	-0.21***

Note: Significance at *p<0.1; **p<0.05; ***p<0.01

Table 3.19: Pearson correlation coefficients between the variables of transition 3 (N=145)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
	Dependent variable																						
1	Transition 3 (=1)																						
	Academic sphere																						
2	Professor (=1)	0.05																					
3	Time devoted to research	-0.03	-0.37***																				
4	Number of publications	-0.14*	0.26***	-0.06																			
5	Average impact factor	-0.02	0.17**	0.02	0.30***																		
6	Basic research	0.04	0.20**	0.08	0.14*	0.16*																	
7	Applied research	0.03	0.08	-0.06	-0.08	-0.07	0.19**																
	Commercial sphere																						
8	Share of publications with industry	-0.08	0.00	-0.03	-0.03	0.18**	-0.14*	0.07															
9	Time devoted to KTT	0.12	-0.04	-0.37***	0.01	0.03	0.18**	0.26***	-0.02														
10	Disclosed IP	-0.05	0.19**	-0.12	0.17**	0.17**	0.19**	0.13	0.08	0.24***													
11	Work experience outside academia	0.02	0.17**	-0.22***	0.02	-0.30***	0.00	0.23***	0.11	0.06	-0.10												
	Control variables																						
12	Female (=1)	-0.12	-0.12	0.08	-0.01	-0.22***	0.09	-0.02	-0.16*	-0.05	-0.01	-0.06											
13	Risk willingness	0.18**	0.14*	0.21**	0.03	0.11	0.14*	0.13	0.03	-0.01	0.00	0.08	-0.01										
14	Organizational focus: between basic and applied	0.09	-0.15*	0.11	0.04	0.03	0.20**	-0.12	-0.13	-0.20**	-0.13	-0.11	-0.09	0.02									
15	Organizational focus: basic	0.09	-0.16**	0.19**	0.11	0.04	-0.06	-0.13	0.03	-0.01	-0.01	-0.13	0.12	0.19**	-0.36***								
16	Organizational focus: applied	-0.14*	0.26***	-0.23***	-0.11	-0.06	-0.17**	0.20**	0.12	0.21**	0.14*	0.20**	0.01	-0.14*	-0.82***	-0.24***							
17	Discipline: Computer Science and Mathematics	0.05	0.01	0.13	-0.08	-0.07	0.08	0.15*	-0.02	-0.08	-0.04	-0.04	-0.08	0.00	0.15*	-0.14*	-0.08						
18	Discipline: Engineering	-0.14*	-0.09	-0.01	-0.11	0.00	-0.07	0.19**	0.10	0.13	0.17**	0.05	-0.12	-0.11	-0.16**	-0.18**	0.28***	-0.24***					
19	Discipline: Humanities	0.06	-0.08	0.03	-0.07	-0.13	0.02	-0.03	-0.01	0.00	0.01	0.04	0.30***	0.07	-0.05	0.17**	-0.05	-0.12	-0.16*				
20	Discipline: Life Sciences	0.06	0.06	0.11	-0.07	0.00	-0.07	-0.12	0.16*	-0.07	-0.10	-0.02	-0.02	0.12	-0.05	0.31***	-0.13	-0.13	-0.18**	-0.09			
21	Discipline: Medicine	-0.08	0.18**	-0.08	0.30***	0.13	-0.03	-0.15*	-0.04	-0.18**	-0.03	-0.11	0.02	0.03	0.08	-0.09	-0.03	-0.12	-0.15*	-0.08	-0.09		
22	Discipline: Physics and Chemistry	-0.07	-0.10	0.04	0.15*	0.19**	0.14*	-0.06	-0.13	0.17**	0.08	-0.09	-0.05	0.01	-0.08	0.16**	-0.02	-0.23***	-0.30***	-0.15*	-0.17**	-0.14*	
23	Discipline: Social Sciences	0.17**	0.10	-0.21**	-0.07	-0.15*	-0.08	-0.08	-0.03	-0.08	-0.16**	0.14	0.05	-0.05	0.15*	-0.14*	-0.08	-0.18**	-0.24***	-0.12	-0.13	-0.12	-0.23***

Note: Significance at *p<0.1; **p<0.05; ***p<0.01

Chapter 4

University scientists' multiple goals achievement: Social capital and its impact on research performance and research commercialization

4.1 Introduction

University scientists' primary goal is to conduct excellent research and distinguish themselves from other competing scientists through impactful contributions to the scientific discourse (Frenken et al., 2017; Grewal et al., 2008). However, in recent decades, the variety of roles and functions performed by university scientists has increased significantly, especially in terms of outreach activities to bridge to industry and society (Fromhold-Eisebith & Werker, 2013; Perkmann et al., 2013; 2021). Particularly, the desire of connecting academics more closely with the industrial side turns the metaphor of the scientist in the ivory tower into an outdated image (Etzkowitz & Leydesdorff, 2000; Fritsch & Krabel, 2012; Haeussler & Colyvas, 2011). The active participation of universities in economic development has turned them into organizations with multiple goals (Fini et al., 2019;

Holstein et al., 2018; Kotlar et al., 2018), which confronts scientists with the challenge of reconciling the goals of a high research performance with the commercial exploitation of their results.

Research performance of scientists is frequently defined as the number of citations per year and publication in a given time-span, reflecting the impact their research has on the scientific discourse and succeeding research (Olmos-Peñuela et al., 2014). Scientists commercializing research results alongside their production of knowledge can be framed as ambidextrous. Chang et al. (2016, p. 9) defines ambidextrous scientists as those with the ability to "simultaneously achieve research publication and research commercialization." The pursuit of each goal is subject to different norms and reward systems, which makes balancing them a difficult endeavor for scientists (Ambos et al., 2008; Cantner et al., 2023; Sauermann & Stephan, 2013). We already know that these goals are not mutually exclusive but that there is a relationship between high research performance and commercialization activities by scientists (e.g. Geuna & Nesta, 2006; Gulbrandsen & Thune, 2017; Siegel et al., 2007; van Looy et al., 2006; 2011), indicating that some scientists can resolve the conflicts between those goals. However, how those scientists manage to achieve multiple goals remains unclear. For the achievement of each of the goals, scientists' social capital seems to be an integral asset. It is the set of resources they can access and mobilize for purposive actions by drawing on the social structure in which they are embedded (Lin, 2017; Portes, 1998). Drawing on the knowledge and resources of scientific peers can give them competitive advantages in scientific competition while connecting with the industry side leads to a larger and more diverse pool of social capital (Hayter, 2016b; van Rijnsoever et al., 2008). Existing research has so far focused on how scientists achieve one of these goals (e.g. Broström, 2019; Chang et al., 2016), however, the literature is silent on the issue of what distinguishes scientists in their achievement of multiple conflicting goals and the role a diverse social capital plays in this context.

This study aims to fill this gap by conceptualizing a quadrant model characterizing scientists by contrasting their multiple goals of research performance and research commercialization. While there already are concepts categorizing scientists by their research orientation (Stokes, 1997), their orientation towards university-industry connections (Lam, 2010) or their collaboration strategies (Bozeman & Corley, 2004), there is no such concept characterizing scientists by their achievement of multiple goals.[1] This study derives four profiles which distinguish scientists by high and low research performance within an intra-disciplinary comparison as well as by their extent of commercialized research results. A variety of influential factors on scientists' research performance have already been investigated by scholars, such as their work experience or their prior scientific training (e.g. Abramo et al., 2012; Broström, 2019; Gulbrandsen & Smeby, 2005; Gulbrandsen & Thune, 2017; Perkmann et al., 2011), while others examined how organizational and individual resources affect scientists' research commercialization (e.g. Ambos et al., 2008; Chang et al., 2009; 2016; Sengupta & Ray, 2017). In this study, both literature streams are combined by a multiple goals perspective and the influence of different forms of social capital is added to empirically investigate their effect on scientists' belonging to one of the derived profiles. Building on social capital theory, three forms are deduced for the university context: bonding, bridging and linking social capital (Granovetter, 1973; Putnam, 2001; Szreter & Woolcock, 2004). The analysis is centered around the individual scientist and hypotheses related to the impact of each form of social capital on scientist profiles are derived.

To test the hypotheses, data of a novel online survey is used. The survey was conducted in the German federal state of Thuringia between December 2019 and January 2020 and collected information on scientists' commercialization activities and industry connections. The sample of respondents from ten universities is representative for Germany regarding key characteristics. The survey data is combined with publication data for each respondent and data about the funding structure for each university. For the empirical analysis multinomial logistic regressions are applied for the main specification as well as for robustness tests.

The results show that with 6.5% only a small fraction of scientists are simultaneously high research performers and commercialize their results. Their achievement of both goals at the same time is driven by all three forms of social capital. Scientists with a high research performance who do

[1]There is one study by Subramanian et al. (2013) focusing on industrial scientists instead of academic scientists, which categorizes them by their research productivity and their frequency of patenting to identify those scientists who create value for the firm.

not exhibit ambidextrous behavior are associated with their bonding social capital, while ambidextrous scientists with a low research performance draw on their bridging and linking social capital. Furthermore, it is shown that the relationship between bonding social capital and research performance is of curvlinear nature. In case of an extensive degree of bonding social capital, the actual advantages of it can turn into disadvantageous effects. The study contributes to the literature about scientists' research performance (e.g. Abramo et al., 2012; Broström, 2019; Gulbrandsen & Smeby, 2005; Gulbrandsen & Thune, 2017; Perkmann et al., 2011) and research ambidexterity in the university context (e.g. Ambos et al., 2008; Chang et al., 2009; 2016; Sengupta & Ray, 2017) by combining and enriching it with a social capital perspective. The conceptualization of scientist profiles and the empirical insights help in categorizing heterogeneous scientists by considering multiple goals (Fini et al., 2019; Holstein et al., 2018; Kotlar et al., 2018) and the role that different forms of social capital can play in achieving them. This can guide policymakers in their consideration on how to reconcile both desired goals and how this can be achieved.

The paper is organized as follows. In section 4.2, a quadrant model contrasting scientists' goals of research performance and research ambidexterity is conceptualized to distinguish between four scientist profiles. Hypotheses are derived with regard to the impact of various forms of scientists' social capital on their belonging to one of the profiles. In section 4.3 the data and empirical approach is presented, followed by the results and robustness tests in section 4.4. Finally, the main findings are synthesized and the main implications of the study are discussed in 4.5.

