KU LEUVEN

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Taste for science, academic boundary spanning and inventive performance of industrial scientists and engineers

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MSI_1612

Taste for Science, Academic Boundary Spanning and Inventive Performance of Industrial Scientists and Engineers

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ABSTRACT

Matching survey data on Ph.D. scientists and engineers currently working in an R&D job in industry with their publications and patents, we study the relationship between their motives and their inventive performance. We find that individuals with a strong taste for science, i.e. motivated by intellectual challenge, independence, and contribution to society, create more novel and valuable patents. We find partial mediation of the effect of taste for science on value-weighted inventive output through academic boundary spanning, proxied by scientific publications co-authored with academic scientists. For novelty of inventive output, we find no mediation through academic boundary spanning. We confirm the negative relation between academic co-publications and annual base salary in industry. This helps to explain why individuals with a strong taste for salary collaborate less with academic scientists, negatively affecting their value-weighted inventive output.

Keywords: taste for science, boundary spanning, industry-science links

Acknowledgements: Financial support from KU Leuven (GOA/12/003 and IMP/16/002), and the Research Foundation - Flanders (FWO, G.0825.12) is gratefully acknowledged. Publication data are sourced from Thomson Reuters Web of Science Core Collection. We wish to thank Bruno Cassiman, Lee Fleming, and Henry Sauermann for the helpful feedback. Errors and omissions remain the authors'.

1. INTRODUCTION

For a long time, economists have studied technological change and economic growth as the outcome of firms' economic incentives to invest in R&D (Nelson 1959). Given that individuals are the locus of inventions inside firms, surprisingly little research has looked at the motives of these individuals as a driver of innovation. The economics of science literature discusses what motivates individual scientists, stressing the importance of pecuniary motives of scientists, but also and perhaps more importantly their non-pecuniary motives (Dasgupta and David 1994, Stephan 2012). In particular, scientists are uniquely characterized by a *taste for science* – a desire for intellectual challenge (the puzzle joy), autonomy, and contribution to society through the diffusion of their acquired knowledge (Merton 1973, Pelz and Andrews 1976, Katz 2004).

Using a large sample of U.S. Ph.D. scientists and engineers working in industry, Sauermann and Cohen (2010) were the first to study the relation between different types of motives and inventive performance. They found strong support for motives of individuals to matter for their inventive performance. They also explored the mechanisms driving the relation between motives and performance. As they did not find support for quantity of effort – number of hours worked – to be the reason why motives affect inventive performance, they looked into one aspect of the nature of effort: attendance of professional meetings, but also here did not find any support. They nevertheless called for future work to further examine the nature of the effort as mediator of the relationship between motives and inventive performance.

In this paper, we follow Sauermann and Cohen (2010) by looking at the individual scientists and engineers within firms as the unit of analysis, their motives to explain their inventive performance, and the mediators that might explain this relationship. Among the set of motives, we are particularly interested in the non-pecuniary motives that taken together shape an individual's "taste for science". We further contribute to the literature by looking at the impact of motives not only on the pure amount of inventive output, but particularly on the nature of this output. In line with Amabile (2013), we characterize the inventive performance of individuals along two related dimensions: novelty and value.

We will test whether industrial scientists and engineers with a strong taste for science produce a more novel and/or more valuable inventive output. In addition, we test explicitly for mediation in the relationship between motives and the nature of inventive output. For mediating mechanisms, we look in line with the literature at both the quantity and nature of effort: we study the number of hours worked, the share of effort devoted to research, and involvement in academic boundary spanning activities. We argue that industrial scientists and engineers with a strong taste for science spend more time on early-stage research rather than late-stage development, and more actively interact with the broader scientific community, which we expect they can translate into more novel and/or valuable inventions (Stern 2004).

To tackle these research questions, we use data on 464 Ph.D. holders in Science & Engineering working in an R&D job in industry at the end of 2005 from the Belgian wave of the OECD's Careers of Doctorate Holders survey (2013). The survey provides information on the initial motives to choose for a Ph.D. and a career as scientist or engineer. We use explanatory factor analysis to derive two common factors – "taste for science" and "taste for salary & career". The survey also provides information on job characteristics, such as number of hours worked, share of time spent on research, annual base salary, and name of the employer. We manually matched the survey information for these individuals to their patents and publications from secondary sources. We use the U.S. inventor database to trace all patents developed by these industrial scientists and engineers (Li et al. 2014). Beyond counting the number of patents, we calculate citation-weighted patent counts to measure the value of inventive output (Trajtenberg 1990). To measure the novelty of inventive output, we count the number of new to the patent corpus words found in the title, abstract, and claims of the patents (Arts and Fleming 2015). The Web of Science database allows us to collect the scientific publications of these individuals, including those co-authored with academic scientists, which we use to proxy for academic boundary spanning involvement (e.g., Cockburn and Henderson 1998, Zucker et al. 2002, Liu and Stuart 2010). At the same time, the matching with patent and publication data allows us to control for unobserved heterogeneity among individuals using pre-sample – before their current job – measures of inventive and scientific performance and to control for the scientific and inventive capacity of the employing firms.

We find that a stronger "taste for science" relates to a more novel and a higher citation weighted inventive output, while a stronger "taste for salary & career" relates to a lower citation weighted inventive output. Looking at potential mediators, we find that those with a stronger taste for science do not work more hours a week. But they spend more of their time on research and they co-publish more with academic scientists. The extent to which they collaborate with academic scientists is associated with a more novel and a higher citation weighted inventive output. Academic boundary spanning partially mediates the relation between taste for science and citation weighted inventive output, but surprisingly boundary spanning does not mediate the relation between taste for science and novelty of output. Despite the positive link between academic boundary spanning and the nature of inventive output, the data also confirm the negative relation between co-publishing with academics and annual base salary in industry, as found by Stern (2004). Consistent with this penalty in salary, those individuals with a strong "taste for salary & career" are less involved in academic boundary spanning. Missing this "entry ticket" to the academic community significantly reduces their ability to create valuable inventions.

Our research contributes to the literature examining the relation between the motives of industrial scientists and engineers and the innovation performance of firms, by providing complementary evidence on how and why "taste for science" and "taste for salary & career" relate not only to the quantity but also the nature of individuals' inventive output (e.g., Sauermann and Cohen 2010, Lacetera and Zirulia 2012). Through our analysis on how academic boundary spanning may act as mediator between taste for science and the nature of inventive output, we also contribute to the literature studying the micro foundations of how scientific research in academia translates into technological innovation in industry (e.g., Allen and Cohen 1969, Fleming and Sorenson 2004, Liu and Stuart 2010). Finally, our results are also informative for the literature that looks at how to attract and accommodate scientists in industry (e.g., Vallas and Kleinman 2008).

