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ABSTRACT

Matching or Clashing: Exploring Scientists' Exit from Academia Through Intentions and Job Offers*

Academically trained scientists play a pivotal role in innovation by advancing the knowledge frontier across industries, prompting firms to increasingly engage in proactive recruitment. This paper investigates academic scientists' career transitions into industry by jointly examining two often separately studied mechanisms: scientists' intentions to leave academia (the supply side) and firms' recruitment efforts (the demand side). We conceptualize intersectoral mobility as the outcome of how these two mechanisms align or diverge. Using survey data from 469 scientists in Germany linked to follow-up information on their actual career outcomes more than three years later, our results show that exit intentions are the predominant predictor of subsequent transitions into industry jobs. Job offers reinforce the impact of existing exit intentions. By contrast, scientists who receive a job offer but do not intend to leave academia are the least likely to transition to private-sector employment. Implications for firms' active recruiting strategies and for universities seeking to retain scientific staff are discussed.

JEL Classification: J63, O31, J24

Keywords: academic scientists, career mobility, industry transition, knowledge transfer, exit intentions, job offers

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1. INTRODUCTION

Doctorate holders contribute substantially to innovation and technological progress by advancing the knowledge frontier across a variety of industries (Herrera et al., 2010; Lee et al., 2010; Buenstorf and Heinisch, 2020). Consequently, firms increasingly seek to employ academically trained scientists to strengthen their internal capabilities and active recruitment—including the targeted hiring of doctorate holders—has become a widespread feature of labor markets: e.g. in the United States, the share of new employees hired through active recruitment rose from 4.9% in 1991 to approximately 14.3% by 2022 (Black et al., 2024), with firms employing highly skilled personnel, such as PhD-level scientists, at the forefront of these proactive hiring practices. Such practices can lead to exit when they meet turnover intentions (Hom et al., 1984; van Breukelen et al., 2004), which are observed also in academia. While most PhD trained scientists express a strong preference for an academic career, less than half ultimately secure permanent positions in academic research (van der Weijden et al., 2016; Lawson and Lopes-Bento, 2024; Kwiek and Szymula, 2025). The private sector in particular has emerged as an attractive option to both early-career and senior researchers, offering higher compensation, structured career paths and dynamic research and development (R&D) environments (Roach and Sauermann, 2010; Agarwal and Ohyama, 2013; Denton et al., 2022), conditions that foster intentions to transition into industry positions.

For scientists to exit, these two dynamics—the scientists' intention to leave academia (the supply side) and firms' proactive efforts to recruit them (the demand side)—must not operate independently. Yet, prior research has predominantly focused on the supply side, investigating how individual motivations, interests, experiences and the academic environment shape scientists' career preferences and trajectories (Roach and Sauermann, 2010; Agarwal and Ohyama, 2013; Conti and Visentin, 2015; Lawson and Lopes-Bento, 2024). The demand side—specifically, how firms' recruitment strategies and active hiring practices influence scientists' decisions to exit academia and whether they have the potential to shift exit intentions, remains absent. This lack of integration is particularly salient given the rising importance of active sourcing and the increasing intensity of collaborations between academia and industry, which often facilitate direct transitions into private-sector employment (Garcia-Quevedo et al., 2012; Fudickar et al., 2018; Muscio and Shibayama, 2023).

Theoretically, the interaction between supply and demand can be situated within labor market job search and matching frameworks (Jovanovic, 1979; Mortensen and Pissarides, 1994), which emphasize that employment outcomes result from the interplay between job seekers' preferences and employers' search and recruitment efforts. Building on these frameworks, we develop a conceptual framework that jointly considers the supply- and demand-side from the perspective of the individual scientist. Specifically, we classify scientists according to two dimensions: whether they express an intention to leave academia to work in the private sector and whether they have received a job offer from the private sector. This results in four distinct groups that capture different configurations of supply and demand.

Empirically, we apply an endogenous multinomial treatment model to examine which individual, work-related, and research characteristics explain supply and demand configurations and how these are ultimately associated with actual exits from academia. Using survey data from 469 scientists in Germany matched with career outcomes three and a half years after the survey, we find that exit intentions (supply side) are the strongest predictor of exit and that job offers (demand side) reinforce the original intent such that those with low intention to exit who receive offers are the least likely to leave for the private sector. By combining both perspectives, this study thus contributes to a more comprehensive understanding of why and how scientists move from academic to industrial employment. In doing so, we bridge two strands of research that have so far remained largely separate—the study of scientists' intentions and the study of firms' talent recruitment strategies.

The remainder of the paper is structured as follows. Chapter 2 reviews the relevant literature on supply- and demand-side drivers influencing scientists' career decisions and outlines the conceptual framework. In chapter 3, we describe the data, measures and our analytical approach. Chapter 4 presents our empirical results that characterize the scientist's group memberships and examine their relationship with actual exit to industry. Finally, chapter 5 discusses the key findings, implications and limitations.

2. RELATED LITERATURE

2.1 Supply and demand in scientists' career transitions

The transition of academically trained scientists into non-academic employment can be understood using job search and matching theories from labor market economics (Jovanovic, 1979; Mortensen and Pissarides, 1994; Bender and Heywood, 2011). These frameworks highlight the frictions and information asymmetries that arise when matching job seekers to vacancies. In this view, the movement of scientists from academia to industry depends on the alignment of individual preferences for non-academic work and the availability of suitable positions in the private sector. Successful transitions require effective "matching" between the characteristics of scientists (supply) and the needs of firms (demand).

On the *supply side*, previous research has identified factors that determine scientists' interest in careers beyond academia (Ryan et al., 2012; Aarnikoivu et al., 2019). These include structural constraints within the academic employment context, such as the prevalence of fixed-term contracts (Fritsch and Krabel, 2012), limited prospects for tenure (Hayter and Parker, 2019), or intense competition for permanent positions (Bloch et al., 2015; Lawson and Lopes-Bento, 2024), which can lead to growing dissatisfaction or uncertainty about long-term career viability within academia, prompting scientists to explore alternatives outside the academic track. In addition, scientists may experience professional misalignment. Scientists whose work emphasizes applied or commercially oriented research may encounter a lack of recognition, support or career advancement within academic institutions that prioritize basic research and journal publications. In such cases, individuals may feel that their professional identity or aspirations are not fully compatible with the academic environment, which can generate a sense of mismatch and being "pushed out" (Roach and Sauermann, 2010; Fritsch and Krabel, 2012; Ryan et al., 2012; Kallio et al., 2024). Moreover, corporate R&D environments offer access to advanced technical infrastructure, multidisciplinary teams, and immediate application contexts for scientific research, which are highly appealing to scientists who lean toward downstream or applied research (Roach and Sauermann, 2010; Conti and Visentin, 2015; Roach and Sauermann, 2024).

On the *demand side*, firms vary in their openness to hire academically trained researchers. While some firms struggle to recognize the value of academic credentials or to accommodate research-oriented work styles (Kyvik and Olsen, 2012; Thune et al., 2012), other firms, particularly those operating in R&D-intensive or technology-driven sectors, actively recruit doctorate holders (Fritsch and Krabel, 2012; Buenstorf and Heinisch, 2020). These firms value the research and analysis skills that scientists bring (Zellner, 2003; Diamond et al., 2014) and may offer attractive research environments, including substantial autonomy, to attract the most promising researchers (Stern, 2004; Arts and Veugelers, 2020). They may also offer attractive job features including higher salaries, greater job security, clearer career progression, and better work-life balance that may promise a better job-match (Agarwal and Ohyama, 2013; Bloch et al., 2015; Aarnikoivu et al., 2019; Arts and Veugelers, 2020). From a personnel economics perspective, such benefits serve as incentive mechanisms that increase the attractiveness of industry employment (Lazear and Shaw, 2007; Lazear, 2018). Scientists may be drawn to firms that offer such competitive compensation, transparent promotion structures and research opportunities, and consider a sectoral move.

2.2 Matching supply and demand

2.2.1 Supply-side mechanism: Exit intentions

Intentions are among the strongest psychological predictors of future behavior (Armitage and Conner, 2001), including job search and actual job change. Within the framework of job search and matching, a scientist's intention to leave academia can be seen as an indication of underlying preferences for employment outside the academic sector. Such exit intentions reflect a scientist's readiness to engage with non-academic labor markets (Blau, 2000, 2007). In this sense, they represent the activation of the supply side: when preferences for external careers align with the perception of more favorable opportunities, the scientist becomes a potential candidate for sectoral mobility. Longitudinal studies provide robust evidence that turnover intentions reliably predict exits from current employment, particularly when supported by job-search behavior or external job offers (Hom et al., 1984; van Breukelen et al., 2004). Among scientists, such intentions mark a critical step in the potential move from academia to industry.