4.2 Conceptual framework and hypotheses

4.2.1 University scientists' multiple goals

Universities are environments in which different activities take place to meet the manifold roles of today's higher education institutes (Etzkowitz et al., 2000). Besides the predominating objective to generate knowledge, scientists are also required to commercially exploit their research results (e.g. Etzkowitz et al., 2000; OECD, 2013; Siegel et al., 2003; Slaughter & Rhoades, 2004). This leads to a duality of generated knowledge from universities by expanding scientific research on the one hand and enabling usable commercial applications on the other (Murray & Stern, 2007). Thus, universities have become significant actors in shaping the knowledge economy. With the expected outcomes of impactful research results and commercial output, universities are organisations with multiple goals (Fini et al., 2019; Holstein et al., 2018; Kotlar et al., 2018) which consequently affect the scientists working within these organisations: they have to work towards achieving those goals while at the same time balancing their resources.

The goal of generating impactful research results is deeply embedded in the academic research system characterized by the freedom of research, an open science mentality and the treatment of knowledge as a public good (Nelson, 1959b; Rosenberg, 1974). Knowledge is generated by the individual scientist for the sake of scientific progress while the process of knowledge generation itself is determined by originality — a norm that entails the ambition to always search for the unknown to discover novel research results (Ziman, 1984). Scientists who manage to discover and publish novel research results significantly contribute to the progress of science. This leads to gaining peer-recognition and reputation, which is the currency of academic competition and puts the individual research performance at the forefront of every scientist's academic strive (Dasgupta & David, 1994). Among scientists there are those notable in particular for their prolific and exceptionally strong contribution towards advancing their research discipline. Scholars already paid attention to such high-performers by focusing on scientists from industry and calling them "star scientists" (e.g. Hess & Rothaermel, 2011; Rothaermel et al., 2007; Zucker et al., 1998; 2002). They are characterized by high scientific and human capital enabling them to generate research output on an outstanding level (Bozeman & Gaughan, 2007; Zucker et al., 1998). However, the definition of star scientists is a heterogeneous endeavour among these studies (Subramanian et al., 2013). While Zucker et al. (1998) and Zucker et al. (2002) define stars among scientists in the field of biotechnology by their genetic sequence contribution to the GenBank database, others consider Nobel Laureates to be star scientists (Higgins et al., 2011). Studies with a focus on university scientists call on their research performance in terms of publication quantity and quality (Baba et al., 2009; Perkmann et al., 2011).

The goal of research commercialization requires, in addition to the production of knowledge, to exploit it commercially by treating knowledge as a private good. Such behavior, contrary to the exploration of knowledge, can be coined as ambidextrous, a term originally used by management studies to describe organizations which are able to pursue two incompatible and conflicting goals simultaneously (Birkinshaw & Gupta, 2013). On the individual level, ambidexterity refers to the capability to achieve contradictory goals by switching between different mindsets and action sets (Bledow et al., 2009).[2] In the context of universities this study follows the definition of scientists' research ambidexterity by Chang et al. (2016, p. 9) as the ability of academic scientists to "simultaneously achieve research publication and research commercialization at the individual level." This means ambidextrous scientists are able to deal with tensions between these opposing endeavours, adapt to different roles and refine and renew their knowledge, skills and expertise (Mom et al., 2009).

The missing link between those two goals is the ability to do both: reach a high research performance and commercialize research results. Achieving both goals encompasses the academic attainments of a star scientist as well as the research commercialization of an ambidextrous scientist.

4.2.2 Towards a quadrant model of scientist profiles

Even though literature provides different classifications of scientist profiles (Bozeman & Corley, 2004; Lam, 2010; Stokes, 1997), there is no classification which considers scientists' achievement of multiple goals. To define profiles, a quadrant model is developed to contrast scientists' research performance with their research commercialization. Consequently, four profiles of scientists can be distinguished by contrasting these two goals (see Figure 4.1).

[2]The importance of considering the individual when looking at ambidextrous organizations has already been addressed in ambidexterity-research (e.g. Keller & Weibler, 2015; Lam et al., 2019; Pertusa-Ortega et al., 2021). Bonesso et al. (2014) emphasizes the need for such a focus because an analysis of ambidexterity of organizations would implicitly assume homogeneity of the respective organization's employees.

Normal scientists: The term "normal scientists" is derived from how Kuhn (1970, p. 10) defines and describes normal science: as "research firmly based upon one or more past scientific achievements, achievements that some particular scientific community acknowledges for a time as supplying the foundation for its further practice". Scientists in this profile represent the baseline in group comparisons and serve as an orientation when considering scientists who deviate from it. These scientists are characterized by a lower output of impactful research compared with high-performers who deviate from the norm. Furthermore, they are not ambidextrous due to the absence of commercialized research results. The lower research performance may be due to the fact that the scientists in this profile are still at the beginning of their academic careers and have yet to establish themselves in academia. Moreover, their research output may be high on a quantitative level, but qualitatively it focuses mainly on research questions that have already been largely answered or on the formalization of existing knowledge (Amara et al., 2019). Another reason could be that this group of scientists have little inclination for publishing research results and peer-recognition, which Roach and Sauermann (2010) call a lower "taste for science". However, they are also referred to as normal scientists because they do not deviate from the usual behavior of merely generating research output. Their absence of commercializing behavior might be because of an unwillingness to act in such a way or the lack of research results that could be commercialized (Louis et al., 1989).

Star scientists: Among this group of scientists are those with a high research performance but no commercialized research results, therefore, not being ambidextrous. Within the process of normal science, scientific knowledge from time to time undergoes socially constructed paradigm shifts and an accepted paradigm (the beliefs, theories, and methodologies) is replaced by a new paradigm (Turnpenny et al., 2011). This is what Kuhn (1970) called revolutionary science which, because of its originality, leads to a higher research impact. The reasons for academics to aim for a high research performance are rooted in the academic reward system (Dasgupta & David, 1994). The academic currency is reputation and peer-recognition, which can typically be achieved through high-impact publishing and also increases the chances of awarded tenure (Lissoni et al., 2011). High research performance could be achieved at the expense of not considering the commercial implementation of research results. In fact, one fear of scientists is that an involvement in commercial activities will hamper their research performance and independence (Baldini et al., 2007; Glaser & Bero, 2005; Hossinger et al., 2020; Lee, 1996).

Ambidextrous scientists: Scientists in this profile exhibit a low research performance, but they are ambidextrous, because in conjunction with their research, they also commercialize their results. The reasons for academics to commercialize their research results are manifold. Besides the opportunity to build financial resources through commercialisation (Bodas Freitas & Nuvolari, 2012; Fini et al., 2009; Hayter, 2011; Walter et al., 2018), for some it is an intrinsically motivated task of excitement to turn their research findings into a useful application (Lam, 2011). Academic career objectives are also defined or even adjusted by the fact that high competition for tenured positions can lead to closer approximation to commercially oriented activities. Evidence for this exists especially for the creation of academic spin-offs, which is often perceived as an alternative career path (Horta et al., 2016). Scientists who are involved in commercialization activities might have fewer resources available for a high research performance (Buenstorf, 2009; Fabrizio & Di Minin, 2008).[3].

Ambidextrous star scientists: These scientists succeed in reconciling the two goals of high research performance and research commercialization. In addition to their high research performance, they also manage to exploit their research results commercially (Buenstorf, 2009; Larsen, 2011; van Looy et al., 2006). Such academics exhibit a hybrid role identity that allows them to follow the ideal of both an academic and a commercial persona (Jain et al., 2009). They figure out a way to conduct their different activities in a complementary way, allowing synergies to lead to positive outcomes (Reymert & Thune, 2023; van Looy et al., 2004). In fact, Fini et al. (2021) have shown that academic entrepreneurship stimulates scholars' attention to a broader and cross-disciplinary range of exploratory endeavours and thus increases the impact of their research.

[3] Buenstorf (2009) discovered such a negative effect only for long-term influences of spin-offs, but not for inventive activities.

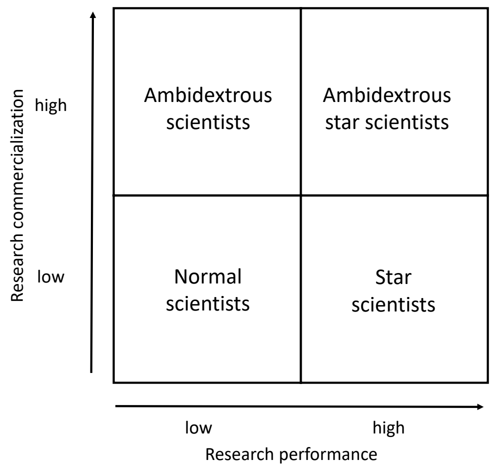

Figure 4.1: Quadrant model considering research performance and research commercialization.

4.2.3 University scientists' forms of social capital

In order to achieve their multiple goals, academics can utilize their social capital. Social capital refers to the set of resources one can access and mobilize for purposive actions by drawing on the social structure in which the individual is embedded (Lin, 2017; Portes, 1998). For both, the conduct of impactful research and the process of commercializing research results, social capital can be a supporting asset. According to van Rijnsoever et al. (2008) a scientist's social capital can generate competitive advantages in individual career development in academia, but to utilize such advantages it is crucial which of the scientist's diverse networks is drawn upon. In the same vein, Hayter (2016a, 2016b) show that along the spin-off creation process of scientists, various networks are essential to connect to, while Karlsson and Wigren (2012) finds a positive correlation between contacts to non-university actors and their propensity to found a firm. This positive correlation is also present for the commercialization of research results via patents and licenses (Kalar & Antoncic, 2016).

According to social capital theory, these social structures and networks can be distinguished into three forms of social capital: bonding, bridging and linking social capital (Granovetter, 1973; Putnam, 2001; Szreter & Woolcock, 2004). They differ in terms of their network type, strength of ties, type of relationships, trust and benefits. *Bonding social capital* captures strong ties within a closed intra-community network, such as peers, with close social proximity and common social identity (Coleman, 1988; Putnam, 2001). Such relationships are characterized by more informal collaborations with thick trust and long-term reciprocity of which actors can benefit in terms of common goal achievement. *Bridging social capital* on the other hand captures weak ties established to external heterogeneous actors of extra-community networks across social distance with different social identity (Burt, 2000; Granovetter, 1973; Putnam, 2001). These relationships reflect more formalized collaborations with thinner trust and reciprocity done for the sake of sharing resources and knowledge. *Linking social capital* is defined as "norms of respect and networks of trusting relationships between people who are interacting across explicit, formal or institutionalized power or authority gradients" (Szreter & Woolcock, 2004, p. 655). Contrary to the other two forms of social capital, which refer to horizontal social networks, this form of social capital constitutes how individuals of intra-community networks are vertically connected to extra-community networks via linking institutions. It was introduced to social capital theory to underline the importance of formal institutions linking dissimilar groups of actors to leverage resources, ideas and information beyond the community (Woolcock, 2001). It is the relationship of intra-community actors with institutions that have relative power over them and expect those actors to establish ties to distinct actors of extra-community networks. In the following, the three introduced forms of social capital are discussed in the context of university scientists and hypotheses are elaborated with regards to the extent in which they influence the profile affiliation of scientists and their multiple goal achievement (also see Table 4.1 for an overview).

