## Delft University of Technology

## Moving up the ladder

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## DOI

10.1080/03075079.2018.1434617

Publication date
2018
Document Version
Final published version
Published in
Studies in Higher Education

## Citation (APA)

Ooms, W., Werker, C., \& Hopp, C. (2018). Moving up the ladder: heterogeneity influencing academic careers through research orientation, gender, and mentors. Studies in Higher Education, 1-22. https://doi.org/10.1080/03075079.2018.1434617

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# Moving up the ladder: heterogeneity influencing academic careers through research orientation, gender, and mentors 

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#### Abstract

We look into the question whether heterogeneity stemming from research orientation, gender, or disciplinary and cultural differences with their PhD supervisors helps or hampers academics' careers. Based on a sample of 248 academics at two leading European universities of technology, we combine multinomial logit models and sequential logit models to understand career advancement. Our results show that heterogeneity stemming from research orientation is helpful. Academics who bridge between the quest for fundamental understanding and socio-economic relevance attain career success. Yet heterogeneity stemming from gender hinders careers: female academics face problems securing tenured positions and full professorships. Mentor-mentee heterogeneity only helps in early career transitions, but hampers advancement later on. Our insights offer suggestions to policymakers, university managers, and academics, because they help to identify promising academics, the right support for sitting staff members, measures correcting for gender imbalances, and can inform strategic choices regarding research orientation and PhD supervisors.


## KEYWORDS

Academic careers; mentoring; heterogeneity; research orientation; gender

## 1. Introduction

Technological progress as well as changing societal and economic requirements have led to important changes in the academic landscape, thereby creating a more complex environment for academics (Etzkowitz and Viale 2010). The general public, policymakers, and university administrators expect academics to adapt and to link their research with societal and economic needs (Hessels and van Lente 2008; Martin 2012), and engage in collaboration and knowledge transfer with industrial and public partners (Perkmann et al. 2013; Erikson, Knockaert, and Der Foo 2015). Yet the career advancement of academics still follows the traditional tenure model, suggesting a predictable linear and upward career ladder (Baruch and Hall 2004). The resulting bifurcation between clear-cut academic career ladders and academics' complex and more demanding environment gives rise to the following research question: How does academics' heterogeneity, in terms of their research orientation, gender, and mentor-mentee heterogeneity, affect their career prospects?

The academic landscape has been changing substantially and has created a more complex and demanding environment for academics. Particularly, universities have increasingly taken a more

[^0]central role in the innovation process (Etzkowitz and Viale 2010), and have even served as nodes of inter- and intraregional knowledge transfer (Fromhold-Eisebith and Werker 2013). Furthermore, technological progress in general is driven by a growing and increasingly specific, complicated, and complex knowledge base that is scattered around the globe (Jones 2009). An important driver of technological progress has been the development of fields such as biotechnology, IT, and nanotechnology, which combine knowledge from many disciplines. In face of the huge amount of knowledge available, many research groups and academics have specialized by narrowing their area of expertize. At the same time, they have broadened the scope of their networks in order to cover the whole spectrum of knowledge relevant to their research (Wuchty, Jones, and Uzzi 2007). These developments in the context of academic research likely have implications for academics' careers.

In the following, we study whether either heterogeneity or homogeneity helps academics to manage several activities in order to meet different sorts of requirements emerging from an increasingly complex environment, as illustrated above. Hence, we suggest that heterogeneity may affect academics' career advancement, and may do so in different ways depending on the source of heterogeneity. Accordingly, we analyse three sources of heterogeneity that may affect academics' ability to build their careers: First, we look into heterogeneity emerging from research orientation, i.e. the extent to which academics choose to deal with heterogeneity in their research projects. There is a balancing act between striving for fundamental understanding, on the one hand, and creating work with economic and societal relevance, on the other hand. We investigate how this balancing act affects academics' career success. Second, we study heterogeneity emerging from gender differences, considering that in many settings, female academics are sparse in research teams and their male counterparts are considered the benchmark. Third, we investigate mentor-mentee heterogeneity, i.e. whether differences from one's PhD supervisor in terms of disciplinary and cultural background affect academics' career advancement. Our results detail how these sources of heterogeneity affect academics' career success.

Our data cover academics in all career stages after receiving their PhD degree, from junior postdocs to senior full professors. We collected the data at the departments of natural sciences and engineering at two European universities of technology. By combining this unique dataset with novel (and theoretically warranted) empirical estimation techniques, our work reflects the theoretically hierarchical (and supposedly linear) career paths of academics, yet allows for heterogeneous transitions and leapfrogging in academic careers.

With our analysis, we go beyond former findings by following up on calls for further investigations in two ways. First, earlier studies have concentrated only on early stages of academic careers (e.g. Fox and Stephan 2001; Roach and Sauermann 2010; van der Weijden et al. 2015), or they have focused on getting tenure (Lutter and Schröder 2016). In contrast, we investigate how specific factors affect academics' progress and success throughout their entire careers. Second, we not only investigate how an increased emphasis on commercialization changes the nature of academia (Larsen 2011), but also systematically study whether research orientation affects academics' careers, and if so, how.

## 2. Theory

### 2.1. Academic career paths

Academic career paths differ between countries, but show similar flat hierarchical structures (e.g. Baruch and Hall 2004). In Figure 1, we illustrate a prototypical career path for academics in the Netherlands and Germany, the two countries from where our sample originates, starting with the stage of an early career position. Following their early career positions, academics may move from an assistant to an associate professorship, and finally transition to a full professorship.


Figure 1. Prototypical academic career path in the Netherlands and Germany.

### 2.2. Heterogeneity emerging from research orientation: Bohr, Pasteur, or Edison

Academics may have substantially different research orientations. Some academics focus on industrial, economic, or societal needs, while others pursue fundamental advancement of the knowledge base (Fabrizio and Di Minin 2008; Azoulay, Ding, and Stuart 2009; Larsen 2011).

We compare academics with three different research orientations (Figure 2) that come with varying degrees of heterogeneity. First, academics mainly focusing on Bohr research, i.e. doing pure basic research with the primary purpose of enhancing the knowledge base of their discipline (Stokes 1997). These academics deal with little heterogeneity of goals, knowledge, and partners (Nowotny, Scott, and Gibbons 2003). Second, academics mainly focusing on Edison research, i.e. pure applied research primarily targeted to contribute to solutions relevant to the economy and society (Stokes 1997). Edison academics collaborate with heterogeneous industrial and public partners and deal with heterogeneous goals which have proven to be difficult to handle (Porac et al. 2004). Third, academics with a Pasteur research orientation, i.e. doing use-inspired research and pursuing two types of goals in their research as they enhance the knowledge base of their field and provide application-oriented solutions (Stokes 1997). Academics focusing mainly on Pasteur research deal with most heterogeneity in their goals, knowledge, and partners. Particularly, while Edison academics mainly pursue innovation targets, Pasteur academics pursue the whole range of targets in science, technology, and innovation (Stokes 1997).

Academics' output and thereby their success criteria depend on their research orientation (Bekkers and Bodas Freitas 2008; Philpott et al. 2011; Abreu and Grinevich 2013). Outputs may range from publications (Bentley, Gulbrandsen, and Kyvik 2015) to practical applications such as patents as well as product and process innovations (Philpott et al. 2011; Ylijoki, Lyytinen, and Marttila 2011). Academics focusing on Bohr research extend the knowledge base by publishing. Academics concentrating on Edison research help to solve socio-economically relevant problems (Lam 2010). Academics focusing on Pasteur research try to meet both scientific and socio-economic goals by transforming their scientific insights into solutions for practical problems and vice versa (Stokes 1997; Lam 2010).

As academics' success criteria ${ }^{1}$ have evolved in the last six decades, their career success increasingly depends on their research orientation. Given that the general public, policymakers, and


Figure 2. Research orientation - Stokes' quadrant model.
university administrators expect academics to contribute to socio-economic problem-solving (Martin 2012; Perkmann et al. 2013), we suggest that career success is most difficult to attain for academics focusing on Bohr research. These academics do not investigate research problems likely to yield applications in the near future. At the same time, we recognize that universities' core task is still to build and extend the knowledge base (Jones 2009; Martin 2012). Therefore, we suggest that academics focusing on Pasteur research have the best chances of career success, as they combine both the quest for fundamental understanding and applied interests. Academics focusing on Edison research primarily do provide solutions to socio-economic problems, but their contribution to the scientific knowledge base is likely less than that of Pasteur academics. Hence, their career opportunities are likely better than those of academics focusing on Bohr research, but worse than those of academics focusing on Pasteur research.