Exit intentions are related to and driven by several personal and job-related features, including scientists' professional identity, job profiles, and job satisfaction. Professional identity reflects the extent to which scientists perceive employment in the private sector as compatible with their self-concept and professional values. Academic researchers differ in their identity orientations, with some identifying primarily as traditional academics and others as applied or entrepreneurial scientists who value collaboration and practical impact (Lam, 2010). Such industry-oriented self-conceptions increase the perceived attractiveness of careers outside academia (Roach and Sauermann, 2010; Lawson and Lopes-Bento, 2024) and the likelihood of pursuing commercialization or industry-related careers (Lawson and Lopes-Bento, 2024; Roach and Sauermann, 2024). This identity can also express in job-related task profiles, with scientists who allocate substantial time to applied research, commercialization, or knowledge and technology transfer more closely embedded in industry-relevant networks. This embeddedness helps scientists develop boundary-spanning skills (Dolmans et al., 2022) and a "taste for industry" (Roach and Sauermann, 2010; Plantec et al., 2023) and reinforces a perceived fit with private-sector roles (Boardman and Ponomariov, 2009; Perkmann et al., 2013), thereby increasing the likelihood of forming intentions to leave academia.

Another key antecedent of exit intentions is job satisfaction. Studies in organizational and career psychology consistently show that employees who experience dissatisfaction with their work environment are more likely to develop intentions to leave (Donohue, 2007; Tschopp et al., 2014). Within academia, similar mechanisms apply: faculty members' satisfaction with their work life, including perceptions of recognition, workload, and professional development opportunities, is a significant predictor of their intentions to leave their institutions or even the profession (Rosser, 2004). Scientists who feel unsupported in their current roles, for example, due to unmet expectations around research autonomy or long-term career prospects, are more likely to consider external options, with the higher compensation and clearer career pathways in the private sector as powerful pull factors (Zhou and Volkwein, 2004; Aarnikoivu et al., 2019; White-Lewis et al., 2023). This is particularly relevant for scientists employed on fixed-term or otherwise precarious contracts. Conversely, for those holding tenure-track or tenured positions, the pressure to explore alternative career options is typically lower (Fritsch and Krabel, 2012; Hayter and Parker, 2019; Lawson and Lopes-Bento, 2024). They exhibit lower levels of turnover intentions and remain committed to academia (Nielsen, 2017; Woolston, 2020).

2.2.2 Demand-side mechanism: Industry job offer

In the job search and turnover literature, receiving a job offer is viewed as a pivotal moment that often prompts career transitions, especially when the offer arrives unsolicited or presents substantially better prospects than the current position (Rynes et al., 1991; Lee and

Mitchell, 1994). Job offers provide clear external signals of a candidate's value and can activate consideration of career changes, even among those who had not actively planned to leave (Lee et al., 2008). In the context of academic scientists, job offers from industry may therefore represent a concrete manifestation of demand-side dynamics: firms that perceive a strong fit may reach out proactively, especially when the scientist's skills and achievements align with industry needs (Lazear and Shaw, 2007; O'Meara et al., 2016).

For such offers to materialize, visibility and perceived relevance are key. Scientists who actively engage in online career platforms (e.g., LinkedIn, Xing[1]) increase their exposure to potential recruiters by presenting their expertise, highlight research achievements, and expand professional networks (Davis et al., 2020; Marin and Nilă, 2021; Howoldt et al., 2023). These platforms facilitate both professional communication and self-promotion (van Dijck, 2013; Ovadia, 2014), which is particularly effective for firms seeking advanced academic skills or highly specialized knowledge (Klier et al., 2015). Consistent with this mechanism, Baruffaldi et al. (2017) show that PhD graduates who transitioned to the private sector are more likely to maintain an active LinkedIn presence and broader professional online networks.

Job profiles, such as working in commercially relevant fields (e.g., engineering, life sciences, computer science) and engaging in collaborative research and knowledge and technology transfer can further raise visibility amongst potential employers and increase the likelihood of receiving industry interest (Fritsch and Krabel, 2012; Sauermann and Roach, 2012; D'Este et al., 2019). They serve as a signal of private-sector readiness and build a reputation within relevant networks (Grimpe and Hussinger, 2013; Perkmann et al., 2021). These activities also provide a basis for firms to assess personal and organizational fit (Lam, 2007; De Grande et al., 2014), and reduce information asymmetries (Pinheiro et al., 2015; Vaira et al., 2024). As a result, scientists with substantial firm involvement are significantly more

[1] Xing is a German-speaking online career platform.

likely to leave for firms interested in applied research and innovation (Perkmann et al., 2013; Hottenrott and Lawson, 2017; Muscio and Shibayama, 2023).

2.2.3 Matching, clashing, and exit: Outcomes of supply–demand interaction

Taken together, the mechanisms described above—(1) scientists' intentions to leave academia and (2) the job offers they receive from industry—can be seen as the demand and supply components of a matching process. Depending on how these two components align, four distinct career transition scenarios emerge (see Figure 1).

In the first scenario, scientists show little interest in non-academic careers and are not approached by firms (Group 1). These scientists often pursue basic research and appear to be in the "right place". Metaphorically described as residing in the "ivory tower", they remain disconnected from industry concerns (Lakitan, 2013; Lee and Miozzo, 2015). This reflects a still partly persistent view that a doctorate is primarily a preparation for an academic career (Neumann and Tan, 2011). We refer to this group of scientists as *Anchored and Undisturbed*. They are expected to be the least likely to leave academia.

On the opposite end, we observe scientists with an optimal match between intentions and opportunities (Group 4). Scientists in this group both want to leave academia and receive a concrete offer from industry. We refer to them as *Ready and Wanted*. Their "taste for industry" is matched by firms' demand for their expertise, making the move to the private sector a natural next step. This reflects insights from the turnover literature which confirmed that a match between exit intention and job offer can reliably predict job mobility (Hom et al., 1984; van Breukelen et al., 2004). These scientists are thus expected to be the most likely to leave academia.

The two remaining groups represent clashing scenarios, where supply and demand diverge. In Group 2, scientists exhibit strong intentions to leave academia and may actively seek employment in the private sector, yet they do not receive concrete job offers. While they may be dissatisfied with academia or exhibit a strong industry-orientation, their limited visibility to firms or the uncertain transferability of their skills can hinder successful matching. In some cases, a lack of prior engagement with non-academic sectors, such as experience in industry collaborations or access to relevant professional networks, further reduces their chances of being recruited (De Grande et al., 2014). We refer to these scientists as *Ready and Waiting*. Conversely, the final scenario captures cases in which scientists receive industry job offers despite having no intention to leave academia (Group 3). These individuals likely possess strong academic prospects guided by a pronounced "taste for science" (Stern, 2004; Roach and Sauermann, 2010; Sauermann and Roach, 2014). However, their accomplishments, such as high-impact publications, patents, spin-offs, or collaborations with industry, enhance their visibility and appeal also with potential industry employers. Some may be considered "star scientists" (Zucker and Darby, 1996), whose research excellence and reputational capital are seen as drivers of innovation within firms (Lacetera et al., 2004; Moretti and Wilson, 2014; Kehoe and Tzabbar, 2015), making them highly attractive. We refer to this group as *Anchored but Sought*.

These two clashing scenarios are where we are able to observe how supply and demand considerations interact and whether the demand-side, which previous studies—where career transitions have been studied solely from the perspective of scientists—have ignored, can alter the career outcomes traditionally associated with the supply-side. That is, if scientists receiving an offer leave academia despite a lack of intention, and whether scientists that lack concrete offers remain in academia despite strong exit intentions.

Building on these considerations, Figure 1 presents a conceptual framework for the transitions of academic scientists to industry. It is structured around the two key mechanisms of supply and demand, as developed through job search and matching theories (Jovanovic, 1979; Mortensen and Pissarides, 1994, see Chapter 2.1). On the *supply* side, exit intentions are shaped by identity, task orientation and dissatisfaction (see Chapter 2.2.1). On the *demand* side, job offers reflect firms' assessment of scientists' visibility, relevance and fit (see Chapter 2.2.2). Together, these mechanisms yield four possible match scenarios that serve as the basis for our subsequent empirical analysis of scientists' actual career move from academia into private-sector employment (O'Meara et al., 2014; White-Lewis et al., 2023; Kallio et al., 2024; Kwiek and Szymula, 2025).