Scientists' bonding social capital

Scientists at universities are predominantly embedded in the academic environment in which they bond with other scientific peers. They share the same norms and logics along the ethos of science guaranteeing the freedom of research, an open science mentality and the treatment of knowledge as a public good (Baldini et al., 2007; Merton, 1973; Nelson, 1959a; Rosenberg, 1974). The internalization of these norms and logics represents the pillars of their academic role identity (Jain et al., 2009). A common orientation towards publication of research is driven by the reward system under which they perform to gain peer recognition and reputation (Dasgupta & David, 1994). To achieve these goals, the dominating motivators for scientists are the quest for fundamental understanding and their enjoyment of puzzle solving (Lam, 2011; Merton, 1968). Since they are sharing the same goals, networking with each other gives them a competitive advantage for several reasons (van Rijnsoever et al., 2008). First, they can combine complementary skills and thus take advantage of the division of labor as well as expand research output in a more time-efficient manner. Second, the mutual intellectual stimulation and discussions about their research can open up new research opportunities. Third, access to equipment and information can be achieved, which in turn facilitates the use of scarce resources. Such research-related benefits have a positive impact on scientists' productivity and increase their chances of promotion along the academic career ladder (Lissoni et al., 2011). Bonding social capital of scientists induces trust in the relationship to peers and eases the exchange of information and resources between them. It can stimulate what Latour and Woolgar (1986) call the "credibility cycle" of scientists. It is the circular process of research performance leading to rewards in terms of higher recognition which eases the access to resources such as staff, equipment as well as data and consequently lets the cycle continue with increased publications (Hessels et al., 2019). Evidence in the literature supports this effect. Besides the trend over the last decades showing a substantial increase in research collaborations in terms of co-authorship (Jones et al., 2008), the usage of scientists' bonding social capital positively impacts their research performance and, thus, their likelihood of being a star scientist as well as their likelihood of being an ambidextrous star scientist (Lee & Bozeman, 2005). Considering the effects of scientists' bonding social capital on the goal of achieving noteworthy research performance mentioned above, the following hypotheses state:

H1a: A scientist's bonding social capital increases the likelihood to be a star scientist instead of being a normal scientist.

H1b: A scientist's bonding social capital increases the likelihood to be an ambidextrous star scientist instead of being a normal scientist.

Scientists' bridging social capital

Scientists' bridging social capital in the context of the dichotomy between research performance and research commercialization refers to the ties to industrial actors. Industry actors operate under a different umbrella of norms and logics than academic scientists, characterized by market competition, rent-seeking under bureaucratic control, secrecy and restrictions on disclosure (Hayter, 2011; Sauermann & Stephan, 2013). These norms fuel the treatment of knowledge as a private good for the goal of commercial exploitation (Dasgupta & David, 1994; Levin et al., 1987; Stephan, 1996). Thus, university scientists are confronted with interactions with actors who have internalized an entrepreneurial role identity (Hayter et al., 2022; Jain et al., 2009). These differences in the norms and goals between scientists and industrial actors result in a thinner trust (Bellini et al., 2018; Bruneel et al., 2010). Even though scientists' bridging social capital is characterized by these mismatches, establishing ties to the industry brings some beneficial effects. It facilitates the flow of non-redundant information, increasing scientists' information diversity (Burt, 2004). It gives scientists commercial insights, creates envisioning industrial applications and changes their perspective to an industrial one (Dolmans et al., 2022). Having a network which also includes industry members can help scientists to overcome a lack of commercialization-specific human capital (Colyvas et al., 2002). Such ties to industrial actors enable scientists to acquire knowledge conversion capability (Sousa-Ginel et al., 2021), which they can use to turn their research results into commercial applications. Moreover, it can help them to adapt their academic role identity by incorporating entrepreneurial elements and, thus, achieve a hybrid role identity that combines academic and commercial norms and logics (Hayter et al., 2022; Jain et al., 2009). Evidence in the literature shows that it is more attractive for scientists who collaborate with industry to create a spin-off and that there is a higher probability they engage in such an activity (Fritsch & Krabel, 2012; Gulbrandsen & Smeby, 2005; Krabel & Mueller, 2009). Furthermore, scientists involved in research collaborations with industry have a higher probability to be engaged in patenting activities (Boardman & Ponomariov, 2009; Prodan & Drnovsek, 2010) and more likely to license inventions (Wu et al., 2015). Considering the effects of scientists' bridging social capital on the goal to achieve research commercialization mentioned above, the following hypotheses state:

H2a: A scientist's bridging social capital increases the likelihood to be an ambidextrous scientist instead of being a normal scientist.

H2b: A scientist's bridging social capital increases the likelihood to be an ambidextrous star scientist instead of being a normal scientist.

Table 4.1: Forms of social capital and their application to university scientists multiple goals achievement

	Bonding SC	**Bridging SC**	**Linking SC**
Network type	Horizontal intra-community	Horizontal extra-community	Vertical links between intra- and extra-community
Ties	Actors with close social proximity and common social identity	Actors with social distance and different social identity	Institutionalised power or authority gradients
Strength of ties	Strong	Weak	Weak
Type of relationships	Informal collaboration with long-term reciprocity	Formalized collaboration with short-term reciprocity	Formalized collaboration with long-term reciprocity
Trust	Thick	Thin	Thick
Benefits	Common goal achievement	Sharing resources and knowledge	Organisational support for linking to external networks (resources and information)
University scientists	Strong ties to peers within the scientific community	Weak ties to industrial actors	Weak ties to industry due to enabling links via university
	Sharing academic identity (norms and logics along ethos of science)	Confronted with entrepreneurial identity (norms and logics of commercialization)	Institutionalization of commercialization behavior by entrepreneurial university
	Informal collaboration to gain competitive advantages	Formal collaboration to gain non-redundant knowledge and resources	Formal relationship to university as employer and its mission of research commercialization
	Common goals: research performance and peer-recognition	Different goals: research publication vs. research commercialization	Institutionalized goal: research commercialization
Multiple goals	Research performance	Research commercialization	Research commercialization

Scientists' linking social capital

Scientists' linking social capital refers to the institutionalization of ties to the industry induced by the university with which they are affiliated. Thus, it encompasses the encouragement and support of commercialization-oriented behavior by formalizing it in the sense of an entrepreneurial university through established organizational structures and policies (Guerrero et al., 2016). In addition to the establishment of technology transfer offices for legal and technical support along the commercialization process (Bradley et al., 2013), this can also be achieved through the establishment of incubators (Kolympiris & Klein, 2017), the integration of commercialization-oriented criteria for promotion and tenure (Grimaldi et al., 2011) or through further educational programs for commercialization (Bolzani et al., 2021). The reciprocity of the relationship between the scientist and their university is characterized by the university's expectation to establish ties to distinct actors of extra-community networks in exchange for providing the scientist with resources to achieve their goals. Universities can function as boundary-spanning organizations activating relations between unrelated actors, namely scientists from academia and industrial actors, which enable the exchange of non-redundant knowledge (Burt, 2007; Comacchio et al., 2012). Scientists are influenced by their environment and the contextual setting in which they act. When scientists perceive their working environment as oriented towards research commercialization due to linkages with industry it significantly influences their own behavior towards such activities (Kalar & Antoncic, 2015). According to in-depth interviews in the UK, Ankrah et al. (2013) find that among the main motive for scientists to interact with the industry is the necessity to engage due to the strategic institutional policy of their university. Universities aiming to link to the industry can be seen as brokers between scientists and industrial actors, which in turn facilitates scientists to establish ties to the industry. Consequently the scientists can access external knowledge and resources which positively influences their propensity to commercialize research results. Considering the effects of scientists' linking social capital on the goal to achieve research commercialization mentioned above, the following hypotheses state:

H3a: A scientist's linking social capital increases the likelihood to be an ambidextrous scientist instead of being a normal scientist.

H3b: A scientist's linking social capital increases the likelihood to be an ambidextrous star scientist instead of being a normal scientist.

Negative effect of bonding social capital

The potential advantages of being embedded in a cohesive network characterized by similarity, social proximity, and the resulting thick trust cannot be denied. However, social capital literature also brings up concerns regarding potential negative effects of bonding social capital (Portes, 1998). An overabundance of bonding social capital in the form of strong ties to actors who are alike, can cause a predominant inflow of redundant knowledge (ter Wal et al., 2016). A too strong reliance on bonding social capital can lead to homophily (a strong bonding with similar actors), which in turn limits a broad perspective and access to unknown information and knowledge (McPherson et al., 2001). This can lead to lock-ins and an increased risk of opportunistic behavior, which can ultimately harm the benefits of interactive learning in the network (Boschma, 2005). Since the professional network of scientists can be considered a homophilous one (Hayter, 2016b), it is reasonable to assume that the benefits of scientists' bonding social capital might become detrimental for their research performance.[4] Thus, the following hypotheses state:

H4a: There is an inverted U-shaped relationship between a scientist's bonding social capital and the likelihood to be a star scientist instead of being a normal scientist.

H4b: There is an inverted U-shaped relationship between a scientist's bonding social capital and the likelihood to be an ambidextrous star scientist instead of being a normal scientist.

[4]No hypotheses are derived that address a possible negative effect of bridging and linking social capital, since social capital theory does not discuss such a relationship in these two forms.

4.3 Data and Method

4.3.1 Data

The data for the empirical investigation consists of primary and secondary data. Regarding the primary data, a novel online survey of academic staff at universities in the German Federal State of Thuringia was conducted. Thuringia is a suitable case for this study, as it adequately reflects the variety in the German research landscape. Four universities and six universities of applied sciences are located within the state. Out of the four universities, one is a technical university and one is affiliated with a university hospital. Among the six universities of applied sciences there is also the rare case of a music college. After the collection of publicly available contact information and characteristics of the scientists from their universities' web pages, 6,301 scientists had been identified to whom an invitation for the web-based survey was sent in December 2019 and January 2020.[5] 1,072 scientists accepted the invitation and participated in the survey, resulting in a response rate of 17%. Of these responses, 15 observations had to be discarded due to missing data. Thus, the working sample for the empirical analysis consists of 1,057 observations. The differences between this working sample of respondents and the initial population are predominantly marginal, and I consider a non-response bias unlikely with a small tendency towards over- and under-representation of some disciplines.[6] The comparison of the working sample with the overall population of scientists at universities in Germany (Statistisches Bundesamt, 2020) reveals representativeness of the sample in terms of academic rank and gender (Table 4.11).