2. INDIVIDUALS' MOTIVES AND INVENTIVE PERFORMANCE

We first review the literature on the motives of scientists and engineers, their link to inventive performance, and the possible mediating channels through which this link is established. We close this section by describing how we will contribute to the literature, specifying our research strategy.

2.1. Motives of scientists and engineers

Research and development in industry is primarily focused on specific commercial applications and largely driven by firms' economic incentives (Nelson 1959). Firms are typically viewed as lacking the incentives to invest in basic research projects which are characterized by high uncertainty about the eventual appropriable economic payoffs (Aghion et al. 2008). By outsourcing more basic research projects to academia, firms provide a credible commitment not to abort or redirect projects with less certain economic returns (Lacetera 2009). In academia, scientists have a strong taste for science, i.e. conduct science because of the intellectual challenge (Merton 1973, Dasgupta and David 1994, Stephan 1996). Academic scientists have the freedom to conduct research projects which they find intellectually challenging, at the frontier of knowledge, even in case there is no immediate economic return (Dasgupta and David 1994). In contrast to academia, firms can direct their scientists and engineers to work on those R&D projects with high perceived appropriable economic value (Aghion et al. 2008). To this end, they can use controls and monetary incentives. Yet, firms' ability to use standard bureaucratic controls and monetary incentives to direct scientists and engineers' performance through effort is limited. Bureaucratic controls are costly to implement and run counter to a creative environment conducive to inventive outcomes. Designing proper incentive schemes to stir inventive performance is challenging for firms. Because of the inherent uncertainty characterizing R&D projects and the uncertainty about their eventual commercial success, it is difficult for firms to link incentives to performance (Prendergast 1999). Moreover, monetary returns may not be the most powerful incentives, requiring industrial scientists and engineers to have strong pecuniary motives. Therefore, understanding what motivates industrial scientists and engineers is important for understanding technological progress and innovation in industry.

Prior studies confirm that individuals with a strong taste for science prefer a job in academia over industry, while those with a strong taste for salary prefer a job in industry (Roach and Sauermann 2010, Agarwal and Ohyama 2012). More recent empirical evidence suggests that there is still a large heterogeneity in tastes among industrial scientists and engineers (Agarwal and Ohyama 2012, Sauermann and Roach 2010). Some individuals working in industry might have a strong taste for science and a weak taste for salary. This is witnessed by industrial scientists and engineers who are willing to trade off salary in return for the freedom to participate in science, i.e. to interact with the academic community and publish (Stern 2004).

2.2. Motives of industrial scientists and engineers and their inventive performance

If there is heterogeneity in motives among industrial scientists and engineers, this might relate to differences in their inventive performance. This link between motives and inventive performance at the individual level has seldom been looked at in corporate innovation studies. In one of the few studies, Sauermann and Cohen (2010) show, for a sample of Ph.D. scientists and engineers working in U.S. industry, how different motives relate to heterogeneity in patenting. They find that individuals with a preference for intellectual challenge, salary, and independence create more patents, while those motivated by job security and responsibility create less patents.

2.3. Mediation via Quantity and Nature of Effort

Motives matter for inventive performance because they affect effort. The willingness of a scientist or engineer to supply creative effort depends on what motivates him/her to do so. Prior research suggests that motives can affect performance either through the quantity of effort or through the nature of effort (Lacetera and Zirulia 2012, Sauermann and Cohen 2010).

(i) Mediation via quantity of effort

Different motives might relate to differences in the quantity of effort exerted and – as a result – increase or decrease the inventive performance of the individual (Lazear 1997). Industrial scientists and engineers motivated by intellectual challenge and independence might spend more time at work when firms offer

them more discretion in choosing R&D projects which they find intellectually inspiring (Lacetera 2009). Individuals motivated by salary or career advancement might work more if it enables them to earn a higher salary or climb the corporate ladder. The empirical evidence is however not supportive of mediation via quantity of effort. Sauermann and Cohen (2010) find no evidence for quantity of effort to mediate the relation between any of the motives they consider and inventive performance.

(ii) Mediation via nature of effort

Motives might relate to heterogeneity in performance through differences in the nature of effort. Conditional on a given number of hours worked, industrial scientists and engineers might allocate their time to different input activities which affect differently their inventive output. First, individuals with a strong taste for science might spend more time on upstream research rather than on downstream development or other tasks such as management (Roach and Sauermann 2010, Agarwal and Ohyama 2012). Second, a taste for science may impact inventive performance because it triggers industrial scientists and engineers to participate in science and connect to the broader scientific community, giving them privileged access to external knowledge which they can use for technological innovation (Allen and Cohen 1969, Tushman 1977, Tushman and Scanlan 1981, Stern 2004). Mediation through engagement in research and academic boundary spanning remains empirically unexplored. Sauermann and Cohen (2010) only considered whether individuals attended professional meetings, an imperfect proxy for the nature of effort reflecting interactions with the broader scientific community. They did not find support for attendance of professional meetings to mediate the effect of any of the motives on inventive performance.

Overall, the discussion of the literature and the existing evidence confirm that a better understanding of what is driving the observed relation between motives of industrial scientists and engineers and their inventive output is important for understanding firms' capacity to innovate. While the evidence strongly supports the importance of individual motives for inventive performance, it remains unclear why motives matter for inventive performance. Which are the mechanisms that mediate the relation between motives and performance? Is it because motives shape what individuals will spend their time and energy on, that it shapes their inventive performance? Finally, what remains unexplored is how

motives affect not just the quantity of inventive output but also the nature of this output. We aim to address these gaps in the literature.

2.4. Our research: Taste for science, academic boundary spanning and the novelty and value of inventive output

We explore the relation between the motives of industrial scientists and engineers and the nature of their inventive output, and the possible mechanisms underlying the observed relation between motives and performance. We exploit the correlation among different motives to look for sets of motives which may jointly shape a "*taste for science*" versus a "*taste for salary & career"*. Rather than looking at the quantity of inventive output of industrial scientists and engineers, we look at how motives shape the *nature of inventive output*, distinguishing the novelty of inventive output from its eventual impact or value (Amabile 2013).