INSERT FIGURE 1 HERE

3. METHOD

3.1 Data collection and sample

To empirically examine how individual career intentions and firm-side demand jointly shape academic scientists' transition into private-sector employment, we conducted a novel online survey targeting knowledge and technology transfer (KTT) behaviors, career preferences, and individual characteristics. The survey was administered in the German Federal State of Thuringia, a region that reflects the heterogeneity of the German research landscape. Thuringia hosts four universities, seven universities of applied sciences, and 25 public and private research institutes. The public research institutes include, for example, institutes of the Max Planck Society, which focus on basic research, and institutes of the Helmholtz Association, the Leibniz Association, and the Fraunhofer Society, which primarily conduct applied research. We excluded private research institutes from further consideration to maintain analytical focus on transitions from academia to the private sector.

We identified 7,785 eligible academic researchers by collecting publicly available contact information and profile data from research institutions' web pages. Between December 2019 and January 2020, we invited these scientists to participate in the survey. A total of 1,409 scientists responded, yielding a response rate of 18.1%. After removing 260 incomplete responses, we retained 1,149 valid cases. Prior work using this dataset (Cantner et al., 2024) confirms minimal non-response bias. Furthermore, a comparison with national statistics from the German Federal Statistical Office (Statistisches Bundesamt, 2020) indicates that our sample is representative of the general academic population in terms of both academic rank and gender.

For this study, we focus on the subset of respondents who were randomly assigned to answer additional questions on career mobility intentions and job offers. After excluding observations with missing values on key variables, the final sample consists of 469 scientists.

3.2 Measures

3.2.1 Dependent variable

Our outcome of interest is whether scientists transitioned into private-sector employment. Using information on current employers collected in June 2023 through LinkedIn (www.linkedin.com), Xing (www.xing.com), and general internet research, we constructed a binary variable, *Industry job*, coded 1 if a respondent was employed in the private sector and 0 otherwise.

3.2.2 Independent variables

To capture the four distinct career transition scenarios described in Chapter 2.2.3, we draw on the two underlying survey measures: scientists' intention to move to the private sector and their receipt of industry job offers.

Three items assessed scientists' intentions to move to the private sector (Ajzen, 2002): (1) "To what extent do you agree or disagree with the following statement: I intend to take up employment in a private company in the foreseeable future."; five-point Likert scale; 1 = "strongly disagree" to 5 = "strongly agree"; (2) "How likely is it that you will take up employment in a private company in the foreseeable future?"; continuous scale from 0% (very low) to 100% (very high); (3) "How often do you look for information about job offers in the private sector?"; five-point Likert scale; 1 = "never" to 5 = "regularly"). We z-standardized and averaged the three intention items (M = -0.06, SD = 0.88, α = .85), following standard recommendations for creating composite indices with differently scaled indicators (Aiken and West, 1991). A mean split was then applied to create the binary variable *Job change intentions* (0 = low intention, 1 = high intention). Of the 469 scientists in our sample, 204 reported high intentions and 265 low intentions.

The variable *Job offer* captures whether respondents have received at least one job offer from private companies or recruitment agencies as a result of their research activities since 2015 (0 = no, 1 = yes). 155 scientists (33%) reported receiving an offer.

Using these two variables, *Job change intentions* and *Job offer*, we assigned each scientist to one of four groups. For the empirical analysis, we constructed four corresponding binary indicators of group membership (0 = no, 1 = yes), which served as key independent variables.

3.2.3 Additional predictors and control variables

We consider several additional variables to account for academic scientists' selection into the four distinct career transition scenarios and their actual move to an industry career in line with the discussion in chapter 2.2.

We assess the extent to which scientists perceive employment in a private company as compatible with their professional self-concept using three items adapted from Obschonka et al. (2015). Respondents indicated their agreement with the following statements: (1) "The idea of working in a company does not fit my self-concept", (2) "The idea of working in a company is completely alien to me", and (3) "The idea of working in a company fits well into the image that I have of myself and my scientific work." All items are measured on a five-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree"). After reverse-coding the first two items, all three items were averaged to create the variable *Industry identity fit* (M = 3.33, SD = 0.98,

α = .72), with higher values indicating a stronger professional identity alignment with private-sector employment.

Following previous research on organizational turnover and career change (e.g. Tschopp et al., 2014), we measure *Job satisfaction* on a five-point Likert scale based on the question: “In general: How satisfied or unsatisfied are you with your current employment?” (0 = “not satisfied at all” to 5 = “very satisfied”). Validation studies have demonstrated that such single-item measures provide reliable and valid assessments of overall job satisfaction comparable to multi-item scales (Wanous et al., 1997; Dolbier et al., 2005).

To capture job security and career prospects in academia, we include an indicator of permanent employment. The variable *Permanent position* takes the value 1 if a respondent holds a tenured or otherwise permanent contract and 0 otherwise. Similar measures of contractual stability have been used in previous studies on scientists’ mobility and exit intentions (e.g. Fritsch and Krabel, 2012).

We also account for how scientists allocate their work time to different tasks. Adapted from Boardman and Ponomariov’s (2009) measurement approach, survey participants reported the average share of weekly working hours (in %) spent on (1) research, (2) teaching, (3) knowledge and technology transfer, and (4) administrative activities (*Share of working time devoted to* ...). These measures capture differences in scientists’ research orientation, boundary-spanning engagement, and academic responsibilities.

To assess scientists’ visibility to private-sector employers, we include an indicator of professional online networking (Davis et al., 2020; Marin and Nilă, 2021). The variable *LinkedIn or Xing account* takes the value 1 if a respondent maintains a profile on one of these platforms and 0 otherwise. Information on platform presence was manually collected in May 2020 through systematic searches on LinkedIn (www.linkedin.com) and Xing (www.xing.com).

The variable *Number of publications* captures each scientist's publication count as recorded in the Web of Science (WoS) and Scopus databases. Publication output is a widely used proxy for scientific productivity (Abramo and D'Angelo, 2014; Lindner et al., 2018). It can also increase visibility to external audiences, including potential private-sector employers (Rotolo et al., 2022). Although firms vary in the extent to which they value academic publication portfolios, a strong publication record may nonetheless signal expertise and general research excellence. We log-transformed the number of publications to account for its skewed distribution.

Share of publications with industry measures the extent of a scientist's direct collaboration with private-sector actors. Following Azoulay et al. (2009), we calculate this variable as the fraction of publications in which at least one co-author has an industry affiliation. Previous studies demonstrate that such collaboration patterns are strongly associated with scientists' mobility into industry and other non-academic career paths (e.g. Fritsch and Krabel, 2012; Tijssen et al., 2017).

The variable *PhD* indicates whether a respondent already holds a doctoral degree (0 = no, 1 = yes). Possessing a PhD signals advanced methodological training and domain-specific expertise, individual characteristics that are particularly attractive to employers in R&D-intensive industries (Herrera and Nieto, 2015; McAlpine and Inouye, 2022). Those still in training may be considered less capable.

We further control for a set of other demographic and employment characteristics known to influence scientists' job transitions into the private sector (Lee et al., 2010; Fritsch and Krabel, 2012; Bloch et al., 2015). To account for gender differences in career trajectories and mobility patterns, we include the dummy variable *Gender* (0 = female, 1 = male). We also control for *German language proficiency* (0 = no, 1 = yes), which is relevant given that German is the dominant working language in our study environment and may shape access to industry positions. The employment context is captured by the control variable *Employed at university* (vs. at public research organizations; 0 = no, 1 = yes), acknowledging that organizational environments differ in their exposure to industry collaboration and mobility pathways. Finally, we include the *disciplinary fields* by using discipline-specific controls for *Engineering Sciences*, *Life Sciences*, *Mathematics and Computer Sciences*, *Natural Sciences*, and *Social Sciences,* as sector transitions are strongly conditioned by field-level differences in labor market structure, industrial demand, and collaboration intensity.