[5] Originally, the survey was extended to research institutes in Thuringia with 1,484 additional survey invitations resulting in 337 additional responses. They are not considered in this study since it focuses on universities only. Published studies that also use the survey data are as follows: Cantner et al. (2023), Cantner et al. (2022) and Huegel et al. (2023).

[6] I compared the characteristics academic rank, gender and discipline between the overall population and the working sample (Armstrong & Overton, 1977) in Table 4.10. There are some statistically significant differences concerning the disciplines. There is, for example, an under-representation of scientists from medicine in the respondents. This might be because the initial data collection included many medical doctors with an affiliation with the university hospital that are not involved in research anymore.

The online survey consisted of a set of questions on the scientists' commercialization activities (the protection of IPR and the creation of an academic spin-off). In addition, their collaboration activities with industry actors were asked about. Furthermore, the survey collected information on scientists' characteristics regarding their socio-demographic situation, their research activity and their working conditions. The items had been discussed with colleagues specialized in research commercialization and practitioners from technology transfer offices. Subsequently, a pre-test of the survey was conducted in a comparable German state with a random sample of scientists, as suggested by Sue and Ritter (2007).

In addition to the survey data, data from secondary sources provides further information about the individual scientists and the universities. First, I collected data on the respondents' publication records from Web of Science (WoS) and Scopus.[7] Second, data was collected on the third-party funding of each university which is provided by the German Ministry for Science and Education.

4.3.2 Empirical specification

To answer the research question and test the hypotheses I estimate a multinomial logistic regression that relates the probability of scientist i belonging to the profile j to the measures for the scientist's forms of social capital and to a set of control variables. The equation is defined as:

$$\Pr\left(y_i = j \mid x_i\right) = \frac{\exp\left(x_i \beta_i\right)}{\sum_{j=1}^{M} \exp\left(x_i \beta_i\right)} \tag{4.1}$$

where $j = 1, \ldots 4$ captures the profiles (Normal scientist, Star scientist, Ambidextrous scientist and Ambidextrous star scientist). $\Pr\left(y_i = j \mid x_i\right)$ is the probability that scientist i is in the profile j, given x_i, whereby x_i is a vector of characteristics of individual i capturing the forms of social capital as well as control variables, and $_j$ is the vector of coefficients pertaining to scientist

[7]The primary source for publication data is WoS. If there was no publication record in WoS for a respondent, Scopus was used which has a larger coverage for some disciplines esp. for social sciences and humanities (Martín-Martín et al., 2021). If, again, there were no publications listed in Scopus, I assumed zero publications, which is especially plausible for PhD researchers at the beginning of their academic careers.

profile j. The forms of social capital are assumed to impact $\Pr(y_i = j \mid x_i)$ by either facilitating research performance, research ambidexterity or both.

4.3.3 Measures

Operationalization of the dependent variable

To contrast the two goals scientists are required to achieve, research performance and research commercialization were independently quantified. As Lin and Bozeman (2006) have noted, there is no standardized way of measuring research performance. The most conventional way to quantify scientists' research performance is by the impact of their published papers in terms of citations (D'Este, Mahdi, et al., 2012; D'Este et al., 2019; Ding & Choi, 2011). In this study, research performance is quantified by the research impact index provided by Olmos-Peñuela et al. (2014). It measures the impact of each individual scientist by the average number of citations per year and publication.[8] The exposure of a scientist's research performance is captured by a 5-years time-span (2015-2019) instead of a cumulative measure referring to research performance along the scientist's career. This period is chosen to contrast research performance with research commercialization within the same time. Consequently, for each publication, the number of citations is divided by the number of years since publication until 2019, taking into account only those publications that fall within the selected time period. The formula is defined as follows:

Research impact index

$$= \frac{\sum_{i=1}^{N} (\text{number of citations}_i) \,/\, ([2020 - \text{publication year}]_i)}{\text{number of publications } (N)} \tag{4.2}$$

In order to avoid distortions in performance rankings, Abramo et al. (2008) recommend to compare only scientists within the same discipline since publication and citation behavior differs substantially between disciplines. Thus, scientists are assigned to seven broader disciplines: *Computer Science*

[8] In doing so, I considered published articles, proceedings and conference papers, as well as books and book chapters, in order to take into account the different publication patterns of all disciplines (Abramo et al., 2008).

and Mathematics, *Engineering*, *Humanities*, *Life Sciences*, *Medicine*, *Physics and Chemistry* and *Social Sciences*. For each discipline the average research impact index was calculated, reflecting the threshold of the dichotomous variable distinguishing between high and low research performance.

The prevalence of scientists' research commercialization was identified by the combination of two survey items. Survey participants were asked to indicate (1) how many spin-offs they created and (2) how many ideas or inventions that can be attributed to potential commercial exploitation or legally protected, they disclosed to their employers between 2015 and 2019. Based on their response, a dichotomous variable was created. If they indicated a spin-off creation, or disclosure of an IPR to the employer, or both, the variable turns 1 and 0 otherwise (Ambos et al., 2008).[9]

The four configurations that correspond to the four scientist profiles were outlined by combining the two dichotomous variables for goal achievement of research performance and research commercialization in the following manner:

- Normal scientists: low research performance with no commercialized research results;
- Star scientists: high research performance with no commercialized research results;
- Ambidextrous scientists: low research performance with commercialized research results;
- Ambidextrous star scientists: high research performance with commercialized research results.

Operationalization of the explanatory variables

To understand the impact of social capital on the probability of a scientist to belong to one of the four profiles, one proxy is used for each of the forms of bonding, bridging and linking social capital. To capture bonding

[9] Determining the threshold between low and high research commercialization by using the average would result in the same split, as the average number of research commercializations by a scientist is 0.42.

social capital I operationalize the number of unique *Co-authors* a scientist worked within the considered time period. This is to map the ties to actors with similar social identity, norms, and common goal pursuit, namely that of generating impactful research output. Drawing on the total number of unique co-authors a scientist has published with is a general measure for their academic network (Ding & Choi, 2011) and thus, a suitable proxy for the degree of their bonding social capital. The variable is log-transformed to account for its right-skewed distribution. It enters the estimation as a linear term as well as a quadratic term. The latter is used to identify the assumed inverted U-shaped relationship discussed in 4.2.3. Bridging social capital is proxied by the number of *S-I collaborations* the scientist was involved in during the considered time-span, also log-transformed because of right-skewedness. It reflects the intensity of bridge building to the industry characterized by different norms and goals of the actors. This variable can be employed to capture the scientist's experience and knowledge exchange with industry in the form of their bridging social capital (D'Este, Mahdi, et al., 2012). For linking social capital, data on the universities' third-party funding structures were obtained. The share of *Industry funding* in total third-party funding is calculated and reflects the institutional environment of an entrepreneurial university linking to industry (Etzkowitz, 1998) which enables scientists' interactions with industry actors (Boardman, 2009). The share of third-party funding from industry is used as a proxy for how strongly scientists' universities link to the industrial external network relative to other external sources.

Control variables

In addition to the measures for social capital, several control variables enter the model that can influence the probability of scientists belonging to one of the profiles. First, to control for scientists' orientations towards *Applied research*, following Amara et al. (2019), they were asked to "assess the extent to which [... their] research is targeted towards practical application". The variables were assessed on a 4-point Likert scale, ranging from "not at all" to "a lot". The reason to control for that is because scientists with a stronger orientation towards applied research are more likely to produce industrial applications (Calderini et al., 2007), which should be a supportive factor for research ambidexterity. Second, in addition to research and commercialization, most university scientists also have teaching as a third pillar to serve, which in turn can affect individual resource availability for the other two goals (Landry et al., 2010; Reymert & Thune, 2023). Therefore, to control for teaching workload, respondents indicated what percentage of their working time is devoted to teaching activities. Third, I control for differences in academic rank by a dummy variable distinguishing between *Professor (=1)* and scientists of other rank in the science system such as post-docs, Phd students, ... (Perkmann et al., 2021).[10] Fourth, to take into account the strong gender gap identified in the literature regarding research performance (see, e.g. Mayer & Rathmann, 2018; Stack, 2004) and research ambidexterity (see, e.g. Abreu & Grinevich, 2017; Tartari & Salter, 2015), I control for scientists' gender and distinguish between *Female (=1)* and others. While differences in research disciplines are already accounted for in the distinction along the quadrant between high and low research performance, there are also differences in terms of their propensity to commercialize research results (see, e.g. Abreu & Grinevich, 2013; Perkmann et al., 2011). There are some disciplines facing higher tensions with regard to the fulfilment of research commercialization (Kalar & Antoncic, 2015; Philpott et al., 2011). Thus, the same seven broader disciplines, previously used for the disciplinary average of research impact, are consulted to take these differences into account. Finally, a dummy variable called *University of applied sciences (=1)* accounts for whether the university to which a scientist belongs to is of such a type or not. An overview of the construction of each variable is presented in Table 4.5 in the Appendix.

4.4 Results

4.4.1 Descriptive results

An overview of the shares of scientists who outperform, underperform, commercialize, or do not commercialize within their discipline is provided in

[10] I treat junior professors equally to full professors.

Table 4.2. It shows how many scientists per discipline are represented in the sample, the discipline's specific threshold for high research performance and the prevalence of commercialized research results within that discipline. The largest group are scientists from the Social Sciences, followed by Engineers, while those from the Life Sciences are the least frequently observed. The heterogeneous citation patterns among disciplines become apparent when examining the average number of citations per year and publication for each discipline. On average, scientists from Life Sciences, Medicine, Physics and Chemistry receive more than two citations per year and publication while the value is smaller than one for the Humanities and Social Sciences. Considering the distinction between high and low research performance, overall, 31.6% (334 of 1,057 observations) are highly performing scientists with those from Physics and Chemistry showing the greatest share of high-performers among their disciplinary peers, followed by scientists from Life Sciences, Computer Science and Mathematics. Turning to research commercialization, only 16.1% of all scientists in the sample have commercialized research results in the considered five-year time span. The discipline with the highest share of commercializing scientists among their disciplinary peers is Computer Science and Mathematics, followed by scientists from Engineering as well as those from Physics and Chemistry. Not surprisingly, scientists from the Social Sciences and Humanities have a relatively low share of commercializing scientists among their disciplinary peers. The share of high performing scientists from Life Sciences is relatively high but, surprisingly, they yield the lowest share of commercialzing scientists.