H1 Academics focusing on Pasteur research are most likely to advance in the academic career, those focusing on Edison research are less likely to do so, and academics focusing on Bohr research have the lowest chances of career advancement.

### 2.3. Female amongst males: heterogeneity emerging from gender differences

There is ample work documenting that women have been underrepresented in science, technology, engineering, and mathematics (STEM) (Blickenstaff 2005; Ding, Murray, and Stuart 2006; Sugimoto et al. 2013). Already at the student stage, there are considerably fewer female STEM students compared to male ones. Thereafter, women leave academia relatively more often than men (Blickenstaff 2005). Those women who stay in academia advance more slowly in their career than men (Cruz-Castro and Sanz-Menéndez 2010). Moreover, women are also more likely to take part-time positions, mainly to balance work and family life (Steffens and Viladot 2015). As a result, STEM
departments are male-dominated environments, in which female academics are treated as the 'female amongst males.' Their male counterparts serve as the benchmark leading to women being considered the other, dissimilar, and heterogeneous (Eagly and Wood 2012).

The underrepresentation of women and gender differences may be explained by individual and collective factors. While productivity differences in terms of academic publications and citations (Bentley 2011; Ghiasi, Larivière, and Sugimoto 2015; Beaudry and Larivière 2016) as well as in patenting activities (Ding, Murray, and Stuart 2006; Meng 2016) may be considered an individual factor, collective factors such as gender differences in collaboration patterns (Bozeman and Gaughan 2011; Abramo, D'Angelo, and Murgia 2013; Uhly, Visser, and Zippel 2015; Villanueva-Felez, Woolley, and Cañibano 2015) may be the underlying cause. At the same time, previous studies stress that collective factors such as family life might not suffice to explain gender differences in productivity (Ginther and Kahn 2004; Bozeman and Gaughan 2011). In sum, it is important to not only focus on individual merits, but also consider bottlenecks in the academic system (e.g. Nielsen 2016).

Taking theoretical considerations and empirical evidence together we suggest the following hypothesis:

H2 Female academics have lower chances of advancing in the academic career than male academics.

### 2.4. Mentor-mentee heterogeneity: the role of PhD supervisors

An important early impetus for academics' research is the PhD supervisor. It is likely that academics' career progress hinges, at least in part, on what they take away from the mentoring experience with their PhD supervisors. PhD supervisors guide, support, and socialize PhD students during their formative years of becoming independent researchers (e.g. Austin 2002). First, they serve as role models for their mentees (Eby et al. 2010; Marquis and Tilcsik 2013). Second, the doctoral training period and early career stage are sensitive periods in which influential imprints may be left (e.g. McEvily, Jaffee, and Tortoriello 2012), which then affect academics long-term career paths as well. Third, the access to the mentors' networks proves important for the career development of mentees, because mentees become visible in the mentors' network of colleagues and gain access to their social capital (Johnson 2007; Scaffidi and Berman 2011; Lutter and Schröder 2016).

Because knowledge generation has become more complex (see Section 1), and therefore increasingly organized in interdisciplinary teams and collaborations (Wuchty, Jones, and Uzzi 2007), having had a supervisor with a heterogeneous background can offer advantages to one's career prospects. Exposure to novel knowledge and problem-solving may improve one's abilities and opportunities as an independent and creative researcher. In general, mentors have proven to be important in early career stages (Azoulay, Liu, and Stuart 2011).

In the following, we analyse whether mentor-mentee heterogeneity or homogeneity helps academics in climbing the academic career ladder. In doing so, we emphasize two sources of heterogeneity: cultural heterogeneity and disciplinary heterogeneity. Cultural mentor-mentee heterogeneity relates to differences in institutional background, such as differences in nationality ${ }^{2}$. Disciplinary mentor-mentee heterogeneity involves differences in the knowledge base.

In cases of cultural mentor-mentee homogeneity, shared formal institutions (such as laws and rules) and informal institutions (such as cultural norms and habits) enable knowledge transfer, interactive learning, and innovation between mentor and mentee (Porac et al. 2004; Boschma 2005). Theoretically, cultural homogeneity may be expected to give mentees advantages, because of processes of similarity-attraction (Williams and O'Reilly 1998) and social categorization (Tajfel 1982). At the same time, too much cultural homogeneity can lead to lock-ins and inertia that hamper the emergence of new ideas. Cultural mentor-mentee heterogeneity during doctoral training may help academics to develop capabilities enabling them to work within culturally heterogeneous research teams (Pull, Pferdmenges, and Backes-Gellner 2015).

Taking theoretical considerations and empirical evidence together, we suggest the following hypothesis for cultural mentor-mentee heterogeneity influencing academics' careers:

> H3 Cultural mentor-mentee heterogeneity between academics and their PhD supervisors reduces the chances of advancing in the academic career.

In cases of disciplinary mentor-mentee homogeneity, mentees may have better opportunities to learn from their PhD supervisors, because they share the same disciplinary language and have complementary knowledge bases and expertise that simplify learning processes (Boschma 2005; Huber 2012). Academics may benefit from having the same knowledge base as their PhD supervisor, as this helps them to develop specific expertise in a well-defined knowledge field and to socialize in the networks of supervisors. However, as mentioned above, too much homogeneity may come at a cost, as it leads to lock-ins which hamper learning and knowledge transfer (Boschma 2005). Mentors and mentees using different but related knowledge bases may understand relevant synergies, identify challenging and relevant research problems, and come up with creative out-of-the-box solutions. Therefore, disciplinary mentor-mentee heterogeneity during doctoral training may help academics to develop capabilities that enable them to collaborate better on interdisciplinary projects in subsequent stages of their careers. Despite some potential advantages of disciplinary mentormentee heterogeneity in specific career stages, when considering career advancement over time, disciplinary mentor-mentee homogeneity is likely most beneficial, as tenured positions are often linked to clearly demarcated area of expertise. We therefore suggest the following hypothesis.

H4 Disciplinary mentor-mentee heterogeneity between academics and their PhD supervisors reduces the chances of advancing in the academic career.

Cultural and disciplinary mentor-mentee heterogeneity may not evenly affect the transition between the different stages of the academic career ladder. Imprinted characteristics of academics left during the mentor-mentee relationship may serve different purposes over time as the individual is exposed to different environments (Marquis and Huang 2010). Studies on careers and inequality imply that 'a given imprint might produce advantage for an individual in one environment and disadvantage in another' (Marquis and Tilcsik 2013, 234). Academia traditionally grants scientists more freedom to pursue their upstream, more fundamental research interests and the reward for academic excellence is expressed primarily in peer recognition rather than money (Stephan 1996; Roach and Sauermann 2010). Furthermore, PhDs who stay in academia have usually also attained higher levels of scientific quality in their research output (Mangematin 2000). Early career positions typically offer more freedom to explore and experiment. More specifically, Millar (2013) found that those finalizing a PhD thesis on an interdisciplinary topic found an academic position much more easily than those who had stayed within disciplinary boundaries. As PhD supervisors with areas of expertise that differ from their PhD students increase the likelihood of interdisciplinary work in the PhD thesis, we suggest that mentor-mentee heterogeneity may have a positive influence on academic careers directly after defending the PhD thesis. We therefore suggest the following hypothesis:

H5 Both cultural and disciplinary heterogeneity increase the chances of achieving early career advancements, yet both reduce the chances of achieving later career advancements.