We are particularly interested in understanding why taste for science matters for the nature of inventive output, i.e. which are the *intermediary mechanisms* driving the observed relationship between "taste for science" and inventive performance. To this end, we look, in line with the literature, not only at the quantity of effort, i.e. *number of hours worked*, but also at the nature of effort exerted.

As we are focusing on the impact of "taste for science" on the novelty and value of inventive output, we will look at how much effort is spent on research as a mediator. Individuals with a taste for science might spend more *time on upstream research* rather than on downstream development, or other tasks, such as management. Because they spend more time on research, they generate more inventions that are also expected to be more novel. Upstream research projects are arguably more intellectually challenging, have more scope for independent thinking, push the frontiers of knowledge into new and unexplored territories, and therefore result in a more novel inventive output. Downstream development projects are more likely to be routinized, structured and target incremental improvements. Inventions originating from upstream research are also expected to have a bigger impact and to be more valuable compared to more incremental inventions, as they are more likely to become breakthrough inventions on

which follow-up inventions build (Verhoeven et al. 2016). Nevertheless, upstream research projects are also characterized by higher degrees of experimentation and carry a higher uncertainty about eventual value (Aghion et al 2008). Because such exploratory projects typically carry more risks and uncertain outcomes, having a higher variability in success, the potential for more novel and breakthrough inventions might simultaneously be associated with a higher probability of failure and an – on average – less valuable inventive output (Arts and Fleming 2015).

Besides spending more time on research, we argue that taste for science influences inventive performance because it triggers industrial scientists and engineers to spend more effort interacting with the broader academic community (Tushman 1977, Tushman and Scanlan 1981). *Academic boundary spanning* is important for inventive performance as it allows individuals to source external knowledge developed in academe, which can enhance the effectiveness of downstream R&D (Allen and Cohen 1969, Cohen and Levinthal 1990, Liu and Stuart 2010). New academic knowledge is difficult to access and absorb, often requiring hands-on involvement through close interaction with academic scientists (Jensen and Thursby 2001, Zucker et al. 2002). By collaborating with academics at the lab bench, industrial scientists and engineers obtain early and privileged access to novel scientific insights, resulting in a more novel inventive output compared to colleagues who do not span the boundary between industry and academia (Cassiman et al. 2012). The resulting inventions might also have a bigger impact and be more valuable. Alternatively, academic boundary spanning might result in a less valuable inventive output because of the higher uncertainty and risk of failure associated with early-stage boundary-spanning research.

3. DATA AND METHODS

3.1. Sample and Data Collection

The main data source for this paper is the Belgian edition of the Careers of Doctorate Holders survey. Created by the Organisation for Economic Co-operation and Development (OECD), Eurostat, and the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics, the

survey aims to gain a better insight into the career trajectories of individuals with a Ph.D. degree.[1] The survey is the starting point for the present analysis as it contains information on individuals' initial motives to choose for a Ph.D. and career as scientist or engineer. In addition, the survey includes detailed information on the job of the Ph.D. holders. The survey was launched in 2006, addressed the full population of Ph.D. holders in Belgium, and the response rate of the survey was 20% (Moortgat and Van Mellaert 2011).

In this paper, we use a subsample of 464 industrial scientists and engineers who formerly obtained a Ph.D. in natural sciences, (bio)medical sciences, engineering and technology, or agricultural sciences (we disregard Ph.D. holders in the social sciences or humanities), who are full-time employed as R&D scientist or engineer in industry at the end of 2005, who answered the relevant survey questions and, who left their name and contact details. This information allowed us to hand-collect for each individual patents and publications from secondary sources. To collect publication data, we used the Web of Science database. To collect patent data, we first used the U.S. inventor database to match each individual to a unique inventor if any (Li et al., 2014)[2]. Second, we used the EPO Worldwide Patent Statistical Database (PATSTAT) to collect patent-family corrected citation data[3]. We use objective information from secondary sources to measure inventive performance and the involvement in academic boundary spanning activities, rather than self-reported information from the survey, as in Sauermann and Cohen (2010). This reduces the likelihood of common method and social desirability bias. The disadvantage is that we can only do this for the subset of individuals who left their name and contact details, which reduces the effective sample size.

3.2. Measures

[1] See Eurostat (2012) or OECD (2012) for more information on the survey. Moortgat and Van Mellaert (2011) discuss the Belgian data collection, and Auriol et al. (2012) provides an overview of the survey methodology.
[2]As we are only looking at USPTO patents, this provides a (quality) selection in our Belgian sample, excluding local and European patents. For the latter, we miss the inventor disambiguation.
[3] By using PATSTAT for citations, we make sure to collect all forward citations for all patent families which include at least one USPTO patent application assigned to a scientist included in our sample. As such, we account for citations received by a different patent from the same family and for citations received from non-U.S. patents.

(i) Outcome variables.

To measure the nature of inventive output of industrial scientists and engineers, we look at whether the patents created during their job are novel and whether these patents are valuable.

Citation-weighted patents. To measure the value of inventive output, we calculate the number of citation-weighted patents (Trajtenberg 1990). We take into account all patents filed between the starting date of the job, which is asked in the survey, and January 1 2006, the reference date of the survey. Citations refer to how often the patent served as prior art for subsequent patents, which correlates with the technological impact as well as with the economic value of the invention (Harhoff et al. 1999, Gambardella et al. 2008)[4].

New words. To measure the novelty of inventive output, we use the measure developed in Arts and Fleming (2015), counting the number of unique words in the patents which appear for the first time in the full patent corpus. To calculate the measure, all words in the title, abstract, and claims, are tokenized for all U.S. patents back to 1975. Numbers and hyphened words were removed, and all patents before 1980 are used to establish a baseline[5].

(ii) Independent variables related to motives.

Individuals' motives are captured in the survey question *"Why did you choose a career in research?"*. This is asked in the survey right after questions on education and before any questions on their job, which appear at the end of the survey. The question explicitly captures initial motives and not current preferences. Respondents could indicate any number of motives from a list. In line with prior research, we apply exploratory factor analysis to examine the relation among different motives (Sauermann and Roach 2012). In the factor analysis, we retain the full sample of scientists and engineers currently employed in

[4] Our main findings are robust to using alternative measures for the value of inventive output: number of claims across all patents or number of times renewal fees are paid. Results not reported.
[5] Our main findings are robust to using alternative measures for the novelty of inventive output: number of new subclass combinations across all patents and number of patents with new technological origins (Arts and Veugelers 2015, Verhoeven et al. 2016). Results not reported.

academia or industry (n=1,114)[6]. Table 1 shows the results of the factor analysis. Both the screeplot and the Kaiser criterion suggest the existence of two latent variables, which jointly explain 87% of the variance in motives.