3.3 Analytical strategy

We employ an endogenous multinomial treatment model (Deb and Trivedi, 2006b, 2006a) to estimate the effect of group affiliation—i.e., the four supply-demand match types defined by scientists' job change intentions and their receipt of industry job offers—on the likelihood of transitioning into private-sector employment. This modeling approach directly reflects our assumption that different combinations of supply-side intentions and demand-side offers create distinct mobility scenarios with potentially heterogeneous effects on actual job changes.

A central challenge in estimating these effects is the possibility of endogenous self-selection into the four groups. Scientists who report high intentions to work in industry or who receive job offers may systematically differ from others in skills, competencies, motivation, or personality traits, many of which are unobserved. If these unobserved characteristics correlate with both group membership and the probability of transitioning into private-sector employment, standard regression approaches would yield biased estimates. In particular, the influence of intentions or job offers on actual job transitions may be overestimated due to unobserved heterogeneity captured in the error term.

To address this issue, we apply an endogenous multinomial treatment model in which group membership is treated as a non-random, endogenously determined treatment. In the first stage, we estimate the likelihood that individual i belongs to one of the four treatment groups:

$$\Pr(Group_i = j) = X_i\alpha_j + \delta_j l_{ij} \quad with\, j = 1, \dots, 4 \tag{1}$$

where X_i represents the vector of predictors and control variables described in Chapter 3.2. These covariates capture observable factors shaping respondents' intentions to leave academia and their likelihood of receiving industry job offers.

The terms l_{ij} denote latent factors representing unobserved individual characteristics influencing group membership, while δ_j are associated factor loadings. Following Deb and Trivedi (2006b), we use scientists' *disciplinary fields* and *German language proficiency* as exclusion restrictions, as these variables affect intention formation and industry recruitment but should not directly influence transition probabilities once intentions and offers are taken into account. To validate this identification strategy, we conducted two diagnostic checks. First, a joint significance test reveals that the exclusion restrictions are indeed strong predictors of group assignment ($\chi^2 = 53.22$, $p < 0.001$), confirming their relevance for identifying variation in treatment status. Second, following standard practice (Wooldridge, 2010), we performed a placebo regression in which the outcome variable (*Industry job*) was regressed on the exclusion restrictions while conditioning on all predictors and controls. The exclusion restrictions are jointly insignificant ($\chi^2 = 2.79$, $p = 0.733$), indicating that, conditional on observable characteristics, they do not directly predict scientists' industry transitions. Together, these tests support the validity of the exclusion restrictions used in the endogenous multinomial treatment model.

In the second stage, we estimate the probability that a scientist transitions into private-sector employment:

$$Industry\ job_i = X_i\beta_i + \sum\nolimits_j \gamma_j Group_{ij} + \sum\nolimits_j \lambda_j l_{ij} \quad with\ j = 1, \dots, \mathrm{h} \qquad (2)$$

where X_i again represents the observable covariates, and where the $Group_{ij}$ indicators constitute the key treatment variables corresponding to the four intention-offer combinations. Including the latent factors l_{ij} in both stages ensures that unobserved heterogeneity affecting both treatment assignment and job transitions is captured and controlled for, with the λ_j parameters acting as selection-correction terms. Equations (1) and (2) are jointly estimated using the MTREATREG routine in Stata (Deb and Trivedi, 2006a).

4. RESULTS

4.1 Descriptive analysis

Table 1 reports descriptive statistics for all study variables. The dependent variable *Industry job* indicates that 11.5% (n = 54) of respondents eventually transitioned from academia to private-sector employment within the observation period, underscoring the empirical relevance of examining the determinants of this career shift.

The distribution across the four intention-offer groups reveals substantial heterogeneity in both supply- and demand-side dynamics. Group 1 (Low intention/No offer; *Anchored and Undisturbed*) is the largest segment of the sample (38.8%), suggesting that many scientists neither express interest in industry employment nor attract external offers. In contrast, 28.1% fall into Group 2 (High intention/No offer; *Ready and Waiting*), reflecting a substantial pool of scientists with latent interest in industry careers but without corresponding demand signals. Group 3 (Low intention/Offer; *Anchored but Sought*), which represents 17.7% of respondents, captures cases where industry employers seek out academic scientists despite limited stated interest. Finally, 15.4% belong to Group 4 (High intention/Offer; *Ready and Wanted*), representing the group most aligned with a potential transition to industry.

Additional predictors and control variables highlight the diversity of employment contexts among respondents. On average, job satisfaction is relatively high (M = 3.934, SD =

0.919), while industry identity fit averages 3.332 (*SD* = 0.978), indicating substantial variation in how compatible scientists perceive private-sector employment to be with their professional self-concept. Roughly half of the sample (49.5%) holds a permanent position. Time allocation patterns confirm the research-intensive nature of their work: scientists spend 52.2% of their weekly working hours on research, followed by 21.7% on teaching, 7.9% on knowledge and technology transfer, and 18.1% on administrative tasks.

Indicators of professional visibility show that only 42% of respondents maintain a LinkedIn or Xing account, and academic productivity varies widely (logged publication count; *M* = 2.020, *SD* = 1.549). Collaboration with industry remains limited overall, with the share of publications co-authored with firms averaging 0.038 (*SD* = 0.129).

Regarding demographic characteristics, 64% of respondents are male, 82.1% report proficiency in German, and 56.1% hold a PhD.[2] The largest disciplinary groups in the sample are Life Sciences (32.2%) and Social Sciences (28.8%), followed by Engineering Sciences (19.4%), Natural Sciences (16.0%), and Mathematics & Computer Sciences (3.6%).

INSERT TABLE 1 HERE

Table 2 presents the correlations between all study variables. To assess potential multicollinearity, we computed variance inflation factors (VIFs) for all study variables (not shown here). The VIF values range from 1.07 (*Share of publications with industry*) to 2.13 (*Group 2*), with a mean VIF of 1.42. All values are well below the commonly used threshold of 5 (Hair et al., 2013), indicating that multicollinearity is unlikely to be a concern in the present analysis.

[2] Our sample includes professors as well as doctoral and postdoctoral researchers. In the German science system, doctoral candidates are typically highly involved in research activities as part of their qualification and are considered members of the academic staff.

INSERT TABLE 2 HERE

4.2 First-stage results: Explaining variation in scientists' supply–demand configurations

The first stage of the endogenous multinomial treatment model examines scientists' selection into the four intention-offer groups. Table 3 presents average marginal effects from a multinomial logistic regression, indicating how a one-unit change in an explanatory variable affects the predicted probability of belonging to each group, while holding all other variables constant. We report average marginal effects rather than logit coefficients because coefficients from nonlinear multinomial models are not directly interpretable in probability terms and depend on an arbitrarily chosen reference category, whereas marginal effects allow a comparison across all four supply–demand configurations.

INSERT TABLE 3 HERE

Scientists in Group 1 (Low intention/No offer; *Anchored and Undisturbed*) show neither interest in industry careers nor receive job offers from the private sector. They are the most firmly anchored in academia. Our analysis reveals that the probability of belonging to this group increases with job satisfaction ($b = 0.064$, $p < 0.01$) and decreases strongly with industry identity fit ($b = -0.167$, $p < 0.01$). Spending more time on KTT activities, compared to research and teaching, lowers the probability of Group 1 membership ($b = -0.502$, $p < 0.05$), indicating that boundary-spanning activities weakens academic anchoring. Maintaining a professional online presence further differentiates this group: scientists without a LinkedIn or Xing account are much more likely to be part of the *Anchored and Undisturbed* scientists ($b = -0.172$, $p < 0.01$). This is consistent with the logic that low outward visibility maintains low exposure to private-sector demand. Holding a PhD makes it significantly more likely to fall into Group 1 ($b = 0.111$, $p < 0.01$), suggesting that holding an academic position after completing doctoral training may reinforce academic career orientation or signal deeper identification with the academic environment. The results in Table 3 also show that researchers in Engineering Sciences are significantly less likely than those in Life Sciences, Mathematics and Computer Sciences, Natural Sciences, and Social Sciences to belong to Group 1 ($b = -0.125$, $p < 0.05$). This reflects a comparatively stronger industrial pull in the engineering fields.