## 3. Methods

### 3.1. Sample

Data collection took place through a web-based anonymized questionnaire between November 2012 and March 2013. Our sample contains data from a survey amongst faculty members at two leading European universities of technology: RWTH Aachen University (Germany) and Delft University of Technology (The Netherlands). We applied two sampling criteria, including only: (1) faculty members conducting research in disciplines present in both universities and (2) faculty members
holding a PhD degree. This ensures sufficient similarity between the samples from both universities with independent researchers from similar disciplines. Technically, our effective response rate is $11 \%$ for the RWTH Aachen University and 19\% for the Delft University of Technology. Yet, from the responses returned it is somewhat difficult to calculate the actual response rate, as the lack of email lists distinguishing between the academic rank of employees at both universities, meant that we had to approach many individuals who were unlikely to be eligible for the final sample. Specifically, there was no feasible (and reliable) way to exclude potential respondents without a PhD degree prior to sending out the questionnaire. We therefore approached 4.496 academics at RWTH Aachen University and 1.490 academics at Delft University of Technology, adding up to 5.986 potential respondents. In the invitation for the questionnaire, it was clearly stated that it was only intended for academics holding a PhD degree. Consequently, recipients of the invitation not holding a PhD degree were advised to refrain from returning the questionnaire. While this procedure yields a technically lower response rate, it was the most reliable way to reach all individuals potentially eligible for the study. Particularly, in this way we followed a more inclusive sampling process, thereby ensuring that our results are prudent and pertaining to all academic ranks alike. Four hundred ninety academics from RWTH Aachen University and 280 academics from Delft University of Technology returned the survey. For our study, 485 academics who returned the web-based questionnaire met both of our sampling criteria. Two hundred sixty-five academics out of these 485 respondents gave sufficient information on their research orientation, but 17 of those academics provided insufficient information on cultural and disciplinary heterogeneity. Therefore, our final sample comprises 248 respondents: 109 respondents working at RWTH Aachen University and 139 respondents working at Delft University of Technology.

### 3.2. Variables

### 3.2.1. Dependent variable: career success

In Germany academics can hold two alternative types of early career positions after receiving the doctoral degree: either postdoc positions or a qualification position to become a full professor, i.e. positions as a Juniorprofessor, Wissenschaftlicher Mitarbeiter or Akademischer Rat auf Zeit (usually temporary contracts with a maximum duration of six years). This is similar to the Dutch system that distinguishes two types of early career positions, i.e. postdocs (Onderzoeker) or lecturer/assistant professor (Universitair docent 2), the latter usually being a five year tenure-track. Subsequently, the Dutch system offers the first advancement option to tenured assistant professorship. In contrast, the German system offers promotions to either W-2 Professor or W-3 Professor, which are sometimes still temporary contracts. Yet most of these positions are tenured. Similarly, the Dutch system offers promotions to tenured associate professorship (Universitair Hoofddocent) and finally for some to tenured full professorship (Hoogleraar). We present the differences in Figure 1 (see Section 2.1).

In order to capture career success, we calculated a variable based on the responses to two questions. First, a categorical variable allowed respondents to indicate their current career stage choosing from: postdoc, assistant professor, associate professor, full professor, or other. ${ }^{3}$ Second, they indicated the year of their PhD defence so that we could calculate the time elapsed since academics obtained their PhD degrees. The variable capturing career success was calculated using both the current career stage as well as the time elapsed since obtainment of the PhD degree.

### 3.2.2. Independent variables: research orientation, gender differences, and mentor-mentee heterogeneity

In order to measure research orientation, we asked respondents to position themselves in Stokes (1997) quadrant model (see Figure 2). Specifically, we asked respondents to indicate how their activities were distributed over three quadrants (Bohr, Pasteur, and Edison) ${ }^{4}$ in the last five years. In order to do so respondents assigned a percentage to each category adding up to $100 \%$. This approach yields a detailed picture of the academic's research orientation. In our analyses, we standardize
the scores for research orientation with the standard deviation. This results in a mean research orientation of zero (0) and standard deviation of one (1). By doing so, we avoid misrepresentation of research orientations that would occur when using cut-off points in a simple dichotomous distinction of the research orientations. Consequently, interpretations capture as to how a one-unit increase in a particular research orientation (relative to the scores of others in this dimension) affects career success in academia.

Gender was measured by a binary variable, taking the value of one (0) for female academic and two (1) for male academics. Respondents were asked: 'What is you gender?'. We use this variable to consider heterogeneity emerging from gender differences.

Cultural heterogeneity was measured by a dichotomous variable. In line with the existing literature (Stahl et al. 2010), we used (dis)similarity in nationality as a proxy to measure cultural heterogeneity. Accordingly, we asked the respondents the following question: 'Did the main supervisor of your PhD thesis have the same nationality as you?' A positive answer to this question implies cultural homogeneity, while a negative answer to this question implies cultural heterogeneity. We operationalized the variable as one (1) if there was cultural heterogeneity between PhD student and supervisor and zero (0) for cultural homogeneity.

Disciplinary heterogeneity was also measured by a dichotomous variable. We asked the respondents: 'Did the main supervisor of your PhD thesis have the same professional education as you?' A positive answer to this question implies disciplinary homogeneity, while a negative answer to this question implies disciplinary heterogeneity. The variable takes on the value of one (1) if there was disciplinary heterogeneity between PhD student and supervisor, while zero (0) indicates disciplinary homogeneity.

### 3.2.3. Control variables

The richness of our dataset allows us to use a wide range of control variables. Considering the differences between the structure of academic careers in Germany and the Netherlands (see Section 3.1), we control for the location using a dummy variable that takes on the value of one (1) if respondents work at the Delft University of Technology and zero (0) if respondents work at RWTH Aachen University. Additionally, given the importance of family influence in academic career choices (Lindholm 2004), we control for the effects of parental experience in the private sector. Likewise, experience in industry jobs (Dietz and Bozeman 2005) may influence whether or not individuals progress in academic careers. Therefore, we control for private sector experience of the respondents in the past five years. Finally, as academic and commercial output strongly influence academic career success, we include the number of peer-reviewed publications and the number of other scientific publications as well as the number of product and process innovations ${ }^{5}$ reported by respondents for the time period 2007-2011 as control variables.

### 3.3. Two models

In order to develop a comprehensive understanding, we focus on all transitions individually, but also allow for unequal transitions and truncations at all levels. Thereby, we account for leapfrogging that might be observed for transitions to either associate or full professorships. That is, theoretically, there is linearity but in practice, we may also observe individuals moving directly to full professor positions. For this reason, we use two types of models. First, we estimate a multinomial model that makes no implicit assumption about the order of outcomes (Wulff 2015). The multinomial model therefore accounts for the possibility that academics may leap particular career stages (accounting for a non-linear career path). In addition to interpreting the signs of the estimation coefficients in the multinomial logit model, we plotted the predicted probabilities for being in each career stage for different degrees of disciplinary and cultural heterogeneity as well as different relative degrees of each research orientation. This aids the interpretation of the results of the multinomial logit model, as
merely interpreting the sign of estimated coefficients may lead to misinterpretation of the direction of the effect (Wulff 2015).

Second, we complement the results from the multinomial model with the use of a sequential logit model (Buis 2011, 2015). The starting levels in academic careers also do not necessarily represent a natural ordering, as some may start as assistant professor while others start as postdoc. Subsequently, moving up the ladder is possible from both starting positions. The sequential logit model decomposes the overall transition effect to become a full professor (the highest attainable career outcome) and models the likelihood of transitions for each consecutive career stage (mirroring a hierarchical academic career path). In sum, individual effects for the explanatory variables on passing the interdependent transitions that precede the final outcome can accumulate over transitions (and may do so at varying degrees).

## 4. Results

### 4.1. Descriptive statistics

Table 1 presents the descriptive statistics and bivariate correlations. As to the personal characteristics, respondents are by and large male ( $72 \%$ ), 20\% of the respondents have private sector experience and about one-third report entrepreneurial/self-employment experience within the family. On average respondents have about 10 peer-reviewed publications, 5 other scientific publications, and about 2 process/product innovations for the period from 2007 until 2011. Figure 3(a) reports that academics place themselves on average quite evenly across the research orientation spectrum (33\% Bohr, 36\% Pasteur, and 31\% Edison), yet standard deviations vary (32\% for Bohr, 24\% for Pasteur, and 25\% for Edison). Figure 3(b) depicts the standardized research orientation with mean research orientation of zero and standard deviation of one. All interpretations are made relative to how other academics perceive themselves.