Insert Table 1 here

Taste for salary & career. The first latent variable correlates with motives for salary, extralegal benefits, and – to a smaller extent – career advancement and job security. *Taste for science.* The second latent variable is labelled taste for science as it strongly correlates with motives for intellectual challenge, independence, and – to a smaller extent – contribution to society. These non-pecuniary motives are typically associated with the institution of science (e.g., Merton 1973, Stephan 2012). Taste for science and taste for salary & career are calculated using the regression scoring method and afterwards normalized for ease of interpretability.

As expected, we find that individuals with a low taste for science or a high taste for salary & career are more likely to select into industry, while those with a high taste for science or a low taste for salary & career are more likely to become academic scientists (see also Roach and Sauermann (2010) for similar results[7]). Nevertheless, there is still a large heterogeneity in tastes among industrial scientists and engineers.

(iii) ***Mediating variables.***

To study through which mediating channels motives impact inventive performance, we will look at both the quantity of effort and the nature of the effort, particularly the extent of involvement in research and boundary spanning activities. *Hours worked*. Respondents report how many hours they work an average on a weekly basis, measuring the quantity of effort. *Research*. Self-reported share of time spent on performing, guiding, or interpreting research in their current job. *Co-publications.* We calculate for each

[6] Our main findings are robust to using only the sample of industrial scientists and engineers in the factor analysis.
[7] We find significant differences in taste for science (TFS) and taste for salary & career (TFC) between individuals working in industry versus individuals in academia: T-test for TFS: t= -10.9055, Pr(|T| > |t|) = 0.0000. T-test TFC: t= 4.2777, Pr(|T| > |t|) = 0.0000). Also in regression analysis, correcting for other controls, Ph.D. holders with a high TFS are more likely to select into academe rather than industry and vice versa for TFC (results not reported).

individual the number of Web of Science (WOS) publications co-authored with academic scientists between the starting date of the current job and January 1 2006[8]. Co-publications with academic scientists have been used by prior firm-level research to measure academic boundary spanning (Cockburn and Henderson 1998, Zucker et al. 2002, Gittelman and Kogut 2003). It is a much more hands-on and active form of interaction with the academic community than reading scientific publications or attending professional meetings. It also provides more variation than a simple yes or no classification into boundary spanning activities.

(iv) ***Control variables.***

First, it is important to control for the skills of the individuals reflecting both their ability and experience. We will look at two dimensions of skills: technological and scientific. Individuals with higher technological skills might be eager to work more hours or spend more time on research because of the higher expected success. Effort invokes less disutility on them. Moreover, companies might assign their best people to the most promising R&D projects. Likewise, the returns from engaging in basic research projects and participating in the academic community will be higher for individuals with stronger scientific skills (Dasgupta and David 1994). Scientifically skilled people might have better access to the academic community, can better and more quickly absorb novel scientific discoveries and realize their commercial potential (Hicks 1995, Stern 2004)[9]. Moreover, companies might allow or even stimulate their more scientifically skilled R&D employees to work on research rather than development projects and to collaborate with academic scientists. As such, the estimated effect of both taste for science, share of time spent on research, and co-publications might suffer from an upward skill bias. To control for this potential bias, we include for each individual a number of pre-sample skill controls.

[8] The large majority (85%) of WOS publications by industrial scientists and engineers are co-authored with academic scientists. Findings are robust to using the total number of WOS publications (results not reported). We believe co-publications with academic scientists provide a cleaner measure for academic boundary spanning.

[9] We find support for the assumption that individuals with a higher ability, as measured by the number of pre sample publications, have better access to the academic community while being employed in industry. The number of pre-sample scientific publications is found to positively affect the number of publications co-authored with academic scientists while being employed in industry. These findings illustrate how not controlling for the ability of individuals might inflate the findings with respect to the effect of academic boundary spanning on performance.

Pre sample patents: we include the number of citation-weighted patents filed before the current job. As such, we include the pre-sample value of the outcome variable as a control for unobserved individual-specific heterogeneity (e.g., Blundell et al. 1999). *Pre sample publications* and *pre sample publication citations*: we also include the number of publications published before the current job and the average number of citations received by these publications within three years. In addition, we also include *Ph.D. scholarship*: a binary measure indicating whether their Ph.D. was funded by a government or private scholarship, which select on prior academic achievement, perceived ability, and a promising Ph.D. proposal; *Time to Ph.D.:* the time needed to complete their Ph.D. relative to peers within the same field; *Ph.D. abroad*: a binary measure indicating whether the individual obtained a Ph.D. abroad. Virtually all individuals in our sample who obtained a Ph.D. abroad studied at a university which is higher ranked than any Belgian university.

Besides controlling for skills, we include a number of additional individual-level control variables. *Job tenure*: the number of years the person has been in their job at the end of 2005; *Job tenure>10:* we include a binary measure equal to one when job tenure is longer than10 years to control for the fact that publication data is only available from 1996 onwards. Hence, for individuals working in the same job for more than 10 years, we capture only those publications of the last 10 years; *Age*: the age of the person at the end of 2005. Tenure and age also correct for the longer time window for older tenured people when counting citations; *Female*: a binary measure equal to one for females; *Belgian*: a binary measure indicating whether the individual has the Belgian nationality; *Married*: a binary measure indicating whether the person is married or officially cohabiting; *Children*: number of children.

We also include indicators for whether the person obtained a *Ph.D. in natural science*, a *Ph.D. in agricultural sciences*, a *Ph.D. in medical sciences*, or a *Ph.D. in engineering and technology*, as there could be field specific fixed effects in the relationship between motives and inventive performance: mostly notably specific profiles for engineers and/or for medical degrees.

Finally, we include a number of firm-level controls. The inventive performance of industrial scientists and engineers might not only be driven by the characteristics of the individuals, but also by the

characteristics of the firm employing them. Most important for our study, firms can differ in inventive performance and scientific orientation, as reflected in the extent to which they patent, and in the extent to which they allow or incentivize employees to collaborate with academic scientists and publish in scientific journals. *Firm patents*: the number of granted patents filed by the firm between the beginning of 2003 until the end of 2005; *Firm co-publications*: the number of publications co-authored by the firm's employees and academic scientists between the beginning of 2003 until the end of 2005[10]. A small number of individuals did not fill in the name of the firm they work for. For this set of individuals, firm patents and co-publications is set at zero, and the binary indicator *Firm name missing* is set at one. Table 2 provides summary statistics for the main variables used in the analysis. Table A.4 in appendix show a correlation matrix.