The distribution of scientists in the sample, across the four quadrants that correspond to the four profiles of the dependent variable, is presented in ascending order in Table 4.3. With 6.52% (69 of 1,057 observations) ambidextrous star scientists, simultaneously outperforming in research and commercializing their results, constitute the smallest group. They are followed by ambidextrous scientists with a low research performance but commercialized research results with 9.56% (101 of 1,057 observations) and star scientists with a high research performance but no commercialization to be reported with 25.07% (265 of 1,057). The largest group with 58.85% (622 of 1,057 observations) are the normal scientists showing a low research performance and no commercialized research results. When looking at the mean values of the measures for the different forms of scientists' social capital, one can already deduce tendencies with regards to their impact on profile affiliation. On average an ambidextrous star scientist as well as a star scientist exhibits a greater bonding social capital in terms of unique co-authors compared to the average ambidextrous or normal scientist. In a similar vein, regarding bridging social capital, an average ambidextrous star and ambidextrous scientist has been involved in more S-I collaborations compared to the other two profiles. Likewise, linking social capital, captured by industry funding, is also on average more pronounced for those profiles with ambidextrous behavior. Considering the control variables, the scientist profiles with the highest orientation towards applied research are those with commercialized research results. Ambidextrous star scientists, on average, have a lower teaching workload than scientists of the remaining profiles. Furthermore, one can elicit that the highest share of professors (35%) is in the profile of ambidextrous star scientists while at the same time this profile shows the least female scientists. 70% of the ambidextrous stars are from the disciplines of *Computer Science and Mathematics*, *Engineering* and *Physics and Chemistry*.

Table 4.2: Research performance and research commercialization by discipline

		Performance					Commercialization			
	obs	average	below	%	above	%	no	%	yes	%
Computer Science and Mathematics	144	1.07	91	63.2	53	36.8	105	72.9	39	27.1
Engineering	173	0.65	125	72.3	48	27.7	130	75.1	43	24.9
Humanities	102	0.17	88	86.3	14	13.7	92	90.2	10	9.8
Life Sciences	87	2.83	54	62.1	33	37.9	80	92.0	7	8.0
Medicine	129	2.72	83	64.3	46	35.7	112	86.8	17	13.2
Physics and Chemistry	150	2.97	91	60.7	59	39.3	119	79.3	31	20.7
Social Sciences	272	0.75	191	70.2	81	29.8	249	91.5	23	8.5
All disciplines	1.057		723	68.4	334	31.6	887	83.9	170	16.1

Table 4.3: Descriptive statistics for the four profiles

	Ambidextrous star				Ambidextrous				Star				Normal			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Co-authors (log)	3.70	1.34	1.10	6.90	1.23	1.63	0	5.40	3.21	1.22	1.10	7.60	0.96	1.38	0	6.20
S-I collaborations (log)	1.05	0.86	0	2.80	0.93	0.82	0	2.80	0.34	0.53	0	2.80	0.25	0.48	0	2.80
Industry funding	0.17	0.12	0	1	0.15	0.11	0	1	0.15	0.08	0	1	0.14	0.10	0	1
Applied research	3.06	0.75	1	4	3.24	0.74	1	4	2.52	0.71	1	4	2.69	0.88	1	4
Teaching workload	20.83	17.67	0	90	25.74	21.85	0	100	24.28	17.90	0	80	27.83	24.38	0	100
Professor (=1)	0.35	0.48	0	1	0.29	0.45	0	1	0.25	0.43	0	1	0.16	0.37	0	1
Female (=1)	0.23	0.43	0	1	0.26	0.44	0	1	0.34	0.48	0	1	0.42	0.49	0	1
Discipline: Computer Science and Mathematics	0.20	0.41	0	1	0.25	0.43	0	1	0.15	0.35	0	1	0.11	0.31	0	1
Discipline: Engineering	0.30	0.46	0	1	0.22	0.41	0	1	0.10	0.30	0	1	0.17	0.37	0	1
Discipline: Humanities	0.04	0.21	0	1	0.07	0.26	0	1	0.04	0.20	0	1	0.13	0.34	0	1
Discipline: Life Sciences	0.03	0.17	0	1	0.05	0.22	0	1	0.12	0.32	0	1	0.08	0.27	0	1
Discipline: Medicine	0.13	0.34	0	1	0.08	0.27	0	1	0.14	0.35	0	1	0.12	0.33	0	1
Discipline: Physics and Chemistry	0.20	0.41	0	1	0.17	0.38	0	1	0.17	0.38	0	1	0.12	0.32	0	1
Discipline: Social Sciences	0.09	0.28	0	1	0.17	0.38	0	1	0.28	0.45	0	1	0.28	0.45	0	1
University of Applied Sciences (=1)	0.28	0.45	0	1	0.30	0.46	0	1	0.14	0.35	0	1	0.29	0.45	0	1
N	69				101				265				622			
Share	6.52%				9.56%				25.07%				58.85%			

4.4.2 Regression results

The results of the empirical analysis are presented in Table 4.4. For the multinomial logit estimation the profile of normal scientists is chosen to be the reference category. The estimates of the remaining profiles are in columns 1-3. First, turning the attention to the impact of scientists' bonding social capital on their profile affiliation, the results show a positive and significant influence of scientists' bonding social capital, in terms of the number of their unique *Co-authors*, on the probability to be in the profile of a star scientist instead of a normal scientist. This result supports hypothesis 1a stating a positive correlation between scientists' bonding social capital and the probability to be a star scientist compared to the baseline profile. The same relationship can be elicited for ambidextrous stars. Bonding social capital also significantly increases the likelihood to be a scientist of this profile instead of being a normal scientist. This gives support for hypothesis 1b.

Regarding the impact of scientists' bridging social capital on their profile affiliation the coefficient for *S-I collaboration* in column 2, which captures the group of ambidextrous scientists, is positive and statistically significant. This provides support in favor of hypothesis 2a, assuming a positive impact of scientists' bridging social capital on the probability to be an ambidextrous scientist compared to the baseline profile. The third column represents ambidextrous stars and also shows a positive and significant correlation of scientists' bridging social capital to the likelihood of belonging to this profile instead of being a normal scientist, which supports hypothesis 2b.

With regard to linking social capital and its influence on being an ambidextrous scientist, column 2 shows a positive and significant correlation between *Industry funding*, the proxy for this form of social capital, and the dependent variable. This supports hypothesis 3a, stating a positive impact of scientists' linking social capital on the probability to be an ambidextrous scientist. Linking social capital also positively impacts the likelihood to be an ambidextrous star instead of being a normal scientist. This is apparent due to the statistically significant coefficient of industry funding in column 3 supporting hypothesis 3b.

Finally, the coefficient of the quadratic term for bonding social capital should provide information on whether an inverted U-shaped relationship prevails and an excess of this form of social capital can turn into a negative effect. Indeed, a strong bonding social capital translates into a negative impact on research performance and reduces the likelihood of being in the star scientist's profile. This is evident from the negative and statistically significant coefficient of *squared co-authors* and, thus, supports hypothesis 4a. According to the estimated curve, the number of unique co-authors that would result in the highest probability to be a star scientist is 177.11.[11] Thus, in the range of 0–177, increasing the number of unique co-authors results in a higher probability to be a star scientist, but beyond that threshold a higher bonding social capital is associated with a decreasing probability. In the same vein, this coefficient is also negatively significant in the third column and reveals an inverted U-shaped relationship between bonding social capital and the likelihood to be an ambidextrous star with the turning point at 279.38 co-authors. This result provides support for hypothesis 4b.

In addition, the control variables reveal some further notable results. A research orientation towards applied research increases the probability to be an ambidextrous scientist as well as to be an ambidextrous star. Being a professor facilitates the probability to be an ambidextrous scientist, with female scientists less likely to belong to this profile. Scientists working at a university of applied sciences are more likely to be ambidextrous stars. The adjusted R^2 is at 0.3662 and indicates a good model fit (McFadden, 1974).

4.4.3 Robustness tests

Two additional multinomial regressions are conducted to test for the robustness of the results. First, a subsample analysis is performed, which excludes scientists from the Humanities and Social Sciences since they can have substantially different preconditions for research commercialization. Second, a stricter threshold for the classification into high and low research performance is used to check the robustness of the results with respect to the determination of this threshold.

[11] This is the antilog of x satisfying the first order condition of the maximization problem for being a star scientist, i.e., $x^{\star} = \beta_{[}coauthors] / \left[-2 * \beta_{[}coauthors^2]\right]$. This turning point falls within the data range (0 – 1,928).

Table 4.4: Multinomial logistic regression on scientist profiles

	Categories of dependent variable:		
	Star	Ambidextrous	Ambidextrous Star
Bonding Social Capital			
Co-authors (log)	3.075***	-0.205	3.526***
	(0.254)	(0.194)	(0.476)
Co-authors (log)^2	-0.297***	0.037	-0.313***
	(0.041)	(0.036)	(0.061)
Bridging Social Capital			
S-I collaborations (log)	-0.003	1.395***	0.942***
	(0.202)	(0.203)	(0.250)
Linking Social Capital			
Industry funding	1.871	1.954*	5.040***
	(1.559)	(1.023)	(1.362)
Control variables			
Applied research	-0.028	0.548***	0.580**
	(0.135)	(0.159)	(0.258)
Teaching workload	-0.003	-0.001	-0.019
	(0.006)	(0.007)	(0.012)
Professor (=1)	0.071	0.549*	0.585
	(0.247)	(0.326)	(0.434)
Female (=1)	0.150	-0.519*	-0.053
	(0.217)	(0.273)	(0.397)
Discipline: Engineering	0.100	-0.644	0.676
	(0.439)	(0.435)	(0.633)
Discipline: Humanities	1.659***	-0.373	2.596***
	(0.486)	(0.497)	(0.899)
Discipline: Life Sciences	-0.781*	-0.693	-1.839**
	(0.474)	(0.610)	(0.913)
Discipline: Medicine	-1.946***	-1.007*	-2.626***
	(0.430)	(0.523)	(0.665)
Discipline: Physics and Chemistry	-0.922**	-0.095	-0.795
	(0.361)	(0.419)	(0.567)
Discipline: Social Sciences	1.290***	-0.874**	0.401
	(0.368)	(0.394)	(0.680)
Univ. of Applied Sciences (=1)	0.367	-0.374	1.027**
	(0.354)	(0.385)	(0.516)
Constant	-5.894***	-3.655***	-11.142***
	(0.675)	(0.646)	(1.334)
N		1,057	
Wald Chi^2		484.86	
Adj. R^2		0.3662	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference category for disciplines: Computer Science and Mathematics

With regard to the first robustness test, scientists from social sciences and humanities are excluded, leaving a subsample of 683 observations (see Table 4.7 in the Appendix). The reason is to adjust for potential differences in industrial applicability of knowledge within the academic disciplines. Scientists in these disciplines are predominantly engaged in activities with no direct commercial output such as consultancy or training (Olmos-Peñuela et al., 2014). The ensuing results are very similar compared to the main model. The proxy for linking social capital, *Industry funding*, is not a driver for being an ambidextrous scientist anymore but, surprisingly, for being a star scientist.