In our sample, we included 24 full professors, 6 associate professors, 5 assistant professors, and 74 postdocs for RWTH Aachen University as well as 21 full professors, 22 associate professors, 16 assistant professors, and 80 postdocs for the Delft University of Technology.

### 4.2. Impact of research orientations on academic career success

We test our hypothesis about the effect of heterogeneity emerging from research orientation on career success (H1) using the two empirical methodologies described in Section 3.3. We provide the results from the multinomial logit model (Table 2), the marginal effects, as suggested in Hoetker (2007), in Table 3, and the corresponding graphical depiction of predicted probabilities (Figure 4; following Wiersema and Bowen 2009). Furthermore, to assess the robustness of our findings in light of the underlying distributional assumption of nested transitions, we report the coefficient estimates from a sequential logit model in Table 4 (as suggested by Buis 2015).

Hypothesis 1 is supported by the results. In particular, Edison academics are more likely to transition to associate professorships (in comparison with Bohr and Pasteur academics), while Pasteur academics are more likely to finally transition to full professor positions. Heterogeneity in terms of ambidextrously combining industry and academia (Pasteur research) is advantageous for becoming a full professor, while a pure focus on industry application is chosen over pure basic research for midcareer transitions.

Correspondingly, Bohr academics do not differ significantly in terms of their transition probabilities across successive stages. None of the coefficients reported is significant, neither for the coefficient estimates in the multinomial or sequential logit models nor for the average marginal effects.

While the coefficient estimates for Edison academics report insignificant effects for all transitions, the average marginal effects for the transitions to associate professorships and to full professorships are significant (Table 3). In particular, we observe that Edison academics are more likely to transition

Table 1. Summary statistics and correlation matrix.

| Variables | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 Career success | 1.85 | 1.20 |  |  |  |  |  |  |  |  |  |  |  |  |
| 2 Disciplinary heterogeneity | 0.33 | 0.47 | -0.133* |  |  |  |  |  |  |  |  |  |  |  |
| 3 Cultural heterogeneity | 0.32 | 0.47 | -0.193* | 0.063 |  |  |  |  |  |  |  |  |  |  |
| 4 Bohr-type | -0.10 | 0.95 | -0.127* | -0.150* | -0.009 |  |  |  |  |  |  |  |  |  |
| 5 Edison-type | 0.05 | 1.00 | 0.014 | 0.045 | 0.015 | -0.573* |  |  |  |  |  |  |  |  |
| 6 Pasteur-type | 0.08 | 1.03 | 0.127* | 0.126* | -0.006 | -0.580* | -0.303* |  |  |  |  |  |  |  |
| 7 Location | 1.56 | 0.50 | -0.020 | 0.134* | 0.182* | -0.274* | 0.073 | 0.239* |  |  |  |  |  |  |
| 8 Gender | 0.72 | 0.45 | 0.273* | -0.059 | 0.002 | -0.197* | 0.093 | 0.123 | 0.187* |  |  |  |  |  |
| 9 Parental private sector experience | 0.29 | 0.45 | -0.003 | 0.069 | -0.065 | -0.083 | 0.170* | -0.051 | 0.058 | 0.064 |  |  |  |  |
| 10 Private sector experience | 0.18 | 0.39 | 0.092 | 0.015 | -0.017 | -0.172* | 0.267* | -0.034 | 0.028 | -0.006 | 0.125* |  |  |  |
| 11 Innovation | 2.13 | 5.27 | 0.131* | -0.004 | -0.114 | -0.182* | 0.183* | 0.023 | -0.039 | 0.136* | 0.021 | 0.109 |  |  |
| 12 Peer-reviewed publications | 10.48 | 14.20 | 0.417* | -0.105 | -0.106 | -0.025 | -0.043 | 0.062 | -0.004 | 0.205* | -0.092 | 0.031 | 0.076 |  |
| 13 Other scientific publications | 5.31 | 10.90 | 0.282* | -0.096 | -0.109 | $-0.132^{*}$ | 0.062 | 0.091 | -0.097 | 0.083 | 0.042 | 0.137* | 0.253* | 0.301* |

Note: Summary statistics and correlation matrix are based on 248 observations.

* $p<.05$.


Figure 3. (a) Unadjusted distribution of research orientation measure. (b) Normalized distribution of research orientation measure.
to associate professorship positions ( $\beta=0.0359, p<.1$ ), but less likely than others to consequently obtain full professorships ( $\beta=-0.0439, p<.1$ ). These effects are also evident graphically, when depicting the predicted probabilities in Figure 4. While for mid-career stages we find that Edison academics are more likely to transition, they do not seem to make the transition to full professorships in the end. This effect is supported by the decomposition results from the sequential logit model (Table 4). Decomposing the probability to become a full professor into the tree sub-transitions we find that the main effect stems from the non-transition in the final stage ( $B=-0.909, p<.01$ ). Individually, we find positive transitions based on the individual marginal effects, yet, cumulatively speaking, Edison academics do not make the transition to a full professorship. They may be likely to arrive at the associate professor level, but they have considerably lower chances to transition to a full professorship conditional on making it to the penultimate stage.

Similarly, although Table 4 reports no significant differences across the transitions for Pasteur academics, the average marginal effects (Table 3) report a positive and significant effect for Pasteur

Table 2. Multinomial logit regression.