Group 2 (High intention/No offer; *Ready and Waiting*) consists of scientists who want to transition into industry but have not been approached by potential employers. The predictors for this group primarily reflect supply-side mechanisms. This becomes evident in the strong negative association between job satisfaction and the probability of Group 2 membership ($b = -0.075$, $p < 0.01$), consistent with dissatisfaction as a central antecedent of exit intentions. Similarly, a stronger industry identity fit increases the likelihood of Group 2 membership ($b = 0.122$, $p < 0.01$), pointing to identity alignment as an important driver of exit intentions even in the absence of demand-side pull. By contrast, higher publication output ($b = -0.034$, p < 0.01) and a greater share of co-publications with industry partners ($b = -0.225$, $p < 0.05$) reduce the likelihood of belonging to this group of the *Ready and Waiting* scientists. This suggests that scientists with stronger research productivity and industry collaboration tend to receive offers, thereby transitioning toward Groups 3 or 4 instead. The negative effects of proficiency in German ($b = -0.205$, $p < 0.01$) and holding a PhD ($b = -0.171$, $p < 0.01$) may reflect that scientists without these attributes perceive fewer long-term academic opportunities and thus express stronger mobility intentions. Alternatively, PhD holders and German-speaking scientists may have better access to academic jobs, dampening the urgency to leave.

Group 3 (Low intention/Offer; *Anchored but Sought*) captures scientists who do not intend to leave academia yet nevertheless receive job offers. These cases reflect demand-driven recruitment, where firms proactively identify attractive candidates. For example, the significant and positive coefficient for job satisfaction ($b = 0.038$, $p < 0.1$) suggests that industry employers may target well-integrated academics. Furthermore, maintaining a LinkedIn or Xing account exposes even academically oriented scientists and significantly increases their probability of being targeted by industry ($b = 0.074$, $p < 0.05$). German language proficiency positively predicts Group 3 ($b = 0.203$, $p < 0.01$), suggesting that industry employers in the regional context (Thuringia, Germany) favor candidates who can operate in the domestic language. Scientists at universities are significantly less likely to fall into this group of the *Anchored but Sought* ($b = -0.075$, $p < 0.1$) compared to those in non-university research institutes, where industry-related activities are on average more prevalent. Disciplinary differences again play a significant role: compared to Life Sciences, Mathematics and Computer Sciences, Natural Sciences, and Social Sciences, researchers in Engineering Sciences ($b = 0.111$, $p < 0.05$) are more likely to receive offers despite low intentions. This result reinforces the strong employer-side demand concentrated in engineering knowledge domains.

Scientists in Group 4 (High intention/Offer; *Ready and Wanted*) both seek industry jobs and receive job offers. This group represents the strongest match between supply-side interest and demand-side pull. Our results show that lower job satisfaction raises the probability of belonging to this group ($b = -0.027$, $p < 0.10$), although the effect is weaker than in Group 2. Once concrete industry job offers are available, dissatisfaction with the current job appears less central than the alignment of opportunities with existing job change intentions. Similarly, industry identity fit again plays a positive role ($b = 0.038$, $p < 0.05$). Professional visibility exerts the strongest positive effect in Group 4: having a LinkedIn or Xing profile substantially increases the likelihood of group membership ($b = 0.120$, $p < 0.01$). This underscores the role of digital networking in enabling successful matches between scientists and firms. Finally, we find that researchers in Engineering Sciences are more likely than those in the other disciplines to fall into Group 4, the *Ready and Wanted* scientists ($b = 0.085$, $p < 0.05$).

Taken together, these results reveal a clear distinction between the determinants of scientists' leave intentions and the determinants of industry employer interest. Identity orientations and job satisfaction primarily shape supply-side patterns, whereas boundary-spanning activities, visibility, and disciplinary background shape demand-side signals. Alignment or misalignment of these forces determines whether scientists remain anchored in academia (Group 1), intend to leave without receiving offers (Group 2), receive offers without intending to leave (Group 3), or are positioned for a viable transition into industry (Group 4).

4.3 Second-stage results: Determinants of scientists' transitions into industry

The second stage of the endogenous multinomial treatment model estimates how both observable characteristics and unobserved selection processes shape scientists' actual transition into private-sector employment. Table 4 presents the coefficients from the treatment-effects regression. The regression model fits the data well (Wald $\chi^2(66) = 3561.81$, $p < 0.001$). The estimated selection terms (λ) indicate substantial endogeneity between the four intention–offer configurations and the transition outcome, justifying the use of the treatment-effects framework.

INSERT TABLE 4 HERE

Group effects on industry transitions

Our results show that, consistent with our expectations, the highest likelihood of transition is observed among scientists who both seek industry jobs and receive offers from industry (Group 4; *Ready and Wanted*; $\beta = 0.050$, $p < 0.01$). Scientists in Group 2 (High intention/No offer; *Ready and Waiting*) also exhibit a higher likelihood of transitioning into industry relative to Group 1 (Low intention/No offer; *Anchored and Undisturbed*). The modest size of the regression coefficient ($\beta = 0.026$, $p < 0.10$) however suggests that intentions alone, in the absence of industry employer interest, translate into only a slight increase in scientists' sectoral mobility. By contrast, Group 3 (Low intention/Offer; *Anchored but Sought*) is associated with a significant negative effect relative to Group 1 ($\beta = -0.166$, $p < 0.01$). Receiving a job offer does not reliably translate into an actual transition when stated intentions to leave academia are weak.

Effects of individual characteristics and work activities

Turning to individual- and job-related predictors, several observations complement the first-stage results. Job satisfaction remains negatively related to industry transitions ($\beta = -0.032$, $p < 0.01$), reinforcing the earlier finding that dissatisfaction is a key driver of exit intentions. Industry identity fit continues to play an important role: individuals whose professional self-concept aligns more strongly with industrial work are significantly more likely to transition ($\beta = 0.076$, $p < 0.01$).

With respect to work-task allocations, the results show that greater involvement in teaching ($\beta = -0.208$, $p < 0.01$) and administrative duties ($\beta = -0.123$, $p < 0.01$), relative to working time spent on research, is associated with lower transition probabilities. Thus, heavier teaching and administrative loads may limit scientists' exposure to industry networks and opportunities, ultimately reducing the likelihood of an actual move.

Furthermore, maintaining a LinkedIn or Xing profile increases the likelihood of moving into industry employment ($\beta = 0.108$, $p < 0.01$), and research collaboration with firms, captured by the share of co-publications, has an even stronger positive effect ($\beta = 0.340$, $p < 0.01$). Together, these results indicate that visibility to external audiences, whether through digital platforms or direct collaboration, not only attracts industry employer interest but also translates into career mobility.

We also find that male scientists are significantly more likely to exit academia for an industry job than female scientists ($\beta = 0.064$, $p < 0.01$). Because gender had no significant effect in the first stage of the analysis, the difference between male and female scientists only arises at the transition stage, not through earlier supply- or demand-side sorting.

The remaining predictors do not exhibit significant independent effects once selection into intention–offer configurations is taken into account, implying that the influence of these characteristics operates primarily through the first-stage mechanisms that shape group membership, rather than through direct effects on the transition decision itself.

Selection effects and unobserved heterogeneity

The selection-correction terms, finally, shed light on the role of unobserved heterogeneity in predicting academic scientists' sectoral mobility. The negative value of $\ln(\sigma)$ (-3.9151, $p < 0.001$) signifies a substantial reduction of unexplained variance, confirming that observed predictors and treatment categories capture much of the structural variation in scientists' transition outcomes. The λ-coefficients further quantify how unobserved characteristics jointly influence group membership and transition probabilities. The selection term for Group 3 is large and positive ($\lambda_3 = 0.294$, $p < 0.001$), suggesting that unobserved traits (such as informal networks, personality characteristics conducive to visibility, or latent career motivations) tend to substantially increase both the likelihood of receiving industry employer interest and the probability of moving to industry. The selection term for Group 2 is also positive but considerably smaller ($\lambda_2 = 0.103$, $p < 0.001$). Accordingly, unobserved characteristics play only a modest role in linking high intentions to actual transitions when job offers are absent. Interestingly, the selection term for Group 4 is positive as well but represents the smallest of the three effects ($\lambda_4 = 0.072$, $p < 0.001$). When strong intentions and industry employer interest are already aligned, unobserved factors add relatively little explanatory power beyond the observed predictors and treatment categories. Importantly, our results reveal that if endogenous selection had not been considered, Group 3 would have erroneously appeared as the most likely to leave academia for an industry position, as suggested by the positive significant lambda (see Table 4). However, accounting for this selection bias, we find that individuals in Group 3 are significantly less likely to leave academia, even when compared to those who did not receive a job offer (Groups 1 and 2).