In the second robustness test the upper quartile of all scientists' citations per year and publication in the respective discipline are used as the threshold to determine whether a scientist is a high or low performer (see Table 4.9 in the Appendix). It is a stricter threshold compared to the mean taken for the construction of the dependent variable in the main model. It leads to a new distribution of scientists' profile affiliations with 4.54% being ambidextrous stars, 11.54% as ambidextrous scientists, 19.77% belonging to the profile of a star scientist and 64.14% normal scientists (see 4.8). The results are again very similar to the main model, except for *Industry funding*, which does not significantly facilitate being an ambidextrous star anymore and, thus, reduces the support for hypothesis 3a.

4.5 Discussion and conclusion

Scientists at universities are increasingly confronted with the necessity to achieve multiple goals at the same time. In addition to a high research performance as the driver of their own academic career, they are also expected to commercialize their research results. University scientists are heterogeneous, which is made obvious not only but also when it comes to meeting these goals. Thus, on the one hand, there is the desire to be a prolific scientist, and on the other hand, there is the commercial exploitation of research results. The latter is frequently coined as research ambidexterity, which describes when scientists have to deal with tensions, adapt to a different role and renew their knowledge so they are able to simultaneously achieve research publication and research commercialization (Chang et al., 2016; Mom et al., 2009). While scholars so far have characterized scientists by their research orientation (Stokes, 1997), their orientation towards university-industry connections (Lam, 2010) or their collaboration strategies (Bozeman & Corley, 2004), this study conceptualizes scientist profiles by contrasting their goal achievement regarding research performance and research commercialization. Four profiles are derived based on scientists' citations per year and publication and the prevalence of commercialized research results: normal scientists with a low research performance and no commercialized research results, star scientists with a high research performance but without commercialized results, ambidextrous scientists with a low research performance but with commercialized results and ambidextrous stars with both, a high research performance and commercialized results. In addition, social capital theory is applied to explain which form of social capital positively influences the achievement of these goals and consequently affects scientists' profile affiliation. Three forms of social capital are defined (Granovetter, 1973; Putnam, 2001; Szreter & Woolcock, 2004) and applied to the university context: bonding social capital as the ties to other scientists, bridging social capital as the ties to the industry and linking social capital as the boundary-spanning activity of the scientists' universities.

Based on this conceptualization of scientist profiles and the theoretical background of social capital, hypotheses are derived to explain how different forms of social capital affect scientists' multiple goals achievement. It is assumed that scientists' bonding social capital positively influences their research performance which increases their likelihood of being a star or ambidextrous star. In addition, scientists' bridging and linking social capital should have a positive impact on their research commercialization and thus increase the probability of belonging to the profile of ambidextrous scientists or ambidextrous stars. Furthermore, it was examined whether the potential negative effect of excessive bonding social capital mentioned in social capital theory can be identified in the context of an inverted U-shaped relationship between this form of scientists' social capital and their profile affiliation. To test these hypotheses, a novel representative survey of scientists in the German state of Thuringia was conducted and combined with data on respondents' publication records as well as on the universities' funding structures. A multinomial logistic regression model was applied to estimate the effect of social capital forms on scientists' profiles.

The descriptive results show that there is a great variety in research performance and commercialization behavior between disciplines. Scientists from Computer Science, Mathematics, Engineering, Physics and Chemistry excel through a relatively high average research performance and a high share of commercializing scientists. Across all disciplines, 16.1% report commercialized research results, a ratio which is in line with previous findings in this field (Abreu & Grinevich, 2013; D'Este et al., 2019; Landry et al., 2010; Llopis et al., 2018). The same applies to the share of those scientists who perform at a high level (31.6%) measured by the average citations per year and publication (Olmos-Peñuela et al., 2014). Regarding scientists' profiles only 6.52% of the scientists can be categorized into the profile of ambidextrous stars achieving both goals. Slightly more, 9.56%, are ambidextrous scientists with commercialized research results but a low research performance, while 25.07% are stars with no commercialization. The remaining normal scientists make up 58.85%.

The regression results support the hypotheses of a positive relationship between scientists' bonding social capital and the probability to be a high research performer in the profile of a star scientist as well as in the one of ambidextrous star. The opportunity to access a larger network of peers who share the same academic goals provides competitive advantages in the competition for publications and citations (Hessels et al., 2019; van Rijnsoever et al., 2008). Regarding the hypothesized positive association between bridging social capital and scientists being ambidextrous as well as being ambidextrous stars, the results indicate support in favor of this relationship. This relationship points to the importance of contacts to the industrial sector for the successful conversion of generated knowledge into commercializable products and services, and the accompanying necessary information and skills along this process (Cantner et al., 2023; Dolmans et al., 2022; Sousa-Ginel et al., 2021). The same holds true for linking social capital and ambidextrous scientists as well as ambidextrous stars indicating a supportive mechanism of universities as boundary spanners between academia and industry (Chau et al., 2017; Slavtchev & Göktepe-Hultén, 2016). These results emphasize the advantage of access to different networks in the achievement of multiple goals such as high research performances and research commercialization (Hayter, 2016b; van Rijnsoever et al., 2008). However, an inverted U-shaped relationship between the number of unique co-authors and the scientist profiles of stars and ambidextrous stars is identified, indicating a disadvantageous effect for excessive bonding of scientists to their scientific peers. The finding of this relationship is in line with previous social capital research and highlights the potential overabundance of redundant information within a cohesive network and a declining value of bonding social capital as a resource for high research performance (Boschma, 2005; Portes, 1998; ter Wal et al., 2016).

Besides the main findings supporting the hypotheses, the results also provide additional interesting insights considering the control variables. Scientists with a stronger orientation towards applied research are more likely to be ambidextrous scientists and ambidextrous stars, which is in line with their higher propensity to generate knowledge relevant for industrial application (Amara et al., 2019; Calderini et al., 2007). It turns out that professorship is a relatively good predictor for being an ambidextrous scientist. Contrary to that, female scientists have a significant disadvantage to belong to this profile, highlighting the striking gender disparities in research commercialization (Abreu & Grinevich, 2017; Tartari & Salter, 2015). The results are considerably robust with regard to a subsample analysis excluding scientists from Social Sciences and Humanities as well as to a stricter threshold for the classification into high and low research performance.

This study contributes to the understanding of how scientists manage to achieve multiple and tension-filled goals by contrasting scientists' research performance with research commercialization. Therefore, a typology of scientists is conceptualized characterizing them through the achievement of these goals. While existing research has so far focused on one of these goals (e.g. Broström, 2019; Chang et al., 2016), this study considers the achievement of both goals at the same time and sheds light on this conflicting challenge for scientists. Additionally, the study provides first insights into the importance of different forms of social capital in the university context by defining scientists bonding, bridging and linking social capital and how these forms of social capital determine research performances and research commercialization (Granovetter, 1973; Putnam, 2001; Szreter & Woolcock, 2004). The results regarding the impact of bonding social capital underline the positive impact of ties to scientific peers but also reveal that this relationship can turn into a disadvantageous effect on being a star and ambidextrous star (Banal-Estañol et al., 2015; van Rijnsoever et al., 2008). The identified relationship between bridging and linking social capital with scientists' goals contributes to the growing literature highlighting the advantages of a hybridization of the academic and commercial system (Owen-Smith, 2003). According to this stream of literature, universities are well advised to create hybrid spaces where multiple logics can prevail so that academic and commercial logics can co-exist (Cantner et al., 2023; Perkmann et al., 2019; Sauermann & Stephan, 2013). Such spaces, in turn, allow the individual scientist to adopt a hybrid role identity and to be both an academic and a commercially-oriented actor at the same time (Jain et al., 2009; Lam, 2010; 2011). This study extends this avenue of research, suggesting a hybrid social capital of scientists consisting of different forms that can serve to achieve multiple goals.

The findings can also be used to derive implications for policy makers and university management to foster multiple goal achievement by scientists. First, since connections between actors within science can facilitate their research performance, policy makers and universities should try to foster collaborative research through incentives such as funding programs for joint research projects and financial support for networking activities, such as conferences. Second, ties between scientists and industry actors should be leveraged to increase scientists' bridging social capital and, thus, increases their propensity to commercialize research results. For this purpose, policy makers can also set up support programs which promote joint projects with industry actors to a greater extent. On the part of university managers, the visibility of outstanding scientists could be promoted in order to draw the attention of interested companies to the scientists' competencies and to reward collaborations between them. Universities should create various accesses to the industry to link the academic environment of its employees with the commercial sector.

The study is subject to several limitations which can be taken up for further research. First, measuring the various forms of scientists' social capital might not capture all facets of contacts and connections (Kawachi et al., 2004). An extension of proxies for bonding social capital could also be relationships with former colleagues or acquaintances through research stays, while informal contacts to industry through meetings at university and non-university events could enrich scientists' bridging social capital. Second, another goal is of high relevance among university scientists and that is the production of human capital through teaching activities (Fromhold-Eisebith & Werker, 2013). Quantifying teaching output at the individual level may be a difficult task, but future typologies of scientists along their multiple goal achievement should take such activities into account (Reymert & Thune, 2023). Third, no qualitative measurement of the ties among the different forms of social capital is made. The scientific quality of the co-authors or the commercial success of the firms to which the scientist is related could have a different impact on the goals pursued by the scientist, which could be accounted for in future analyses of this kind.

Besides these limitations, further research on scientist profiles should take into account additional outreach activities which are not related to commercialization in the industrial context, such as the societal engagement of scientists (Benneworth & Cunha, 2015; Bornmann, 2013; Fini et al., 2018) for which bridging social capital, captured by contacts to society or involvement in citizen sciences, might be of interest (Franzoni & Sauermann, 2014). In addition, the field of quantitative and qualitative network analyses offers a wide range of research possibilities through which the network structures of the different forms of scientists' social capital can be further illuminated.

4.6 Appendix

4.6.1 Variable construction

Table 4.5: List of variables and their construction.