|  | Model A |  |  | Model B |  |  | Model C |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variables | (1) Assistant Professor | (2) Associate Professor | (3) Full Professor | (4) Assistant Professor | (5) Associate Professor | (6) Full Professor | (7) Assistant Professor | (8) Associate Professor | (9) Full <br> Professor |
| Disciplinary heterogeneity | $\begin{gathered} 0.222 \\ (0.516) \end{gathered}$ | $\begin{gathered} -0.515 \\ (0.498) \end{gathered}$ | $\begin{gathered} -0.554 \\ (0.472) \end{gathered}$ | $\begin{gathered} 0.194 \\ (0.514) \end{gathered}$ | $\begin{gathered} -0.466 \\ (0.499) \end{gathered}$ | $\begin{gathered} -0.530 \\ (0.473) \end{gathered}$ | $\begin{gathered} 0.262 \\ (0.522) \end{gathered}$ | $\begin{gathered} -0.422 \\ (0.501) \end{gathered}$ | $\begin{gathered} -0.563 \\ (0.476) \end{gathered}$ |
| Cultural heterogeneity | $\begin{gathered} -0.391 \\ (0.528) \end{gathered}$ | $\begin{gathered} -0.695 \\ (0.509) \end{gathered}$ | $\begin{gathered} -1.155^{* *} \\ (0.499) \end{gathered}$ | $\begin{gathered} -0.429 \\ (0.531) \end{gathered}$ | $\begin{array}{r} -0.769 \\ (0.515) \end{array}$ | $\begin{gathered} -1.080^{* *} \\ (0.495) \end{gathered}$ | $\begin{gathered} -0.393 \\ (0.531) \end{gathered}$ | $\begin{gathered} -0.725 \\ (0.510) \end{gathered}$ | $\begin{gathered} -1.075^{* *} \\ (0.500) \end{gathered}$ |
| Location | $\begin{aligned} & 1.051^{*} \\ & (0.597) \end{aligned}$ | $\begin{aligned} & 1.392^{* *} \\ & (0.558) \end{aligned}$ | $\begin{array}{r} -0.051 \\ (0.437) \end{array}$ | $\begin{gathered} 1.034^{*} \\ (0.589) \end{gathered}$ | $\begin{aligned} & 1.511^{* * *} \\ & (0.550) \end{aligned}$ | $-0.003$ | $\begin{aligned} & 01.187^{* *} \\ & (0.603) \end{aligned}$ | $\begin{aligned} & 1.560^{* * *} \\ & (0.558) \end{aligned}$ | $\begin{gathered} -0.180 \\ (0.446) \end{gathered}$ |
| Gender | $\begin{gathered} 0.497 \\ (0.634) \end{gathered}$ | $\begin{gathered} 0.261 \\ (0.576) \end{gathered}$ | $\begin{aligned} & 1.849 * * \\ & (0.725) \end{aligned}$ | $\begin{gathered} 0.454 \\ (0.633) \end{gathered}$ | $\begin{gathered} 0.238 \\ (0.573) \end{gathered}$ | $\begin{aligned} & (0.427) \\ & 1.960^{* * *} \\ & (0.736) \end{aligned}$ | $\begin{gathered} 0.538 \\ (0.632) \end{gathered}$ | $\begin{gathered} 0.355 \\ (0.571) \end{gathered}$ | $\begin{aligned} & 1.784^{* *} \\ & (0.727) \end{aligned}$ |
| Parental private sector experience | $\begin{gathered} 0.035 \\ (0.542) \end{gathered}$ | $\begin{gathered} -0.040 \\ (0.500) \end{gathered}$ | $\begin{gathered} 0.091 \\ (0.440) \end{gathered}$ | $\begin{gathered} -0.011 \\ (0.546) \end{gathered}$ | $\begin{gathered} -0.113 \\ (0.504) \end{gathered}$ | $\begin{gathered} 0.135 \\ (0.448) \end{gathered}$ | $\begin{gathered} -0.072 \\ (0.554) \end{gathered}$ | $\begin{gathered} -0.085 \\ (0.505) \end{gathered}$ | $\begin{gathered} 0.118 \\ (0.448) \end{gathered}$ |
| Private sector experience | $\begin{gathered} 1.094^{*} \\ (0.595) \end{gathered}$ | $\begin{gathered} 0.772 \\ (0.546) \end{gathered}$ | $\begin{gathered} 0.285 \\ (0.539) \end{gathered}$ | $\begin{gathered} 0.914 \\ (0.602) \end{gathered}$ | $\begin{gathered} 0.649 \\ (0.559) \end{gathered}$ | $\begin{gathered} 0.469 \\ (0.557) \end{gathered}$ | $\begin{gathered} 1.055^{*} \\ (0.592) \end{gathered}$ | $\begin{gathered} 0.815 \\ (0.549) \end{gathered}$ | $\begin{gathered} 0.368 \\ (0.545) \end{gathered}$ |
| Innovation | $\begin{gathered} -0.033 \\ (0.072) \end{gathered}$ | $\begin{gathered} 0.014 \\ (0.035) \end{gathered}$ | $\begin{gathered} -0.015 \\ (0.037) \end{gathered}$ | $\begin{gathered} -0.051 \\ (0.083) \end{gathered}$ | $\begin{gathered} 0.008 \\ (0.037) \end{gathered}$ | $\begin{gathered} -0.007 \\ (0.036) \end{gathered}$ | $\begin{gathered} -0.036 \\ (0.073) \end{gathered}$ | $\begin{gathered} 0.014 \\ (0.036) \end{gathered}$ | $\begin{gathered} -0.015 \\ (0.037) \end{gathered}$ |
| Peer-reviewed publications | $\begin{aligned} & 0.090^{* * *} \\ & (0.023) \end{aligned}$ | $\begin{aligned} & 0.086^{* * *} \\ & (0.021) \end{aligned}$ | $\begin{aligned} & 0.090^{* * *} \\ & (0.020) \end{aligned}$ | $\begin{aligned} & 0.091^{* * *} \\ & (0.023) \end{aligned}$ | $\begin{aligned} & 0.087^{* * *} \\ & (0.021) \end{aligned}$ | $\begin{aligned} & 0.088^{* * *} \\ & (0.020) \end{aligned}$ | $\begin{aligned} & 0.090^{* * *} \\ & (0.023) \end{aligned}$ | $\begin{aligned} & 0.085^{* * *} \\ & (0.021) \end{aligned}$ | $\begin{aligned} & 0.088^{* * *} \\ & (0.020) \end{aligned}$ |
| Other scientific publications | $\begin{gathered} -0.007 \\ (0.046) \end{gathered}$ | $\begin{gathered} 0.042 \\ (0.026) \end{gathered}$ | $\begin{aligned} & 0.054^{* *} \\ & (0.024) \end{aligned}$ | $\begin{array}{r} -0.008 \\ (0.046) \end{array}$ | $\begin{gathered} 0.047^{*} \\ (0.026) \end{gathered}$ | $\begin{aligned} & 0.059^{* *} \\ & (0.025) \end{aligned}$ | $\begin{gathered} -0.004 \\ (0.045) \end{gathered}$ | $\begin{gathered} 0.048^{*} \\ (0.026) \end{gathered}$ | $\begin{aligned} & 0.055^{* *} \\ & (0.025) \end{aligned}$ |
| Bohr-type | $\begin{gathered} 0.081 \\ (0.289) \end{gathered}$ | $\begin{gathered} -0.272 \\ (0.297) \end{gathered}$ | $\begin{gathered} -0.140 \\ (0.247) \end{gathered}$ |  |  |  |  |  |  |
| Edison-type |  |  |  | $\begin{gathered} 0.282 \\ (0.255) \end{gathered}$ | $\begin{gathered} 0.369 \\ (0.224) \end{gathered}$ | $\begin{gathered} -0.264 \\ (0.227) \end{gathered}$ |  |  |  |
| Pasteur-type |  |  |  |  |  |  | $\begin{gathered} -0.381 \\ (0.278) \end{gathered}$ | $\begin{gathered} -0.156 \\ (0.229) \end{gathered}$ | $\begin{gathered} 0.326 \\ (0.205) \end{gathered}$ |
| Constant | $\begin{gathered} -5.009^{* * *} \\ (1.145) \end{gathered}$ | $\begin{gathered} -5.073^{* * *} \\ (1.089) \end{gathered}$ | $\begin{gathered} -3.495^{* * *} \\ (0.941) \end{gathered}$ | $\begin{gathered} -4.898^{* * *} \\ (1.115) \end{gathered}$ | $\begin{gathered} -5.324^{* * *} \\ (1.068) \end{gathered}$ | $\begin{gathered} -3.771^{* * *} \\ (0.929) \end{gathered}$ | $\begin{gathered} -5.274^{* * *} \\ (1.131) \end{gathered}$ | $\begin{gathered} -5.384^{* * *} \\ (1.070) \end{gathered}$ | $\begin{gathered} -3.335^{* * *} \\ (0.936) \end{gathered}$ |
| $R^{2}$ Nagelkerke | 0.386 | 0.386 | 0.386 | 0.403 | 0.403 | 0.403 | 0.403 | 0.403 | 0.403 |
| Akaike information criterion | 1.972 | 1.972 | 1.972 | 1.950 | 1.950 | 1.950 | 1.949 | 1.949 | 1.949 |
| $x^{2}$ Correctly classified | 103.10 | 103.10 | 103.10 | 108.55 | 108.55 | 108.55 | 108.77 | 108.77 | 108.77 |
| $N$ | 248 | 248 | 248 | 248 | 248 | 248 | 248 | 248 | 248 |
| Change in $X^{2}$ base model | 1.279 | 1.279 | 1.279 | 6.725* | 6.725* | 6.725* | 6.942* | 6.942* | 6.942* |

Note: The table reports coefficients from a multinomial logit model using maximum likelihood. Standard Errors are reported in parentheses.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.

Table 3. Marginal effects from multinomial logit regression.

|  | Bohr-type | Edison-type | Pasteur-type |
| :--- | :---: | :---: | :---: |
| Marginal effect on the probability <br> of | Average Marginal Effect | Average Marginal Effect | Average Marginal Effect |
| (AME) | (AME) | (AME) |  |
| Assistant Professor | $0.0117(0.0205)$ | $0.0196(0.0175)$ | $-0.0300(0.0191)$ |
| Associate Professor | $-0.0222(0.0264)$ | $0.0359^{*}(0.0188)$ | $-0.0173(0.0191)$ |
| Full Professor | $-0.0103(0.0277)$ | $-0.0439^{*}(0.0239)$ | $0.0463^{* *}(0.0209)$ |

Note: Coefficients in column correspond to the marginal effects for the independent variables calculated at the mean levels of the remaining variables. Standard errors are shown in parentheses.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.