4.4 Robustness check

To examine the robustness of our findings to alternative forms of mobility, we re-estimated the second stage of the endogenous treatment-effects model using two alternative binary outcomes: remaining with the same academic employer (*No job change*) and moving to another academic employer (*Mobility within academia*). The results are reported in Table 5. Group 1 (Low intention/No offer; *Anchored and Undisturbed*) again serves as the reference category. Across both alternative outcomes, the core pattern of the main analysis remains intact. Scientists in Group 2 (High intention/No offer; *Ready and Waiting*) are significantly more likely to remain in their current positions ($b = 0.126$, $p < 0.01$) and less likely to move within academia ($b = -0.187$, $p < 0.01$), consistent with their intention profile being directed toward industry rather than academic mobility. Group 3 (Low intention/Offer; *Anchored but Sought*) shows the strongest tendency to stay (Model 1: $b = 0.324$, $p < 0.01$; Model 2: $b = -0.027$, $p < 0.10$): despite receiving offers, they are the least mobile overall, reinforcing our central finding that job offers alone rarely induce movement among scientists without exit intentions. By contrast, Group 4 (High intention/Offer; *Ready and Wanted*) exhibits elevated mobility, characterized by both a reduced likelihood of remaining in their current role ($b = -0.096$, $p < 0.01$) and an increased likelihood of moving to another academic employer ($b = 0.266$, $p < 0.01$). This suggests that the combination of strong exit intentions and external recognition (via job offers) does not channel scientists exclusively towards industry, but appears to heighten overall labor-market responsiveness, potentially reflecting broader job-search activity both inside and outside academia.

Importantly, in both models, the selection-correction terms are highly significant, confirming substantial endogenous self-selection into intention-offer configurations and underscoring the appropriateness of the endogenous multinomial treatment-effects framework. Taken together, the results in Table 5 corroborate the main conclusion: exit intentions are the dominant determinant of labor-market transitions, while job offers primarily reinforce existing preferences rather than redirecting scientists into alternative academic or non-academic career paths.

INSERT TABLE 5 HERE

5. DISCUSSION, IMPLICATIONS AND LIMITATIONS

Not all scientists remain within the academic sector throughout their careers. Some are drawn to the private sector, driven by, for example, monetary incentives or the desire for more secure employment (Roach and Sauermann, 2010; Ryan et al., 2012; Agarwal and Ohyama, 2013; Dorenkamp and Weiß, 2018; Aarnikoivu et al., 2019; Kallio et al., 2024). At the same time, firms actively seek academically trained scientists, recognizing the value of their expertise and the advanced skills cultivated within academia (e.g. Zucker et al., 2002; Kaiser et al., 2018).

In this paper, we combined both perspectives, by examining the intersection of both the supply side—measured by academic scientists' intention to transition into private sector employment—and the demand side—i.e., academic scientists' receipt of job offers from private firms—in the actual job change of academic scientists transitioning to private-sector employment. We proposed a supply and demand framework, categorizing scientists into four distinct groups: (1) *Anchored and Undisturbed* , who neither expressed an intention to move to the private sector nor received a job offer form the private sector; (2) *Ready and Waiting*, who show a high intention to switch to private sector employment but who have not received a job offer from the private sector; (3) *Anchored but Sought*, scientists with a low intention to transition to the private sector but who have received a job offer; (4) *Ready and Wanted,* who both have a high intention to move to the private sector and have received a job offer.

Utilizing data from a large online survey of scientists in the German Federal State of Thuringia, we showed that a clash of supply and demand, that is Groups 2 and 3, is common and affecting almost half of respondents. In endogenous multinomial treatment models that account for the selection into the four groups, we find that scientists with a strong intention to take up private sector employment (Groups 2 and 4) are significantly more likely to do so compared to those without such an intention (Groups 1 and 3). Surprisingly, scientists who received a job offer but did not intend to leave academia (Group 3; *Anchored but Sought*) are the least likely to transition to private sector employment—even less likely than those who neither expressed an intention to leave nor received an offer (Group 1; *Anchored and Undisturbed*). A possible explanation is that scientists in Group 3 consciously reject such offers because the reflective effect of receiving an offer—realizing that suitable positions exist in industry—remains limited in the absence of an actual intention to leave academia. Importantly, without accounting for the endogenous selection, Group 3 would have appeared as the most likely to leave academia. They likely are attractive to firms due to their work in domains close to industry (in engineering and public research organizations), coupled with strong publication records (Sauermann and Roach, 2014) and involvement in knowledge transfer or prior industry collaborations (Olmos-Peñuela et al., 2014), which have been shown to benefit firm performance (Zucker and Darby, 2001; Higgins et al., 2011). Yet, precisely these qualities also secure them favorable career prospects within academia (Stern, 2004), reducing their incentive to move to the private sector once this endogenous sorting is accounted for.

We thus find that the supply side (scientist's intention) is most relevant in the transition out of academia with the *Ready and Wanted* (Group 4) and *Ready and Waiting* (Group 2) most likely to exit. The demand side can only reinforce these intentions: such as with an increased likelihood to exit for the *Ready and Wanted* compared to *Ready and Waiting*; and a decreased likelihood to exit for the *Anchored but Sought* (Group 3) compared to the *Anchored and Undisturbed* (Group 1). These insights contribute to the job matching and search literature (Jovanovic, 1979; Mortensen and Pissarides, 1994), which emphasize that employment outcomes result from the interplay between job seekers' preferences and employers' search and recruitment efforts. In the academic setting, we showed that job seekers' preferences dominate and are reinforced by employer demand.

The findings also contribute to the economics of science literature on scientists' career preferences and trajectories (Roach and Sauermann, 2010; Agarwal and Ohyama, 2013; Conti and Visentin, 2015; Lawson and Lopes-Bento, 2024), highlighting the importance of the demand side for bolstering exit from academia for those with a taste for industry, and for those who experience low job satisfaction in academia. The finding that those with a low exit intention are not swayed by industry offers is also reassuring to science, where the potentially detrimental "brain drain" from academia to industry continues to be discussed (Day et al., 2023; Gofman and Jin, 2024; Jurowetzki et al., 2025).

Implications

Our findings offer several implications for firms' active talent recruiting strategies and for universities. First, our results indicate that firms can play an active role in attracting academically trained scientists through direct job offers. In this context, social career platforms have become important matching tools. They help firms to identify suitable candidates and allow scientists with an interest in industry employment to achieve visibility and signal their intent. At the same time, companies also find scientists attractive who have no such intentions themselves. For these scientists, which prefer to remain in academia, temporary mobility schemes or collaborative arrangements may offer an alternative channel for knowledge exchange without requiring a permanent exit. Policies supporting joint research projects or dual appointments could therefore be particularly effective. Such initiatives would not only strengthen the connection between academic research and industrial application but also allow scientists to gain industry-relevant experience while maintaining their academic roles.

Moreover, firms themselves may reflect on why some scientists choose not to transition despite active recruitment efforts. This hesitation may signal that working conditions, research autonomy or recognition mechanisms in the private sector are not perceived as sufficiently attractive (Stern, 2004; Sauermann and Stephan, 2013; Sauermann and Roach, 2014). Although some firms already allow employees to publish or engage in exploratory research, broader adoption of such practices could make industry employment more appealing to research-oriented scientists (e.g. Rotolo et al., 2022).

The difference between those that leave and stay also reveals concerning trends. Our results show that dissatisfaction in academia drives scientists' intentions and eventual exit into the private sector (e.g. Ryan et al., 2012; Dorenkamp and Weiß, 2018). Exit surveys, which are already being conducted at some universities such as Harvard University,[3] can help to identify the reasons for dissatisfaction and distinguish between factors specific to the institution and broader systemic issues. Where organizational responsibility appears plausible, they can enable scientific institutions to address these issues proactively or provide insights to adjust conditions at a superordinate level in order to retain strong or boundary-spanning researchers.

Limitations

[3] See for the Faculty Retention and Exit Survey: https://coache.gse.harvard.edu/faculty-retention-and-exit-survey.

This paper has some important limitations that should open up avenues for further research. First, our study does not clarify the causal relationship between receiving a job offer and scientists' interest in industry jobs. Future research could explore this relationship, particularly given that many scientists are unaware of the value of their skills outside of academia (Scaffidi and Berman, 2011; Hayter and Parker, 2019). Understanding if and how job offers may shift scientists' intent could provide more nuanced insights into the decision-making processes of researchers considering a move to private sector employment.