Variable	**Construction**	**Data type**
Dependent variable		
Scientist profiles	Quadrant model contrasting 1: Research performance & 2: Research ambidexterity 1: Research impact index: Average number of citations per year and publication (Olmos-Peñuela et al., 2014) (Data collected from Web of Science and Scopus) 2: Commercialization of research results (yes/no) (Survey items: *Disclosure of an idea or invention (that can be attributed to potential commercial exploitation or can be legally protected) to the employer* & *Completed foundation of a firm, i.e. the launch of business activities.*)	Categorical
Bonding social capital		
Co-authors	Number of unique co-authors	Numerical
Bridging social capital		
S-I collaborations	Survey item: *Realisation or participation in a research cooperation with company participation.*	Numerical
Linking social capital		
Industry funding	University's share of third-party funding from industry	Numerical
Control variables		
Applied research	Survey item: *Please assess the extent to which your research is targeted towards practical application.* (4-point Likert-scale: "Not at all" to "To a large extent")	Numerical
Teaching workload	Survey item: *How was your scientific working time distributed on average during the last 5 years over the following activities?* (in %; for the activity "Teaching")	Numerical
Professor (=1)	Survey item: *Which of the following options describes your current position best?*	Binary
Female (=1)	Survey item: *Please indicate your gender.*	Binary
Discipline	Data collected from participants webpages.	Categorical
Uni. of Applied Sciences (=1)	Distinction of organizations between 1=University of Applied Sciences & 0=Traditional University	Binary

4.6.2 Additional descriptive statistics

Table 4.6: Descriptive statistics of complete sample

	mean	sd	min	max
Co-authors (log)	1.73	1.74	0	7.60
S-I collaborations (log)	0.39	0.62	0	2.80
Industry funding	0.14	0.10	0	1
Applied research	2.73	0.85	1	4
Teaching workload	26.28	22.34	0	100
Professor (=1)	0.21	0.41	0	1
Female (=1)	0.38	0.48	0	1
Discipline: Computer Science and Mathematics	0.14	0.34	0	1
Discipline: Engineering	0.16	0.37	0	1
Discipline: Humanities	0.10	0.30	0	1
Discipline: Life Sciences	0.08	0.27	0	1
Discipline: Medicine	0.12	0.33	0	1
Discipline: Physics and Chemistry	0.14	0.35	0	1
Discipline: Social Sciences	0.26	0.44	0	1
University of Applied Sciences (=1)	0.25	0.43	0	1
N		1,057		

4.6.3 Robustness tests

Table 4.7: Multinomial logistic regression on scientist profiles with sub-sample excluding scientists from Social Sciences and Humanities.

	Categories of dependent variable:		
	Star	Ambidextrous	Ambidextrous Star
Bonding Social Capital			
Co-authors (log)	2.482***	-0.084	3.389***
	(0.287)	(0.221)	(0.625)
Co-authors (log)^2	-0.225***	0.010	-0.299***
	(0.043)	(0.043)	(0.076)
Bridging Social Capital			
S-I collaborations (log)	-0.028	1.259***	0.820***
	(0.204)	(0.220)	(0.263)
Linking Social Capital			
Industry funding	4.024***	1.650	4.501**
	(1.363)	(1.617)	(2.052)
Control variables			
Applied research	-0.019	0.474**	0.421
	(0.161)	(0.188)	(0.265)
Teaching workload	-0.008	-0.005	-0.026**
	(0.006)	(0.008)	(0.013)
Professor (=1)	0.059	0.910**	0.905*
	(0.323)	(0.436)	(0.485)
Female (=1)	-0.122	-0.896**	-0.065
	(0.257)	(0.350)	(0.428)
Discipline: Engineering	-0.287	-0.409	0.551
	(0.464)	(0.468)	(0.663)
Discipline: Life Sciences	-0.544	-0.669	-2.058**
	(0.456)	(0.600)	(0.908)
Discipline: Medicine	-1.956***	-0.870	-2.628***
	(0.423)	(0.536)	(0.678)
Discipline: Physics and Chemistry	-0.735**	-0.136	-0.907
	(0.349)	(0.414)	(0.576)
Univ. of Applied Sciences (=1)	0.889*	-0.616	1.155*
	(0.501)	(0.517)	(0.690)
Constant	-5.077***	-3.211***	-10.113***
	(0.757)	(0.782)	(1.632)
N		683	
Wald Chi^2		282.29	
Adj. R^2		0.3058	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference category for disciplines: Computer Science and Mathematics

Table 4.8: Distribution of scientists across the four quadrants with stricter threshold

Profiles	N	%
Ambidextrous star	48	4.54
Ambidextrous	122	11.54
Star	209	19.77
Normal	678	64.14

Table 4.9: Multinomial logistic regression on scientist profiles with stricter threshold for high research performance.

	Categories of dependent variable:		
	Star	Ambidextrous	Ambidextrous Star
Bonding Social Capital			
Co-authors (log)	3.102***	-0.049	3.613***
	(0.313)	(0.181)	(0.601)
Co-authors $(\log)^2$	-0.319***	0.016	-0.309***
	(0.051)	(0.034)	(0.080)
Bridging Social Capital			
S-I collaborations (log)	-0.146	1.224***	1.064***
	(0.208)	(0.185)	(0.279)
Linking Social Capital			
Industry funding	1.056	2.200**	2.670
	(2.223)	(0.976)	(2.352)
Control variables			
Applied research	0.030	0.559***	0.562**
	(0.135)	(0.154)	(0.271)
Teaching workload	-0.003	-0.002	-0.025*
	(0.006)	(0.006)	(0.014)
Professor (=1)	0.024	0.651**	0.207
	(0.241)	(0.306)	(0.505)
Female (=1)	0.137	-0.416*	-0.280
	(0.217)	(0.250)	(0.484)
Discipline: Engineering	0.826*	-0.428	1.408**
	(0.445)	(0.421)	(0.715)
Discipline: Humanities	3.282***	-0.281	4.410***
	(0.545)	(0.495)	(1.066)
Discipline: Life Sciences	-0.687	-0.526	-14.918***
	(0.447)	(0.546)	(0.674)
Discipline: Medicine	-1.491***	-0.965**	-2.042***
	(0.462)	(0.473)	(0.785)
Discipline: Physics and Chemistry	-0.837**	-0.055	-1.005
	(0.384)	(0.375)	(0.681)
Discipline: Social Sciences	1.438***	-0.774**	0.565
	(0.364)	(0.369)	(0.860)
Univ. of Applied Sciences (=1)	0.170	-0.373	1.109*
	(0.339)	(0.373)	(0.587)
Constant	-6.571***	-3.784***	-12.090***
	(0.762)	(0.625)	(1.743)
N		1,057	
Wald Chi^2		3580.00	
Adj. R^2		0.3250	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reference category for disciplines: Computer Science and Mathematics

4.7 Supplementary material

4.7.1 Non-response analysis and sample representativeness

Table 4.10: Non-response analysis.

Variable	Surveyed	Response	Sample	Difference
Professor (=1)	0.20	0.21	0.21	-0.014
Female (=1)	0.37	0.38	0.38	-0.001
Computer Science and Mathematics	0.12	0.13	0.14	-0.018*
Engineering	0.14	0.16	0.16	-0.019
Humanities	0.13	0.10	0.10	0.032***
Life Science	0.06	0.08	0.08	-0.019**
Medicine	0.23	0.12	0.12	0.108***
PhysicsnChemistry	0.13	0.14	0.14	-0.013
Social Sciences	0.19	0.26	0.26	-0.071***
N	6,301	1,072	1.057	

Note: Group comparison based on Wilcoxon rank-sum tests.
Significance levels at *** p<0.01, ** p<0.05, * p<0.1.

Table 4.11: Representativeness.

Variable	Germany	Sample
Professor (=1)	0.19	0.21
Female (=1)	0.40	0.38

Data for the overall population of scientists at universities in Germany is taken from (Statistisches Bundesamt, 2020).

4.7.2 Correlation table

Table 4.12: Pearson correlation coefficients (N=1,057).

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Co-authors (log)														
2	S-I collaborations (log)	0.20***													
3	Industry funding	0.17***	0.00												
4	Applied research	-0.09***	0.29***	0.02											
5	Teaching workload	-0.16***	-0.06*	-0.08**	-0.07**										
6	Professor (=1)	0.14***	0.11***	0.01	0.06**	0.29***									
7	Female (=1)	-0.11***	-0.08**	-0.01	-0.02	-0.07**	-0.13***								
8	Discipline: Computer Science and Mathematics	0.05	0.14***	0.04	0.10***	-0.03	-0.03	-0.15***							
9	Discipline: Engineering	-0.13***	0.21***	0.04	0.18***	0.07**	0.00	-0.06**	-0.18***						
10	Discipline: Humanities	-0.24***	-0.16***	-0.19***	-0.07**	0.07**	0.03	0.09***	-0.13***	-0.14***					
11	Discipline: Life Sciences	0.12***	-0.06**	-0.09***	-0.15***	-0.08***	-0.04	0.07**	-0.12***	-0.13***	-0.10***				
12	Discipline: Medicine	0.27***	-0.01	0.42***	0.00	-0.14***	-0.04	0.13***	-0.15***	-0.16***	-0.12***	-0.11***			
13	Discipline: Physics and Chemistry	0.22***	0.05	-0.11***	-0.06**	-0.14***	-0.08**	-0.07**	-0.16***	-0.18***	-0.13***	-0.12***	-0.15***		
14	Discipline: Social Sciences	-0.23***	-0.17***	-0.11***	-0.04	0.19***	0.12***	0.03	-0.23***	-0.26***	-0.19***	-0.18***	-0.22***	-0.24***	
15	University of Applied Sciences (=1)	-0.29***	0.08***	-0.06*	0.16***	0.28***	0.15***	-0.05	-0.12***	0.54***	0.00	-0.13***	-0.18***	-0.22***	0.03

Chapter 5

Conclusion

The thesis contributes to the general understanding of the knowledge and technology transfer (KTT) process from academia to the industry with a focus on the individual scientist as the transfer agent. This involves examining the process from various perspectives and in various parts. The overarching research objectives of the thesis are, first, to uncover scientists' initiation of the transfer process by investigating the antecedents of their transfer opportunity recognition and the factors influencing their choice of a transfer channel, second, to add to our understanding of scientists' phase transitions along the process and the influence of their embeddedness within the academic and commercial sphere and, third, to examine the influence of different forms of social capital on multiple goals achievement by scientists. In the three core chapters 2-4, the KTT process from academia to the industry is analyzed based on these three objectives.

To achieve these research objectives, this thesis was subject to an iterative process. The thesis recombines different streams of literature, different data sources and various econometric methodologies. The main data source is primary data collected through a survey of scientists in the German Federal State of Thuringia, which was supplemented by secondary data in the form of bibliometric data of the surveyed scientists as well as organizational characteristics of the universities and research institutes with which the respondents are affiliated. In the following, I summarize the key findings and contributions, formulate policy recommendations and point out avenues for further research.