Insert Table 2 here

The summary statistics in Table 2 illustrate the high variance in motives among the industrial scientists and engineers. At the same time, it illustrates the large skew in inventive performance. There are also large differences between scientists and engineers in the number of co-publications.

3.3. Social Desirability and Common Method Bias

The use of survey data can introduce two common types of bias. First, a social desirability bias might cause individuals to list those motives which they believe to be socially desirable (Moorman and Podsakoff 1992). This introduces a bias in case it affects the relationship between motives, mediators, and inventive performance. This type of bias is unlikely in our case because the measures for academic boundary-spanning and inventive performance are collected from other sources than the survey. Moreover, the survey question on motives is proximally separated from questions on the job and employer, which appear at the end of the survey. Therefore, it seems unlikely that respondents changed

[10] Although not all firms have patents and co-publications in the observation window, our results are robust for the subsample of individuals working in firms with at least one patent, for the subsample of individuals working in firms with at least one co-publication, and for the subsample of individuals working in firms with at least one patent and at least one co-publication.

their motives to provide a desirable explanation for their performance or collaboration with academic scientists. A second type of bias might result from using a common method to measure outcome, mediator and explanatory variables (Podsakoff et al. 2003). Our analysis is unlikely to suffer from common method bias because information on motives, boundary spanning, and inventive performance are collected from three separate sources.

3.4. Specification and Estimation Method

We are interested in the relationship between motives and the nature of the inventive output P_{if} (*citation weighted patents* and *new words*) created by individual *i* since the beginning of his/her current job in firm *f* until the end of 2005.

$$(1)\ P_{if} = f(\propto + \beta_1\ taste\ for\ science_i + \beta_2\ taste\ for\ salary\ \&\ career_i + \gamma\ scientist\ controls_i + \delta\ firm\ controls_f + \varepsilon_{if})$$

Given that our outcome variables are non-negative integers, we estimate the regressions using Poisson quasi maximum likelihood (PQML) and report robust standard errors clustered at the firm level. PQML renders consistent estimates under correct mean specification and is robust to a large number of zero's and to overdispersion of the dependent variable (Gourieroux, Monfort, and Trognon 1984; Silva and Tenreyro 2006). We account for differences in job tenure at the end of 2005 by estimating the models with exposure, i.e. by including the log of job tenure as a control variable with the coefficient constrained to one (Long and Freese 2005).

We explicitly test for mediation of the effects of taste for science and taste for salary & career on inventive output through hours worked, time spent on research, and academic boundary spanning measured through co-publications. To this end, we use the procedure of Baron and Kenny (1986). First, we predict the main, reduced form, effects of tastes on inventive performance, corresponding with model (1) above. Second, we predict the effects of tastes for science and taste for salary & career on the potential mediators. Third, we re-estimate model (1) but include the mediator variables, corresponding with model (2) below.

(2) $P_{if} = f(\propto + \beta_1\ taste\ for\ science\ _i + \beta_2\ taste\ for\ salary\ \&\ career_i + \beta_3\ co-publications_i + \beta_4\ research_i + \beta_5\ hours\ worked_i + \gamma\ scientist\ controls_i + \delta\ firm\ controls_f + \varepsilon_{if})$

To test for mediation, we check whether the coefficients of taste for science and taste for salary & career in (2) are smaller compared to the coefficients in (1) using seemingly unrelated estimation (*suest* command in Stata). In addition, we use nonparametric bootstrapping with 5,000 replications to test the robustness of these mediation results and calculate the direct, indirect, and total effects of taste for science and taste for salary & career on inventive performance, as well as the bias-corrected confidence intervals around these effects (Preacher and Hayes 2008). Because we have multiple mediators and outcome variables measured in counts, we use generalized structural equation models to calculate the effects (*gsem* command in Stata).

4. RESULTS

4.1. Descriptive Results

Table 3 illustrates our main research questions with descriptive statistics. Individuals with a strong taste for science (i.e. above the median sample value) not only create more patents, but differentiate themselves even more on *citation weighted patents* and *new words* (all differences are statistically significant). Their higher inventive output does not correlate with a higher input as they do not work more hours. But, they spend a larger share of their time on research and are also more involved in academic boundary spanning, publishing more in collaboration with academic scientists. The latter difference is however not statistically significant.

Boundary spanning, as witnessed through co-publications with academic scientists, matters for the quantity, value, and novelty of inventive output. Those scientists and engineers who score above the sample median on co-publishing display a higher inventive performance, not only in terms of quantity of patents, but also and even more outspokenly on *citation weighted patents* and *new words*, although the latter is only significant at the 10% level. Individuals spending a large share of their time on research are also more productive, but none of these effects are statistically significant. Finally, individuals who work

more hours create not only more patents, but also score higher on *citation weighted patents* and *new words*, but the effect on *new words* is not statistically significant.

Insert Table 3 here

4.2. Regression Analysis

(i) Taste for science, taste for salary & career, and inventive performance.

The analyses reported in Table 4, corresponding with model (1), confirm that scientists and engineers with a stronger taste for science have a significantly higher citation-weighted and a more novel inventive output. The differences are sizeable: a one standard deviation higher score on taste for science implies a 82% higher citation-weighted patent count and a 102% higher new word count. Not surprisingly, taste for science has a stronger effect on novel output than on citation weighted output. Once controlled for the taste for science, those with a stronger taste for salary & career display a lower citation weighted output as well as a lower novel output, but only the first effect is significant at the 10% level. A one standard deviation higher score on taste for salary & career is associated with a 32% lower citation-weighted patent count. In contrast to Sauermann and Cohen (2010), who found a positive relation between motives for salary and number of patents, we find a negative relation between taste for salary & career and citation-weighted patents[11]. In the mediation analysis below, we explore potential explanations for these findings.

Insert Table 4 here

(ii) Hours worked, time spent on research, and academic boundary spanning as mediators.

As a *first step* to understand the mechanisms mediating the relationship between motives and inventive performance, we test whether taste for science and taste for salary & career significantly affect our three potential mediators: hours worked, self-reported share of time spent on research, and boundary spanning activities proxied by academic co-publications. Table 5 shows that individuals with a high taste for science do not spent significantly more hours working. But they do spend a significantly larger share of

[11] When regressing the number of patents, we also find a significant negative effect associated with "taste for salary & career", see Table A.3.

their time on research and are significantly more engaged in academic boundary spanning. A one standard deviation higher score on taste for science implies 22% more time spent on research and a 34% higher co-publication count. Taste for salary & career, while having no significant effect on hours worked nor on time spent on research, is significantly negatively related to academic boundary spanning activities. A one standard deviation higher score on taste for salary & career is associated with 28% fewer co-publications with academic scientists.