Second, based on the Theory of Planned Behavior (Ajzen, 1991), we assume that career transitions from academia to industry are generally preceded by an intention to leave, except in cases of impulsive actions. However, we do not have data on the underlying reasons for scientists' intentions, and therefore the supply side, to pursue positions in the private sector. Factors, which remain unobservable to us, include frustration or concerns about limited career prospects within academia (van der Weijden et al., 2016; Ortlieb and Weiss, 2018; Balzano et al., 2025), which we currently bundle under job satisfaction. Future research could further disentangle the specific drivers of dissatisfaction and intent.

Third, our research focused solely on the viewpoint of scientists, neglecting that of firms. While previous studies have examined firms' demand for academic labor and their recruitment preferences (e.g. Garcia-Quevedo et al., 2012; Barge-Gil et al., 2021), little is known about their active sourcing strategies and underlying motivations. To gain a more comprehensive understanding of the transition from academia to industry, future research should therefore also address the perspective of firms that actively seek to attract academically trained scientists. This aspect of the "war for talent" (Chambers et al., 1998) remains largely unexplored.

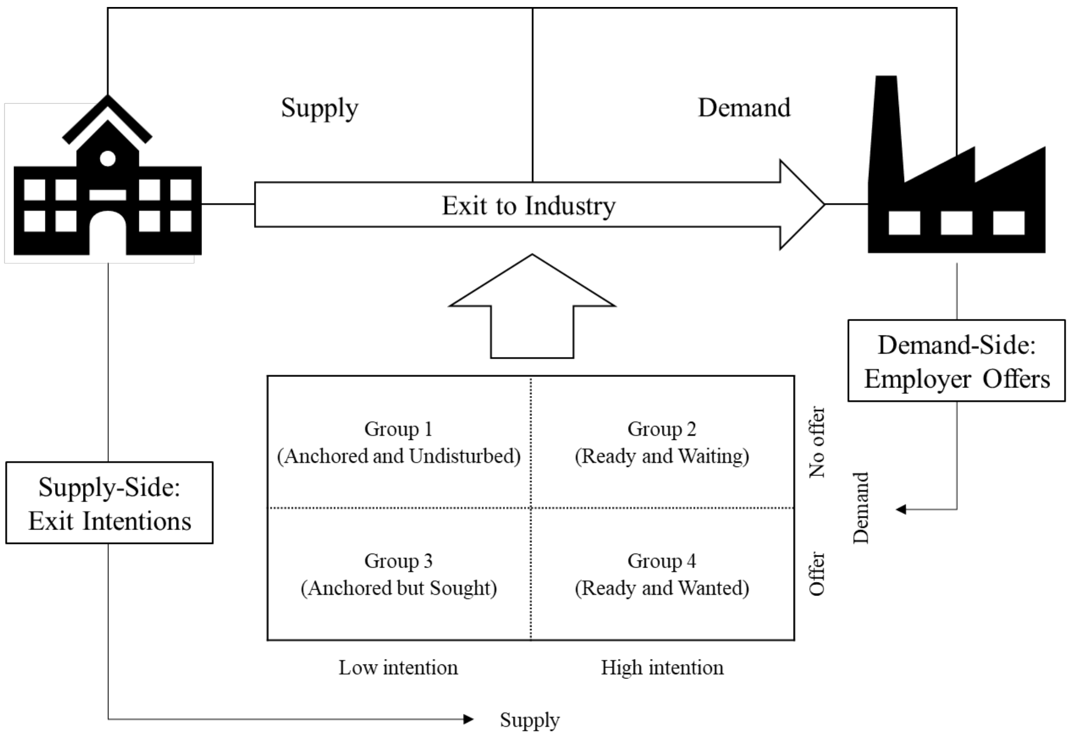

Figure 1. Conceptual framework.

Table 1

Descriptive Statistics for Study Variables

Variable	Mean	SD	Min	Max
Dependent variable				
Industry job (0 = no; 1 = yes)	0.115	0.320	0	1
Independent variables				
Group 1 (Low intention/No offer)	0.388	0.488	0	1
Group 2 (High intention/No offer)	0.281	0.450	0	1
Group 3 (Low intention/Offer)	0.177	0.382	0	1
Group 4 (High intention/Offer)	0.154	0.361	0	1
Additional predictors and control variables				
Job satisfaction	3.934	0.919	1	5
Industry identity fit	3.332	0.978	1	5
Permanent position (0 = no; 1 = yes)	0.495	0.501	0	1
Share of working time devoted to research	0.522	0.255	0	1
Share of working time devoted to teaching	0.217	0.195	0	0.900
Share of working time devoted to KTT activities	0.079	0.115	0	1
Share of working time devoted to administrative tasks	0.181	0.163	0	0.900
LinkedIn or Xing account (0 = no; 1 = yes)	0.420	0.494	0	1
Number of publications (log)	2.020	1.549	0	6.087
Share of publications with industry	0.038	0.129	0	1
PhD (0 = no; 1 = yes)	0.561	0.497	0	1
Gender (0 = female; 1 = male)	0.640	0.481	0	1
German language proficiency (0 = no; 1 = yes)	0.821	0.384	0	1
Employed at university (0 = no; 1 = yes)	0.806	0.396	0	1
Engineering Sciences	0.194	0.396	0	1
Life Sciences	0.322	0.468	0	1
Math & Computer Sciences	0.036	0.187	0	1
Natural Sciences	0.160	0.367	0	1
Social Sciences	0.288	0.453	0	1

Note. n = 469.

Table 2

Correlations of Study Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Industry job (0 = no; 1 = yes)	1												
(2) Group 1 (Low intention/No offer)	-0.23*	1											
(3) Group 2 (High intention/No offer)	0.18*	-0.50*	1										
(4) Group 3 (Low intention/Offer)	-0.08	-0.37*	-0.29*	1									
(5) Group 4 (High intention/Offer)	0.18*	-0.34*	-0.27*	-0.20*	1								
(6) Job satisfaction	-0.16*	0.22*	-0.23*	0.09	-0.10*	1							
(7) Industry identity fit	0.23*	-0.47*	0.39*	-0.01	0.16*	-0.16*	1						
(8) Permanent position (0 = no; 1 = yes)	-0.18*	0.22*	-0.21*	0.11*	-0.15*	0.13*	-0.21*	1					
(9) Share of working time devoted to research	0.12*	-0.10*	0.21*	-0.14*	0.03	-0.08	0.12*	-0.46*	1				
(10) Share of working time devoted to teaching	-0.16*	0.17*	-0.12*	0.01	-0.10*	0.10*	-0.10*	0.45*	-0.62*	1			
(11) Share of working time devoted to KTT activities	0.07	-0.14*	0.00	0.10*	0.09	0.03	0.05	-0.08	-0.29*	-0.24*	1		
(12) Share of working time devoted to administrative tasks	-0.04	0.05	-0.19*	0.14*	0.01	-0.02	-0.11*	0.25*	-0.62*	-0.05	0.03	1	
(13) LinkedIn or Xing account (0 = no; 1 = yes)	0.15*	-0.22*	0.00	0.09*	0.20*	0.02	0.07	0.00	-0.05	0.05	0.03	0.00	1
(14) Number of publications (log)	-0.13*	0.16*	-0.27*	0.13*	-0.03	0.07	-0.19*	0.20*	-0.03	-0.11*	0.00	0.18*	0.02
(15) Share of publications with industry	0.08	-0.06	-0.06	0.09*	0.07	0.03	0.09*	-0.06	0.02	-0.11*	0.11*	0.01	0.02
(16) PhD (0 = no; 1 = yes)	-0.17*	0.28*	-0.36*	0.10*	-0.03	0.08	-0.30*	0.27*	-0.27*	0.12*	0.05	0.24*	0.06
(17) Gender (0 = female; 1 = male)	0.02	0.02	-0.11*	0.06	0.05	0.06	-0.03	0.06	-0.05	0.03	0.02	0.03	0.04
(18) German language proficiency (0 = no; 1 = yes)	-0.04	0.10*	-0.19*	0.16*	-0.06	0.02	-0.04	0.25*	-0.37*	0.25*	0.08	0.22*	-0.09
(19) Employed at university (0 = no; 1 = yes)	0.02	0.01	0.04	-0.08	0.01	-0.05	0.00	0.10*	-0.20*	0.35*	-0.20*	0.04	0.06
(20) Engineering Sciences	0.04	-0.19*	0.00	0.11*	0.14*	-0.09*	0.07	-0.12*	-0.01	-0.05	0.13*	-0.02	0.02
(21) Life Sciences	-0.02	0.06	-0.01	-0.02	-0.05	0.04	0.02	0.02	0.18*	-0.22*	-0.05	0.02	-0.04
(22) Math & Computer Sciences	0.00	-0.06	0.08	0.03	-0.05	0.04	0.04	-0.03	0.00	0.03	-0.01	-0.02	0.04
(23) Natural Sciences	0.12*	-0.11*	0.06	0.00	0.07	-0.07	0.08	-0.14*	0.09*	-0.11*	0.05	-0.05	0.05
(24) Social Sciences	-0.11*	0.22*	-0.08	-0.09	-0.10*	0.08	-0.17*	0.21*	-0.24*	0.34*	-0.10*	0.04	-0.04

Note. * $p<0.05$. $n = 469$.