5.1 Main findings and contributions

With respect to the first research objective of this thesis, to uncover scientists initiation of the transfer process, Chapter 2 provides valuable insights. By conceptualizing the initiation of the transfer process for the first time in the transfer literature, this chapter contributes to the process theory of KTT from academia to industry. Drawing on the existing research on opportunity recognition in the entrepreneurship literature and adapting it to the academic transfer context, initiation is divided into the simultaneous recognition of a transfer opportunity and choice of a transfer channel for pursuing the opportunity. Regarding antecedents for scientists' transfer opportunity recognition and factors influencing which channel they chose, we argue in the following way: According to the scientific and technical human capital of academics, we hypothesize that prior academic and non-academic knowledge, research quality and relations to industrial actors increase scientists' probability to recognize a transfer opportunity. We further assume that their research orientation, risk willingness and the existence of channel-specific role models influence their choice of the transfer channel. Our survey data shows that fewer than half of the scientists recognized a transfer opportunity in the last five years. For the empirical analysis we use binary dependent variables for transfer opportunity recognition and for each of the three channels Science-Industry collaboration, intellectual property rights and academic spin-off, and perform seemingly unrelated regressions. The results reveal that both scientists' prior academic and non-academic knowledge significantly increases their probability to recognize a transfer opportunity. Surprisingly, we find a significantly negative relationship between opportunity recognition and their scientific quality. Furthermore, we can show that an applied research orientation significantly increases scientists' probability to chose the intellectual property rights channel, while this relationship also holds true for basic research and the choice of the spin-off channel. The results also point to risk willingness as a significant predictor for the choice of the spin-off channel and an significant influence of role models for both, the intellectual property rights and spin-off channel. This chapter fills the gap in the literature regarding the transfer process by conceptualizing and empirically examining it for the first time. The change of perspective to the beginning of the process compared to existing research captures all scientists who have an idea for a potential transfer, regardless of its successful implementation, and thus overcomes the survival bias of previous analyses in this field.

Chapter 3 is dedicated to the second research objective of this thesis and provides insights into scientists‘ phase transitions in the transfer process and the influence of their embeddedness within the academic and commercial spheres. We first present a comparison of the academic and commercial spheres in order to emphasize their differences in terms of the norms, relation to knowledge, motivation, reward system, competition and competencies that prevails within them. We relate these differences between the two spheres to the academic spin-off creation process and examine the importance of scientists' embeddedness in the spheres for their phase transitions along the transfer process. We argue that the importance of the academic sphere decreases while the importance of the commercial sphere increases. By applying dominance analysis to the three logistic regressions reflecting the phase transitions, we find that the relative importance of the academic sphere decreases throughout the ASO creation process, while the commercial sphere becomes increasingly important. Our results also reveal that the commercial sphere consistently has a higher importance than the academic sphere for transitioning from one phase to the next, even from the early stages of the process, challenging existing perceptions. This chapter contributes to the transfer literature, especially the strand of literature dealing with academic spin-offs, through its micro-level perspective on the individual scientist, which has received little attention to date. With our quantitative tracking of scientists along the process, we can assess scientists' discontinuation of their entrepreneurial pursuit along the ASO creation process. By exploring the impact of scientists' embeddedness in the academic and commercial spheres on their progression along the ASO creation process, we contribute to a better understanding of the complex relationships in the process.

Chapter 4 deals with the third research objective, which revolves around the influence of different forms of social capital on scientists' multiple goals achievement. In this chapter, I draw a line from universities, which are considered organizations with multiple goals — generate impactful research results and transfer knowledge and technology to industry — to the individual scientist as part of this organization, who is expected to achieve these goals. The approach in Chapter 4 contributes to the literature of academic transfer to industry for two reasons. Firstly, I consider two conflicting goals of academics: achieving high research performance and commercializing research results. I contrast these by developing a quadrant model and identifying four profiles that illustrate the variations in achieving these two goals: normal scientists, star scientists, ambidextrous scientists and ambidextrous star scientists. The allocation of each scientist to one of the profiles is based on their number of citations per year and paper with regard to research performance, and on their survey responses on sold intellectual property rights and created spin-offs with regard to research commercialization. Secondly, I refer to social capital theory to make its classification into bonding, bridging and linking social capital applicable to the context of university scientists and discuss the possible relationship between these forms of social capital on their multiple goals achievement. Descriptive results reveal that only 6.52% are ambidextrous star scientists, simultaneously outperforming in research and commercializing their results. Ambidextrous scientists with a low research performance but commercialized research results amount to 9.56%, star scientists with a high research performance but no commercialization account for 25.07% and the biggest group with 58.85% are the normal scientists showing a low research performance and no commercialized research results. The results of a multinomial regression model on the scientists' profile affiliation indicate that all three forms of social capital significantly increase the probability to be an ambidextrous star. Bonding social capital facilitates scientists' research performance while bridging and linking social capital increases their behavior towards research commercialization. In addition, it is shown that there is an inverted U-shaped relationship between bonding social capital and research performance, which points to disadvantageous effects in case of an extensive degree of this form of social capital. This chapter contributes to our understanding of how scientists manage to achieve multiple conflicting goals. Previous research has so far focused on the achievement of one of these goals and its influencing factors. I link the strands of research on scientists' research performance and commercialization, establish the first classification of scientists based on these two goals, and explore the role of different forms of social capital in their achievement.

5.2 Policy implications

The results of this thesis make it possible to derive implications for policy makers and research management that differ, on the one hand, in terms of where the scientist is in the process and, on the other, in terms of the transfer channel.

First, the results from all core chapters of this dissertation make it clear that building bridges between academic scientists and industrial actors is essential for the transfer of knowledge and technologies. This link between the academic realm and industry is not only the logical consequence of a successful transfer of research results into industrial application, but a significant influencing factor both in the initiation and along the entire process. A heterogeneous knowledge stock, especially if it is enriched by industry-related experience and interaction with the user side, has a positive effect on the recognition of transfer opportunities. This increases the input side of the transfer, i.e. the frequency of transfer efforts initiated. Academic institutions could create further incentives for scientists to engage with industry by reducing administrative burdens and recognizing their transfer activity alongside their academic qualifications. Also along the process, when phase-specific activities and challenges have to be overcome, embedding in the commercial sphere is advantageous, at least for the academic spin-off channel. Contrary to previous assumptions, embedding in the commercial sphere is already of greater relative importance in the first phase of this channel than being embedded in the academic sphere. One approach could be to increase the exposure of academic scientists to the commercial sphere through the implementation of entrepreneurship education initiatives. Finally, industry contacts in the context of academic knowledge transfer are a source of bridging social capital for scientists, which in turn represents an important resource in the successful transfer implementation and the achievement of multiple goals. This increases the output side of the transfer, i.e. the frequency of implemented transfer. To this end, it is advisable for policymakers to set up further support programs that promote joint research projects between academic and industrial actors.

Second, the process perspective shows that individual phases and phase transitions do not allow for a one-size-fits-all approach when setting up support initiatives. The activities and challenges that need to be addressed for the transition to the next phase are different and require tailored support. As shown in the case of the academic spin-off process, this could be early-stage funding, access to lab facilities, mentorship programs, market validation support, industry partnerships, and regulatory guidance, among others. This enables effective progress in the process.

Third, it should also be taken into account that transfer can take place via different channels and that these also require tailored support, depending on which channel a scientist chooses for the transfer. It became clear that role models can influence the choice of channel. On the one hand, these role models help to raise awareness of transfer, but they can also act as best-practice examples and mentors to provide experience and advice when pursuing a transfer opportunity in a particular channel. Furthermore, the comparatively high risk of an engagement in the spin-off channel should be taken into account. To lower the risk of foregone academic rewards, one approach could be to reduce time constraints for spin-off projects and grant scientists an entrepreneurial leave term to realize their idea.

Fourth, the results of this dissertation show that the individual scientist and their personal and research-related characteristics should also be taken into account. The small number of scientists who manage to both achieve high research performance and commercialize research results (Chapter 4) is also reflected in the negative correlation between research impact and the likelihood of recognizing a transfer opportunity (Chapter 2). Targeted programs that raise awareness of transfer among high performers and create incentives in the reward system could increase their engagement in transfer. It was also shown that female scientists, at least in the spin-off channel, seem to experience specific hurdles along the process. Policymakers should develop targeted support mechanisms to address these disparities and provide equal opportunities for all scientists to participate and succeed in entrepreneurial endeavors.

5.3 Limitations and further research avenues

The dissertation is subject to several limitations that merit careful consideration and which can be taken up for further research.

The primary data source for the analyses in this dissertation comes from a self-designed survey questionnaire. Surveys are generally prone to various forms of bias, which were taken into account when developing the survey items so that their occurrence was prevented as far as possible (e.g. social desirability bias or question order bias) and a clear non-response bias could also not be identified. Nevertheless, the significance of the results is limited by the fact that only correlative and no causal relationships were identified. The results are based on cross-sectional data, which in turn makes it difficult to accurately capture process experiences based on past events. To ensure a high validity of the data, respondents were always reminded of the surveyed period of 5 years and phase sections were clearly delineated in their description. Nevertheless, future research on the transfer process should also draw on longitudinal data and, for example, investigate possible changes in process effectiveness through transfer-oriented policy measures at university level in order to gain causal insights. Even if Thuringia is an exciting case for such studies due to its diversity of research institutions, samples from other regions should also be generated and used.

Furthermore, although Chapter 3 examined the transfer process in its individual phases and transitions, this study is limited to the academic spin-off channel. Transfer channels are heterogeneous in terms of their phase-specific activities and challenges, which in turn could have an impact on the importance of embedding in the academic and commercial spheres. The relative importance of embedding in the respective spheres during phase transitions should therefore also be investigated for other transfer channels. Although differences in the transfer channels were examined in Chapter 2 with regard to the factors influencing the choice of channel for pursuing a transfer opportunity, it should also be noted that, in addition to the three commercial transfer channels examined in this dissertation, there are others that establish a link to commercial application, such as paid consulting activities by scientists in companies. In addition to the industrially oriented understanding of transfer in this thesis, it is also discussed more broadly in the literature and includes non-commercial activities such as political consulting or scientists' societal engagement. The choice of channel and phases of channels in both the industrially oriented and broad conceptions of transfer require further investigation in future research.

Finally, this dissertation is dedicated to the individual scientist in the transfer process in order to identify factors influencing the transfer agent. This is based on the assumption that every transferred research result can be attributed to a scientist. This may be true for the majority of cases, but often the transfer process is a team effort, whether by a founding team, a group of inventors, or a team of scientists from one or more universities collaborating with a company. Future research should include teams as well as individuals when studying transfer initiation, phase transitions and transfer implementation, e.g. through multilevel analyses.

In conclusion, the thesis has highlighted how the KTT process from academia to industry unfolds and which factors influence the initiation of this process, the phase-transitions within it and the implementation of the transfer in addition to the achievement of academic goals. While this analysis could not examine all transfer channels and every single step of the process, I hope that these contributions have broadened the understanding of the transfer process and inspired further research in this direction.

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Hiermit erkläre ich,

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