## Predicted Probabilities of Transition <br> Ordered by Relative Degree of Research Orientation From Low to High



Figure 4. Predicted probabilities of career transition for Edison and Pasteur research orientations.

Table 4. Coefficient estimate from sequential logit model.

| Variables | Sequential Logit Model |  |  |
| :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) |
|  | Assistant Professor | Associate Professor | Full Professor |
| Bohr-type | -0.102 (0.181) | -0.249 (0.321) | 0.342 (0.474) |
| Edison-type | 0.083 (0.168) | -0.273 (0.264) | $-0.909 * * *(0.314)$ |
| Pasteur-type | 0.003 (0.153) | 0.535* (0.273) | 0.604** (0.303) |

Note: The table reports coefficients from a sequential logit model following Buis (2015). Robust standard errors are reported in parentheses. The model reporting has been abbreviated to preserve lucidity. The full model is available upon request from the authors.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.
academics transitioning to full professor positions ( $\beta=0.0463, p<.05$ ). The same picture emerges when inspecting the results graphically in Figure 4, in terms of the predicted probabilities in each transition stage. Decomposing the overall effect to transition to a full professorship, the sequential logit model reports that when cumulating the individual effects, Pasteur academics do not differ much in their probabilities when being considered for an assistant professorship, yet they are increasingly likely to be promoted to associate professorships ( $\beta=0.535, p<.1$ ) and consequently full professorships ( $\beta=0.604, p<.05$ ). In other words, the transition to the associate professor level carries most weight when it comes to achieving the final outcome (i.e. obtaining a full professorship) and

Pasteur academics are at an advantage in securing such positions. Therefore, they are also most likely to reach the full professor level.

### 4.3. Gender differences affecting career success

We test our hypothesis about the effect of heterogeneity emerging from gender on career success $(\mathrm{H} 2)$ using the same two models as in the previous section.

Hypothesis 2 is affirmed for the transition to a full professorship in our multinomial logit model (Table 5), where we see a positive effect (favouring male academics) of gender on career success ( $B=1.852, p<.01$ ). The same effect is observed regarding the average marginal effects, that highlight males are more likely to transition to full professorships ( $B=0.2067, p<.05$ ). A visual examination of the predicted probabilities for career transitions also show this effect (Figure 5).

Interestingly, when we decompose the overall effect of transitioning to a full professor position, we find that the advantage of male academics in later career stages (obtaining full professorships), stems from transitions earlier in the academic career. That is, the sequential logit model (Table 8) shows that males are significantly more likely to move from an early career position into an assistant professor position ( $\beta=0.880, p<.05$ ). Subsequently, both males and females who obtained an assistant professorship have rather equal chances to secure associate professorships. However, when it comes to transitioning to full professorships, males are once again at a strong and significant advantage relative to those females who made it to the associate professor level ( $\beta=2.390, p<.05$ ).

Generally speaking, when we inspect the differences between males and females in more detail, we find that male academics produce significantly more publications and innovation. In fact, we found that for both non-tenured and tenured positions, males have a much higher publication track record ( $M=6.9, S D=7.4$ and $M=19.2, S D=21.1$ ) than females ( $M=4.4, S D=4.7$ and $M=$ $12.6, S D=8.7$ ), when looking only at peer-reviewed publications. Differences in both groups are statistically significant ( $p<.05$ ). The same goes for innovation output, where in tenured positions the average innovation output for females $(M=1, S D=2.5)$ is similar to their innovation output in

Table 5. Multinomial logit regression.

|  | Model A |  |  |
| :--- | :---: | :---: | :---: |
|  | $(1)$ | $(2)$ | $(3)$ |
| Variables | Assistant Professor | Associate Professor | Full Professor |
| Location | $0.989^{*}$ | $1.285^{* *}$ | -0.272 |
|  | $(0.567)$ | $(0.528)$ | $(0.401)$ |
| Parental private sector experience | 0.121 | -0.016 | 0.132 |
|  | $(0.531)$ | $(0.494)$ | $(0.429)$ |
| Private sector experience | $1.07^{*}$ | 0.842 | 0.351 |
|  | $(0.578)$ | $(0.537)$ | $(0.521)$ |
| Innovation | -0.031 | 0.024 | -0.007 |
|  | $(0.072)$ | $(0.034)$ | $(0.037)$ |
| Peer-reviewed publications | $0.090^{* * *}$ | $0.087^{* * *}$ | $0.091^{* * *}$ |
|  | $(0.023)$ | $(0.021)$ | $(0.020)$ |
| Other scientific publications | -0.008 | $0.046^{*}$ | $0.058^{* *}$ |
|  | $(0.045)$ | $(0.026)$ | $(0.024)$ |
| Gender heterogeneity | 0.447 | 0.304 | $1.852^{* * *}$ |
|  | $10.624)$ | $(0.566)$ | $(0.715)$ |
| Constant | $-4.968^{* * *}$ | $-5.327^{* * *}$ | $-3.690^{* * *}$ |
|  | $(1.103)$ | $(1.049)$ | $(0.895)$ |
| $R^{2}$ Nagelkerke | 0.354 | 0.354 | 0.354 |
| Akaike Information Criterion | 1.942 | 1.942 | 1.942 |
| $X^{2}$ Correctly classified | 92.58 | 92.58 | 92.58 |
| $N$ | 248 | 248 | 248 |
| Change in $X^{2}$ base model | $0.000^{* * *}$ | $0.000^{* * *}$ | $0.000^{* * *}$ |

Note: The table reports coefficients from a multinomial logit model using maximum likelihood. Standard Errors are reported in parentheses.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.

## Predicted Probabilities of Transition

Female=0; Male= 1


Figure 5. Predicted Probabilities of career transition for gender heterogeneity.
non-tenured positions ( $M=0.9, S D=1.9$ ), while for men the innovation output rose in tenured positions ( $M=3.2, S D=7.3$ ) compared to non-tenured positions ( $M=2.0, S D=4.7$ ). In line with this result, tenured females report significantly less Pasteur-type research. Looking at the overall research productivity, we find that significant differences exist between non-tenured males and females, as females produce much less. These differences do not exist for tenured academics. Here, overall research productivity is a composite measure of the reported output of: peer-reviewed journal papers, papers in other journals, book chapters, books, edited books, edited special issues, as well as non-scientific papers and books. Also, males were slightly more likely to be acting as journals editors on the junior level, but there were no gender differences with respect to editor positions for the full professorial level. We find no significant differences between male and female researchers on other aspects, such as their collaborations. Hence, actual gender differences in output and editorship are more apparent during the early career than later in the academic career. Interestingly, tenured females report significantly less Pasteur research, which is the one research orientation that seems to help academics to become full professor (see Section 4.2).

### 4.4. Disciplinary and cultural mentor-mentee heterogeneity affecting academic career success

With regard to H 3 , we find a negative and significant effect of cultural heterogeneity only for the final transition to a full professorship position ( $\beta=-1.156, p<.05$; see Table 6 ). Because it proves to be difficult to interpret output from non-linear models (Hoetker 2007) we also report the marginal effects in Table 7. The marginal effects corroborate the effects for cultural heterogeneity ( $\beta=$ $-0.1106, p<.05)$. Transitions to academic positions involve a sequence of choices, in which those that did not transition early cannot possibly transition later. Using a sequential logit model in cases with interdependent transitions allows us to estimate the relationship between explanatory variables and the odds of passing each transition (Buis 2015). The individual effect of an explanatory variable on the final outcome (becoming a full professor) is then a weighted sum of the effects on passing transitions (see Table 8).