To further explore why those with a high taste for salary & career are less likely to be engaged in co-publishing with academics, we analyze in Table A.1 in appendix the relationship between salary and co-publications. In line with the finding of Stern (2004) that people working in industry pay to be scientists, we confirm a significant negative relationship between co-publications and annual base salary, controlling for scientific ability. Hence, industrial scientists and engineers need to trade off co-publishing with academic scientists against a higher salary[12]. This finding correlates with why individuals with a high taste for salary shy away from academic boundary spanning, as they care more about the associated wage loss.

Insert Table 5 here

The *second step* in the mediation analysis is to establish that the mediator variables significantly affect inventive performance while controlling for taste for science and taste for salary & career (Baron and Kenny 1986). As shown in columns 2-4 in Table 6, a standard deviation increase in hours worked, share of time spent on research and co-publications, implies a 32%, 36% and 25% increase in *citation-weighted patents* respectively[13]. If we include the three mediators together (column 5), only co-

[12] Marginal effects indicate that a standard deviation increase in co-publications implies a 3% lower annual base salary. The person with the highest number of co-publications in our sample (75) has a 35% lower salary compared to a scientist with zero co-publications.

[13] Scientists with the largest number of co-publications have a 1,181% higher citation-weighted patent count compared to scientists with zero co-publications. Spending 100% of time at work on research implies a 200% increase in citation-weighted patents compared to spending 100% of time on development or other tasks. Scientists with the largest number of hours worked have a 335% higher citation-weighted patent count compared to scientists with the lowest number of hours worked.

publications remains a highly significant predictor of citation weighted inventive output. As shown in columns 7-10 of Table 6, co-publications and hours worked significantly affect the number of *new words* while time spent on research surprisingly has no effect. A standard deviation increase in hours worked and co-publications implies a 33% and 20% increase in new words respectively[14]. In line with the findings for citation-weighted patents, only co-publications remains significant if we jointly include the three mediators (column 10). Together, these results confirm the positive effect of quantity of effort on inventive performance, like in Sauermann and Cohen (2010). But the nature of this effort seems to matter even more for performance, particularly academic boundary spanning as proxied by co-publications, and particularly for *citation weighted patents*.

Insert Table 6 here

The *third and final step* of the mediation analysis is to check whether the effects of taste for science and taste for salary & career on performance decrease with inclusion of the mediators. As illustrated in columns 1-5 of Table 6, the effect of *taste for science* on *citation-weighted patents* decreases significantly after including the mediators[15]. Especially the inclusion of co-publications and to a smaller extent share of time spent on research reduce the effect of taste for science. Including the three mediators, the coefficient of taste for science drops from 0.61 to 0.38. A one standard deviation higher score on taste for science implies a 43% higher citation-weighted patent count compared to a 82% higher citation weighted patent count in the model excluding the three mediators. Although we find significant support for mediation through the nature of effort, the mediation is only partial as the effect of taste for science remains significant after inclusion of our mediators.

[14] Scientists with the largest number of co-publications have a 717% higher new word count compared to scientists with zero co-publications. The difference in new words between scientists with the largest number of hours worked and those with the lowest number is 354%.

[15] We perform a Wald test to compare the coefficients between the different models using seemingly unrelated estimation (*suest* in Stata 14). Coefficient taste for science in column (1) versus (5): chi2(1)= 2.76; p-value of one sided test = 0.0484.

In contrast, the negative effect of *taste for salary & career* on *citation-weighted patents*, albeit marginally significant, is fully mediated by academic boundary spanning [16]. The large negative coefficient of taste for salary, significant at the 10% level (column 1), becomes much smaller and insignificant after including co-publications. This finding suggests that those with a comparable taste for science but a stronger taste for salary & career perform worse in generating citation-weighted patents because they engage less in bench-level collaboration with academic scientists. Once controlled for their lesser involvement in academic boundary spanning, those with a strong taste for salary & career are no longer significantly underperforming.

For *novelty of inventive output*, we do not find significant support for mediation of the effect of *taste for science* through the three channels considered. The positive effect of taste for science on novelty is reduced somewhat after including the mediators, particularly academic boundary spanning, but not significantly. Although academic boundary spanning does lead to a more novel inventive output, and individuals with a high taste for science do engage more in academic boundary spanning, this seems surprisingly not to be the major factor behind why taste for science leads to more novel inventive output. This suggests that taste for science has mostly a pure innate effect on novelty not mediated by the quantity and nature of effort. Or there might be other mediators not yet controlled for which can explain the relationship between taste for science and novelty of inventive output.

To test the robustness of the mediation results, we use nonparametric bootstrapping with 5,000 replications and a generalized structured equation model to calculate the direct, indirect, and total effects of taste for science and taste for salary & career on inventive performance (Preacher and Hayes 2008). We restrict the analysis to *citation-weighted patents* as outcome because we did not find support for mediation in the regressions with new words as outcome. Overall, the results are in line with our previous findings. As illustrated in Table 7, the total effect of *taste for science* on citation-weighted patent output is significant. This total effect is first and foremost composed of a significant positive direct effect. But taste

[16] Coefficient taste for salary in column (1) versus (5): chi2(1)= 2.88; p-value of one sided test = 0.0447.

for science also has a significant positive indirect effect on citation-weighted patents through its stimulating effect on academic boundary spanning, itself a significant driver of value weighted inventive output. The total indirect effect via co-publications is significantly positive[17]. The bootstrapping therefore confirms the robustness of the direct effect of "taste for science" on citation-weighted patent output and the positive indirect effect through academic boundary spanning. As the indirect effect is much smaller, it also confirms that mediation through the three channels identified is only partial. The total effect of *taste for salary & career* on citation-weighted patents is negative but not significant at the 5% level[18]. While the direct effect is negative and constitutes the largest component of the total negative effect, it is however not significant. The indirect effect through academic boundary spanning is however significantly negative. Individuals with a strong taste for salary & career have a lower citation-weighted patent output because they are less involved in academic boundary spanning, but this effect is only a small component of the total effect of taste for salary & career on performance.