Table 2 (cont.)

Correlations of Study Variables

Variables	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(14) Number of publications (log)	1										
(15) Share of publications with industry	0.04	1									
(16) PhD (0 = no; 1 = yes)	0.42*	-0.07	1								
(17) Gender (0 = female; 1 = male)	0.22*	0.07	0.11*	1							
(18) German language proficiency (0 = no; 1 = yes)	-0.01	-0.01	-0.02	0.09	1						
(19) Employed at university (0 = no; 1 = yes)	-0.19*	-0.12*	-0.05	-0.07	0.22*	1					
(20) Engineering Sciences	-0.15*	0.08	-0.21*	0.09	0.06	-0.03	1				
(21) Life Sciences	0.22*	-0.02	0.17*	-0.14*	-0.11*	-0.20*	-0.34*	1			
(22) Math & Computer Sciences	-0.03	0.04	-0.01	0.07	0.06	0.07	-0.10*	-0.13*	1		
(23) Natural Sciences	0.21*	0.00	0.02	0.16*	-0.02	0.04	-0.21*	-0.30*	-0.08	1	
(24) Social Sciences	-0.24*	-0.06	-0.01	-0.09*	0.05	0.18*	-0.31*	-0.44*	-0.12*	-0.28*	1

Note. * $p<0.05$. $n = 469$.

Table 3

First-Stage Multinomial Logit Results: Determinants of Group Membership

Variables	Group 1: *Anchored and Undisturbed*	Group 2: *Ready and Waiting*	Group 3: *Anchored but Sought*	Group 4: *Ready and Wanted*
	(1)	(2)	(3)	(4)
Industry identity fit	-0.167***	0.122***	0.007	0.038**
	(0.018)	(0.017)	(0.017)	(0.017)
Job satisfaction	0.064***	-0.075***	0.038*	-0.027*
	(0.020)	(0.017)	(0.020)	(0.015)
Permanent position (0 = no, 1 = yes)	0.001	0.022	0.040	-0.063
	(0.045)	(0.043)	(0.039)	(0.043)
Share of working time devoted to teaching	0.065	-0.024	0.028	-0.069
	(0.130)	(0.125)	(0.112)	(0.114)
Share of working time devoted to KTT activities	-0.502**	0.197	0.129	0.176
	(0.210)	(0.152)	(0.141)	(0.124)
Share of working time devoted to administrative tasks	-0.125	-0.169	0.136	0.158
	(0.116)	(0.124)	(0.104)	(0.104)
LinkedIn or Xing account (0 = no, 1 = yes)	-0.172***	-0.022	0.074**	0.120***
	(0.035)	(0.033)	(0.032)	(0.031)
Number of publications (log)	0.015	-0.034**	0.021	-0.002
	(0.015)	(0.013)	(0.013)	(0.011)
Share of publications with industry	0.013	-0.225**	0.150	0.062
	(0.168)	(0.107)	(0.140)	(0.112)
PhD (0 = no, 1 = yes)	0.111***	-0.171***	0.035	0.025
	(0.041)	(0.038)	(0.038)	(0.034)
Gender (0 = female, 1 = male)	0.017	-0.027	-0.019	0.029
	(0.040)	(0.038)	(0.037)	(0.035)
German language proficiency (0 = no, 1 = yes)	0.063	-0.205***	0.203***	-0.061
	(0.059)	(0.044)	(0.074)	(0.042)
Employed at university (0 = no, 1 = yes)	-0.018	0.045	-0.075*	0.048
	(0.049)	(0.052)	(0.043)	(0.041)
Engineering Sciences	-0.125**	-0.071	0.111**	0.085**
	(0.055)	(0.052)	(0.048)	(0.041)
Math & Computer Sciences	-0.106	0.169	0.069	-0.131
	(0.100)	(0.112)	(0.089)	(0.133)
Natural Sciences	-0.088	0.017	0.025	0.047
	(0.060)	(0.054)	(0.054)	(0.045)
Social Sciences	0.070	-0.063	-0.008	0.002
	(0.050)	(0.052)	(0.050)	(0.049)

Note. Reported estimates are average marginal effects ($\frac{\partial y}{\partial x}$) from a multinomial logit model predicting intention–offer group membership. Robust standard errors in parentheses. Reference categories are *Share of working time devoted to research* (working time allocation) and *Life Sciences* (disciplinary fields). *$p < .10$, **$p < .05$, ***$p < .01$. $n = 469$.

Table 4

Second-Stage Treatment-Effects Results: Transition from Academia to Industry

Variables	Coefficient (*b*)	Robust SE
Treatment indicators[a]		
Group 2: *Ready and Waiting*	0.026*	0.014
Group 3: *Anchored but Sought*	-0.166***	0.019
Group 4: *Ready and Wanted*	0.050***	0.012
Individual- and job-related predictors[b]		
Industry identity fit	0.076***	0.006
Job satisfaction	-0.032***	0.003
Permanent position (0 = no, 1 = yes)	0.010	0.008
Share of working time devoted to teaching	-0.208***	0.023
Share of working time devoted to KTT activities	-0.013	0.026
Share of working time devoted to administrative tasks	-0.123***	0.033
LinkedIn or Xing account (0 = no, 1 = yes)	0.108***	0.014
Number of publications (log)	-0.004	0.003
Share of publications with industry	0.340***	0.015
PhD (0 = no, 1 = yes)	-0.019	0.016
Gender (0 = female, 1 = male)	0.064***	0.013
Employed at university (0 = no, 1 = yes)	0.034	0.024
Selection-correction terms		
Ln(σ)	-3.915***	0.181
λ(Group 2)	0.103***	0.009
λ(Group 3)	0.294***	0.004
λ(Group 4)	0.072***	0.005
Constant	-0.038	0.043
Wald χ^2	3561.81***	
Log pseudolikelihood	-510.45	

Note. Reported estimates are second-stage coefficients from an endogenous multinomial treatment-effects model with 400 simulation draws. Exclusion-restriction variables are *disciplinary fields* and *German language proficiency*. [a]Reference category is *Group 1: Anchored and Undisturbed*. [b]Reference category is *Share of working time devoted to research* (working time allocation). *p < .10, **p < .05, ***p < .01. n = 469.

Table 5

Second-Stage Treatment-Effects Results: Competing Career Outcomes

Variables	No job change	Mobility within academia
	(1)	(2)
Treatment indicators		
Group 2: *Ready and Waiting*	0.126***	-0.187***
	(0.011)	(0.011)
Group 3: *Anchored but Sought*	0.324***	-0.027*
	(0.007)	(0.014)
Group 4: *Ready and Wanted*	-0.096***	0.266***
	(0.010)	(0.021)
Selection-correction terms		
Ln(σ)	-4.710***	-3.837***
	(0.201)	(0.307)
λ(Group 2)	-0.240***	0.197***
	(0.003)	(0.005)
λ(Group 3)	-0.347***	0.009**
	(0.002)	(0.004)
λ(Group 4)	0.027***	-0.288***
	(0.002)	(0.003)

Note. Reported estimates are second-stage coefficients from endogenous multinomial treatment-effects models with 400 simulation draws. Exclusion-restriction variables are *disciplinary fields* and *German language proficiency*. Reference category is *Group 1: Anchored and Undisturbed*. Robust standard errors in parentheses. Coefficients of the additional predictors and control variables are not shown for brevity. *$p < .10$, **$p < .05$, ***$p < .01$. $n = 469$.

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