The results for cultural heterogeneity derived from the multinomial model suggest a negative effect of heterogeneity on the likelihood of eventually becoming a full professor. When decomposing

Table 6. Multinomial logit regression.

|  | Model A |  |  | Model B |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variables | (1) <br> Assistant <br> Professor | (2) <br> Associate <br> Professor | (3) <br> Full <br> Professor | (4) <br> Assistant <br> Professor | (5) <br> Associate Professor | (6) <br> Full <br> Professor |
| Location | $\begin{aligned} & \hline 0.926 \\ & (0.576) \end{aligned}$ | $\begin{aligned} & \hline 1.370^{* *} \\ & (0.540) \end{aligned}$ | $\begin{gathered} \hline-0.168 \\ (0.412) \end{gathered}$ | $\begin{aligned} & \hline 1.088^{*} \\ & (0.574) \end{aligned}$ | $\begin{aligned} & \hline 1.406^{* * *} \\ & (0.535) \end{aligned}$ | $\begin{gathered} \hline-0.107 \\ (0.412) \end{gathered}$ |
| Gender | $\begin{aligned} & 0.459 \\ & (0.627) \end{aligned}$ | $\begin{aligned} & 0.291 \\ & (0.567) \end{aligned}$ | $\begin{aligned} & 1.830^{* *} \\ & (0.716) \end{aligned}$ | $\begin{aligned} & 0.465 \\ & (0.626) \end{aligned}$ | $\begin{aligned} & 0.345 \\ & (0.570) \end{aligned}$ | $\begin{aligned} & 1.915^{* * *} \\ & (0.718) \end{aligned}$ |
| Parental private sector experience | $\begin{aligned} & 0.103 \\ & (0.534) \end{aligned}$ | $\begin{gathered} -0.008 \\ (0.495) \end{gathered}$ | $\begin{aligned} & 0.169 \\ & (0.432) \end{aligned}$ | $\begin{aligned} & 0.078 \\ & (0.535) \end{aligned}$ | $\begin{gathered} -0.076 \\ (0.499) \end{gathered}$ | $\begin{aligned} & 0.065 \\ & (0.435) \end{aligned}$ |
| Private sector experience | $\begin{aligned} & 1.06^{*} \\ & (0.581) \end{aligned}$ | $\begin{aligned} & 0.838 \\ & (0.539) \end{aligned}$ | $\begin{aligned} & 0.336 \\ & (0.523) \end{aligned}$ | $\begin{aligned} & 1.062^{*} \\ & (0.581) \end{aligned}$ | $\begin{aligned} & 0.837 \\ & (0.543) \end{aligned}$ | $\begin{aligned} & 0.339 \\ & (0.531) \end{aligned}$ |
| Innovation | $\begin{gathered} -0.032 \\ (0.074) \end{gathered}$ | $\begin{aligned} & 0.025 \\ & (0.035) \end{aligned}$ | $\begin{gathered} -0.005 \\ (0.037) \end{gathered}$ | $\begin{gathered} -0.036 \\ (0.073) \end{gathered}$ | $\begin{aligned} & 0.017 \\ & (0.035) \end{aligned}$ | $\begin{gathered} -0.015 \\ (0.037) \end{gathered}$ |
| Peer-reviewed publications | $\begin{aligned} & 0.090^{* * *} \\ & (0.023) \end{aligned}$ | $\begin{aligned} & 0.086^{* * *} \\ & (0.021) \end{aligned}$ | $\begin{aligned} & 0.090^{* * *} \\ & (0.020) \end{aligned}$ | $\begin{aligned} & 0.089^{* * *} \\ & (0.022) \end{aligned}$ | $\begin{aligned} & 0.086^{* * *} \\ & (0.021) \end{aligned}$ | $\begin{aligned} & 0.089^{* * *} \\ & (0.020) \end{aligned}$ |
| Other scientific publications | $\begin{gathered} -0.008 \\ (0.046) \end{gathered}$ | $\begin{aligned} & 0.046^{*} \\ & (0.026) \end{aligned}$ | $\begin{aligned} & 0.057^{* *} \\ & (0.024) \end{aligned}$ | $\begin{gathered} -0.005 \\ (0.045) \end{gathered}$ | $\begin{aligned} & 0.046^{*} \\ & (0.026) \end{aligned}$ | $\begin{aligned} & 0.057^{* *} \\ & (0.024) \end{aligned}$ |
| Disciplinary heterogeneity | $\begin{gathered} 0.209 \\ (0.510) \end{gathered}$ | $\begin{gathered} -0.460 \\ (0.493) \end{gathered}$ | $\begin{gathered} -0.534 \\ (0.462) \end{gathered}$ |  |  |  |
| Cultural heterogeneity |  |  |  | $\begin{gathered} -0.390 \\ (0.526) \end{gathered}$ | $\begin{gathered} -0.696 \\ (0.508) \end{gathered}$ | $\begin{gathered} -1.156^{* *} \\ (0.496) \end{gathered}$ |
| Constant | $\begin{gathered} -4.936^{* * *} \\ (1.096) \end{gathered}$ | $\begin{gathered} -5.316^{* * *} \\ (1.058) \end{gathered}$ | $\begin{gathered} -3.680^{* * *} \\ (0.903) \end{gathered}$ | $\begin{gathered} -4.970^{* * *} \\ (1.113) \end{gathered}$ | $\begin{gathered} -5.283^{* * *} \\ (1.053) \end{gathered}$ | $\begin{gathered} -3.626^{* * *} \\ (0.900) \end{gathered}$ |
| $R^{2}$ Nagelkerke | 0.362 | 0.362 | 0.362 | 0.375 | 0.375 | 0.375 |
| Akaike Information Criterion | 1.956 | 1.956 | 1.956 | 1.939 | 1.939 | 1.939 |
| $X^{2}$ Correctly classified | 95.09 | 95.09 | 95.09 | 99.35 | 99.35 | 99.35 |
| $N$ | 248 | 248 | 248 | 248 | 248 | 248 |
| Change in $\chi^{2}$ base model | 2.518* | 2.518* | 2.518* | 6.772* | 6.772* | 6.772* |

Note: The table reports coefficients from a multinomial logit model using maximum likelihood. Standard Errors are reported in parentheses.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.

Table 7. Marginal effects from multinomial logit regression.

| Marginal effect on the probability <br> of | Disciplinary heterogeneity <br> Average Marginal Effect <br> (AME) | Cultural heterogeneity <br> Average Marginal Effect <br> (AME) | Gender heterogeneity <br> Average Marginal Effect <br> (AME) |
| :--- | :---: | :---: | :---: |
| Assistant Professor | 0.0302 | 0.0006 | -0.0032 |
| Associate Professor | $(0.0355)$ | $(0.0362)$ | $(0.0448)$ |
|  | -0.0311 | -0.0281 | -0.0257 |
| Full Professor | $(0.0433)$ | $(0.0442)$ | $(0.0512)$ |
|  | -0.0551 | $-0.1106^{* *}$ | $0.2067^{* *}$ |
|  | $(0.0521)$ | $(0.0548)$ | $(0.084)$ |

Note: Coefficients in column correspond to the marginal effects for the independent variables calculated at the mean levels of the remaining variables. Standard errors are shown in parentheses.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.
the overall effect into the various transition stages, the sequential logit model highlights that academics who are culturally heterogeneous from their PhD supervisors are less likely to make it to an assistant professorship in the first place ( $\beta=-0.788, p<.05$ ). This means that cultural mentormentee heterogeneity already hampers academics' careers at an early stage.

With respect to H 4 , we find that for disciplinary heterogeneity none of the coefficients is significantly different from zero for individual marginal transitions in the multinomial logit model. However, the results of the sequential logit model in Table 8 reveal a negative effect of disciplinary heterogeneity on the likelihood of becoming an associate professor. While those academics differing from their PhD supervisor in their disciplinary profile have similar chances of getting a position as an assistant professor, they have less chances of obtaining associate professor positions ( $\beta=-0.948, p<.1$ ).