Insert Table 7 here

It is particularly important to control for skills and other unobserved heterogeneity among individuals captured by our pre-sample measures of inventive and scientific performance. Individuals with a higher pre-sample citation-weighted patent count, whose Ph.D. was funded by a scholarship, or who finished their Ph.D. in a relatively short period of time, perform better in their current job in industry (Table 4). Controlling for pre-sample scientific publications is important because those with a stronger pre-sample scientific track record are more likely to collaborate with academic scientists in their current job in industry (see columns 1-3 of Table 5).

4.3. Socialization of Motives and Endogeneity

[17] While the indirect effect of taste for science via time spent on research is not significant at the 5% level, the total indirect effect via co-publications and time spent on research is significant and larger than the indirect effect via co-publications only.

[18] Also in the results reported supra in Table 4, the negative effect of taste for salary & career on citation-weighted patent count was only significant at the 10% level.

A main concern is that motives, and taste for science in particular, change because of socialization in the type of job and firm, or because of a change in inventive performance (Gundry 1993). Individuals with more science-related job activities, working for science-oriented firms, or with a more successful track record of scientific or inventive performance might indicate to have (acquired) a stronger taste for science. This might bias the effect of the reported taste for science on co-publications and on inventive performance. The literature typically treats motives related to job attributes as pre-determined, exogenously given and stable over time (e.g., Amabile et al. 1994). This is confirmed by empirical evidence tracing the same industrial scientists and engineers at different points in time, showing how motives related to intellectual challenge and independence – the key components of taste for science, are very stable over time and not affected by changes in inventive performance of the individual (Sauermann and Cohen 2010, p. 2142).

As already discussed supra, our survey data aim to measure taste for science at the start of the career, not at the current juncture. Nonetheless, we check for a potential change in motives due to socialization in the type of firm or due to inventive performance. We do this in several ways. First, we include different pre-sample measures of inventive performance, both at the level of the individual as well as at the firm level. This allows to control for a change in motives due to a higher or lower inventive performance. Overall, as the reported results hold including these controls, we conclude that a change in taste for science due to a high or low inventive or scientific performance or selection into a high or low inventive or scientific firm environment, is unlikely to drive the observed relationship between taste for science, academic boundary spanning, and inventive performance.

Second, we replicate the analysis using firm fixed effects, which account for any unobserved firm-level factors causing motives to change. Unfortunately, this exercise greatly reduced sample size, as the panel structure of our data forces us to restrict in this case the sample to firms with at least two surveyed individuals. Nonetheless, as illustrated in Table A.2 in appendix, we continue to find a strong significant total effect of taste for science on citation-weighted and novel inventive output. We also continue to find a strong positive effect of taste for science on co-publications, share of time spent on

research, and even on hours worked, while taste for salary & career correlates negatively with academic boundary spanning and even with hours worked. We continue to find co-publications to positively affect inventive performance. But we do not find support for academic boundary spanning to mediate substantially the impact of motives on performance. Although industrial scientists and engineers with a high taste for science are more likely to be engaged in academic boundary spanning, and the latter significantly improves their inventive performance, this is not the main story behind why taste for science improves inventive performance in the model when including firm fixed effects.

4.4. Robustness Checks

Because our measures of inventive performance rely on patents, and because not all individuals are patenting, one might wonder to what extent our results are driven by the selection into patenting rather than by variation in inventive performance. Column 1 of Table A.3 in appendix shows that taste for science and taste for salary & career have no significant effect on the likelihood of having at least one patent. As such, it is unlikely that our results only reflect a selection into patenting.

Although we observe the share of time spent on research, this might involve both basic as well as applied research. Because basic research can benefit more from academic boundary spanning and is more likely to result in co-publications, the observed correlation between co-publications and inventive performance might be driven by selection into basic research projects rather than by academic boundary spanning itself. Although the survey does not include a direct measure for the involvement in basic research projects, we additionally include an imperfect control for basic research involvement: a binary indicator for whether their job is related to the research conducted during their doctoral studies (e.g., Stern 2004). Our findings remain robust across all models after including this proxy for basic research (results not reported but available upon request) [19].

[19] Results remain unaffected if we use an alternative proxy for the involvement in basic research: a binary indicator for whether a Ph.D. degree was a required qualification for their job in industry (results not reported).

Given the skewness of inventive performance, our results might be driven by a few very productive individuals with a high taste for science and a low taste for salary. As illustrated in column 2 of Table A.3, our main results are unaffected after dropping the most productive individuals with a citation-weighted patent count above 75 (3% of the full sample, 13% of the patenting individuals)[20].

Because citation-weighted patents capture both the quantity and value of patents, and we are interested to see any differential effect on quantity versus value, we replicate the analysis using the number of patents and the number of citations separately in columns 3-4 and 5-6 of Table A.3 respectively. Although results are robust to using either measure of performance, taste for science, taste for salary & career, and co-publications seem to have a stronger effect on citations than on number of patents. A one standard deviation increase in taste for science increases the number of patents with 64%, while it increases the number of citations with 83%. While the mediation effects through academic boundary spanning are significant for citations[21], they are not significant in the models with number of patents as outcome. This latter result is consistent with Sauermann and Cohen (2010) who also did not find support for their self-reported measure of professional meeting attendance to mediate the impact of motives on the self-reported number of patents. Overall, the comparison of counts of citations versus counts of patents suggests that the impact of taste for science, both directly and as well as indirectly through academic boundary spanning, is more pronounced for the value than for the quantity of inventive output.

5. DISCUSSION AND CONCLUSION

Prior research in the economics and strategy of innovation mostly overlooked that firms' capacity to innovate hinges on the individual scientists and engineers who engage in R&D inside firms and on what

[20] The most productive scientists have a taste for science equal to 0.26 and a taste for salary & career equal to -0.12 .
[21] Co-publications and time spent on research significantly mediate the positive relationship between taste for science and number of citations (Coefficient taste for science in column (5) versus (6): chi2(1)= 2.81; p-value of one sided test = 0.0468; For taste for salary & career, co-publications significantly mediate the negative relationship with number of citations (Coefficient taste for salary and career in column (5) versus (6): chi2(1)= 3.00; p-value of one sided test = 0.0416) .

drives these individuals to perform. By contrast, the economics of science literature underlines the importance of individuals' motives, particularly non-pecuniary motives or taste for science, as a driver of productivity in an academic environment. In this paper, we bridge both streams of literature and illustrate that the taste for science of industrial scientists and engineers is strongly related not only to the quantity but also to the nature of their inventive output.