Table 8. Coefficient estimate from sequential logit model.

|  | Sequential Logit Model |  |  |
| :--- | :---: | :---: | :---: |
|  | $(1)$ | $(2)$ | $(3)$ |
| Variables | Assistant Professor | Associate Professor | Full Professor |
| Disciplinary heterogeneity | $-\mathbf{0 . 3 2 0}$ | $-\mathbf{0 . 9 4 8}$ | $\mathbf{0 . 0 1 9}$ |
|  | $\mathbf{0 . 3 1 8 )}$ | $\mathbf{0 . 5 7 8 )}$ | $\mathbf{( 0 . 6 1 2 )}$ |
| Cultural heterogeneity | $-\mathbf{0 . 7 8 8 ^ { * * }}$ | $-\mathbf{0 . 5 0 2}$ | $-\mathbf{0 . 5 0 6}$ |
|  | $\mathbf{0 . 3 7 9 )}$ | $\mathbf{( 0 . 6 1 9 )}$ | $\mathbf{( 0 . 6 3 2 )}$ |
| Gender heterogeneity | $\mathbf{0 . 8 8 0 ^ { * * }}$ | $\mathbf{0 . 7 9 9}$ | $\mathbf{2 . 3 9 0 ^ { * * }}$ |
|  | $\mathbf{0 . 3 8 6 )}$ | $\mathbf{( 0 . 7 6 4 )}$ | $\mathbf{( 1 . 0 1 8 )}$ |

Note: The table reports coefficients from a sequential logit model following Buis (2015). Robust standard errors are reported in parentheses. The model reporting has been abbreviated to preserve lucidity. The full model is available upon request from the authors.
${ }^{*} p<.1,{ }^{* *} p<.05,{ }^{* * *} p<.01$.

Subsequently, academics that manage to transition to the associate level nonetheless are equally likely to reach the full professor level. However, taking the two previous transitions together, only few academics exhibiting disciplinary heterogeneity with their PhD supervisors will actually become full professors. Instead, most of them are likely to be stuck in assistant professor positions.

Figure 6 reports similar effects as the individual marginal effects and it confirms that probabilities are strongly decreasing for the first and last transition. The negative effect on the final outcome reported in Tables 7 and 8 is mainly driven by two groups of academics. The first group consists of academics who are culturally different from their PhD supervisors and unable to make the first transition from their early career position (for example, as post-doctoral researchers) to assistant professorship positions. The second group consists of academics differing from their PhD supervisors in disciplinary terms and unable to make the transition from the assistant professorship to associate professorship positions. Consequently, academics from both groups are not eligible for any subsequent transition to a full professorship thereafter. Only exceptionally, academics who differ from their PhD supervisor in terms of culture and discipline manage to get to the next level early on, and their subsequent chances to obtain full professorship positions are similar. Hence, cultural and disciplinary mentor-mentee heterogeneity hampers academics in early and mid-career stages.

Predicted Probabilities of Transition 0=Homogeneity; 1= Heterogeneity


Figure 6. Predicted probabilities of career transition for disciplinary and cultural heterogeneity.

## 5. Conclusion

Our results on research orientation suggest that academics at European universities of technology are particularly successful when they are able to deal with heterogeneity in their research. Academics have the best chances of climbing the academic ladder all the way to the top when they succeed at bridging between the quest for fundamental understanding and socio-economically relevant applications of their research, i.e. when they conduct predominantly Pasteur research. We suggest the considerable career success advantages of academics with a Pasteur research orientation are rooted in the changing role of universities and the increasing pressure on academics to contribute to socio-economic goals. Presumably, Pasteur academics are more successful in securing funds for their research, as eligibility for funds depends increasingly on societal relevance and impact (e.g. Bridle et al. 2013) while at the same time still significantly contributing to the knowledge base of their discipline.

Moreover, inspecting our results related to gender, male academics are at an advantage in climbing the academic career ladder. Simply by inspecting the descriptive statistics for female career advancement, we can already infer that females are at a distinct disadvantage. That is, only 12 out of the 69 women in our sample have secured a tenured position. Our analyses show two main exit points of females in academic careers, i.e. the transition to a tenured position (assistant professorship) and the transition to the full professorship stage. The gender imbalance in academic careers seems to emerge because of differences between individuals in terms of their academic performance. We reaffirm differences in academic publishing between male and female researchers (Bentley 2011; Ghiasi, Larivière, and Sugimoto 2015; Beaudry and Larivière 2016), and find that differences are most considerable among non-tenured staff. Interestingly, women report much less Pasteur research orientation than men. As women getting tenure are as productive as men and Pasteur research is the orientation most likely helping academics with the last step on the academic ladder, this seems to be an important reason for women not making it to full professor. Our results point again towards the important question of whether gender differences are due to individual choices turning into individual merits or whether they are due to bottlenecks in the academic system (e.g. Nielsen 2016).

Our results on mentor-mentee heterogeneity suggest that it works in early career stages but does not improve academics' career prospects in the long run. Our observations correspond with previous findings that PhD students finishing an interdisciplinary thesis secure a subsequent position in academia easily, but indeed face difficulties securing tenured positions (e.g. Millar 2013). Early in their career academics with culturally and disciplinary heterogeneous PhD supervisors successfully make the initial step up the academic ladder. That is, these academics have equal chances of obtaining early career positions and assistant professorship positions, respectively. Directly after finishing their PhD thesis, academics often hold brief appointments in various institutions that often also require international mobility (e.g. McAlpine 2016). In that respect, cultural heterogeneity between supervisor and student may come with advantages for those seeking early career positions. However, thereafter, mentor-mentee heterogeneity obstructs academics when trying to secure tenured positions in academia. We suggest that two mechanisms explain advantages for academics with homogenous mentors. First, academics with homogenous mentors have more opportunities to build their careers based on the knowledge base and the networks of their mentors. Second, mentors tend to support mentees similar to themselves, because of processes of similarity-attraction and social categorization (Tajfel 1982; Williams and O'Reilly 1998; Stahl et al. 2010).

Our insights are relevant for policymakers, university managers, and academics themselves in identifying the most promising academics, supporting current staff members, correcting for gender imbalances, and making strategic choices regarding research orientation and PhD supervisors.

Academics climbing the career ladder in an increasingly complex and more demanding environment inspired us to study whether more heterogeneity or more homogeneity emerging from
research orientation, gender differences, or the mentor-mentee relationship positively influences academics' career advancement. Our findings raise questions regarding the effect of mentormentee heterogeneity on career success. For example, questions about how mentees benefit from mentor-mentee heterogeneity or homogeneity, e.g. via capabilities obtained or via access to networks. Furthermore, the gender imbalance we identify is likely explained by two problems for women climbing the academic ladder at different stages. Very recent work in Beaudry and Larivière (2016) reports that women in health science publish less and receive fewer citations, and Jappelli, Nappi, and Torrini (2017) document differences in research evaluations across various sub-disciplines. These problems may be related to differences in research performance and research orientation. It would be interesting to identify the underlying causes. Why are women publishing less in early career stages, and why are some able to catch up later? Why do women innovate less and focus less on Pasteur research, which would give them the best chances to become full professors? Despite all efforts, gender inequality is still rife. We believe it to be important to better understand whether these are discretionary choices, or whether or not female academics are forced to meet gendered expectations deeply embedded in academia, which may substantially limit their room to manoeuvre (Sugimoto et al. 2013).

## Notes

1. Teaching is another important success criteria for academics. However, there is no indication that the social contract for universities has changed in this respect (Martin 2012). Therefore, we do not include teaching in our analysis.
2. In case of 'cultural heterogeneity,' mentee and mentor are from different nationalities, while in case of 'cultural homogeneity,' mentee and mentor have the same nationality. The exact operationalization is detailed in Section 3.2.2.
3. On the questionnaire, we gave translations to the German and Dutch equivalents of the different positions.
4. We illustrated the differences between the categories of Bohr, Pasteur and Edison research in the web-based survey. Moreover, earlier interviews carried out about related research questions indicated that academics at these two universities are either aware of this categorization or easily included it in their own perception of their research orientation.
5. We did not include patents for measuring commercial output as academics patent as an exception rather than as a rule (Agrawal and Henderson 2002). The findings in our survey support these former findings as 222 respondents report zero patents in the five year period.

## Acknowledgements

The survey was carried out during the Marie Curie research project on 'Academics Driving Innovation Systems' (No. 275357 - ARDIS) at RWTH Aachen University, Germany. We thank the rectors of Delft University of Technology, Karel Luyben, and of the RWTH Aachen, Ernst Schmachtenberg, as well as their staff members for sending the web-based survey to the respondents. Moreover, we appreciate Philip Marschall's and Jan Oelze's research assistance in programming the web-based survey.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## Funding

Claudia Werker gratefully acknowledges the funding by the European Commission as part of the Seventh Framework Programme [grant number 275357] for this project.

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