We find that industrial scientist and engineers with a strong taste for science have a more novel and a higher value-weighted inventive output. Looking at potential explanations driving this relationship, we find that individuals with a taste for science do not work more hours a week. But they spend more of their time on research and engage more in academic boundary spanning, proxied by co-publications with academic scientists. Bench-level collaboration with academics is associated with a higher value-weighted and a more novel inventive output, and partially mediates the relation between taste for science and value weighted inventive output. Surprisingly, academic boundary spanning does not mediate the relation between taste for science and novelty of output. In addition, we find that individuals with a strong taste for salary & career co-publish less with academics, arguably because of the tradeoff between co-publishing and salary, for which we also find empirical evidence in our data. Their lower inclination to collaborate with academic scientists results in a lower value weighted inventive output, all else equal.

Our paper makes several contributions to the literature. First, we contribute to the thin literature studying the relation between the motives of industrial scientists and engineers and firm innovation by providing insight into the mechanisms through which motives affect the inventive performance of individuals, particularly academic boundary spanning. We further contribute to this emerging line of research by studying how motives affect the nature rather than just the amount of inventive output. Not all patented inventions are intrinsically novel and valuable. Most new inventions only introduce an incremental rather than a radical change with respect to prior art and have little economic value (Scherer and Harhoff 2000). We illustrate to what extent and through which mechanisms motives affect not just the amount of inventive output but also the novelty and value of that output.

Second, we add to the larger literature studying how scientific research in academe translates into technological progress in industry (e.g., Jaffe 1989). Prior research already illustrated the importance of academic boundary spanning, measured by co-publications with academic scientists, for firm-level innovation (e.g., Cockburn and Henderson 1998). Yet, this line of research, which is mostly at the firm- and macro-level, has largely overlooked that higher ability individuals have a stronger incentive to interact with the academic community because of the higher expected returns (Stern 2004). This introduces an upward selection bias in estimating the effect of academic boundary spanning on firm innovation. We contribute to this line of research by analyzing the individual-level implications of crossing the boundary between industry and academia while accounting for individual ability. Studying individual scientists and engineers provides a more granular insight in the mechanism of how academic science translates into applied research and innovation in industry (Liu and Stuart 2010). As the knowledge from early stage research in universities is partly tacit in nature and difficult to access and absorb for use in industry, bench-level collaboration with academics allows industrial scientists and engineers to access this external knowledge and translate into commercial applications (Zucker et al. 2002, Cassiman et al. 2012). Controlling for individual ability and job characteristics, our findings confirm that industrial scientists and engineers who co-publish with academic scientists have a more novel and higher value weighted inventive output compared to industrial scientists and engineers working for the same firm who do not engage in such external collaboration. Individuals with a high taste for science and a strong pre-sample scientific track record are most likely to engage in such boundary spanning.

Our findings have implications for industrial scientists and engineers and the managers who recruit and manage them. First, because of the difficulties with command-and-control systems and provision of the right incentives to stimulate inventive performance, it is important to hire scientists and engineers who are intrinsically motivated. Individuals with a strong taste for science are simply more creative and productive, even after controlling for ability, number of hours worked, time spent on research, and interaction with the academic community. The fact that taste for science remains a strong

and significant predictor of performance is arguably because the actual intensity of cognitive effort per hour worked is not captured by any of our mediators (Kahneman 1973, Sauermann and Cohen 2010). This particularly holds for the novelty of inventive output.

Second, our findings suggest that a firm's policy to allow, or potentially even stimulate, its scientists and engineers to interact with the academic community seems to pay off in terms of higher inventive performance. Our results confirm and generalize prior firm-level research for the pharmaceutical sector illustrating how pro-publication incentives foster innovation at the firm level (Cockburn and Henderson 1998). Firms' policies of paying a lower salary in return for the freedom to participate in the scientific community and publish is presumably counterproductive in terms of fostering innovation (Stern 2004). Individuals who care about salary will interact less with the academic community, will not absorb valuable external knowledge, and consequently develop less valuable inventions.

Our study has several limitations that should be taken into account when interpreting the results. First, although the survey and secondary sources provide information on a range of motives and potential mechanisms mediating the relation between motives and performance, there might be other motives and mediators which are not captured in our study. In particular, the desire for peer recognition is not included in the survey while it is considered as a crucial motive for scientists (Merton 1973). As for the mediating variables, we only found partial mediation for academic boundary spanning on value weighted inventive output and no significant mediation on novel output. The search for other mediators that may account for why industrial scientists and engineers with a high "taste for science" are more successful is still on. Second, we remain reluctant to interpret causal relations between motives, mediators, and performance. Although prior research illustrates that motives related to intellectual challenge and independence are stable over time and not affected by changes in performance (Sauermann and Cohen 2010), we only have one wave of survey data so that we cannot rule out the possibility that motives changed due to socialization in the job or due to a change in performance. Last but not least, other dimensions of inventive output await further exploration.

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TABLE 1: Rotated Factor Loadings and Unique Variances (n=1,114)

Motives	Taste for salary & career	Taste for science	Uniqueness
Intellectual challenge	0.18	**0.90**	0.15
Independence	0.03	**0.88**	0.22
Contribution to society	0.30	**0.50**	0.67
Salary	**0.87**	0.07	0.24
Extralegal benefits	**0.92**	0.06	0.15
Career advancement	**0.59**	0.25	0.60
Job security	**0.81**	0.27	0.27
Eigenvalue	3.25	1.45	
% of variance	60%	27%	

The sample includes all Ph.D. holders working as scientist or engineer in academia or industry, varimax rotation, loadings above 0.5 in bold

TABLE 2: Summary Statistics for Industrial Scientists and Engineers (n=464)

Variable	Description	Mean	Stdev.	Min.	Max.
Inventive performance					
Patents	Number of granted patents filed during current job	0.81	3.14	0.00	42.00
Zero patents	Binary: zero granted patents filed during current job	0.80		0.00	1.00
Citation-weighted patents	Number of citation-weighted granted patents filed during current job	8.12	44.29	0.00	699.00
New words	Number of words in the title, abstract, or claims, appearing for the first time in the USPTO patent corpus, found in the granted patents filed during current job	1.58	12.94	0.00	263.00
Motives					
Taste for science	Latent variable obtained from factor analysis, standardized	-0.19	0.98	-1.65	1.88
Taste for salary & career	Latent variable obtained from factor analysis, standardized	-0.04	0.49	-0.45	2.68
Potential Mediators					
Co-publications	Number of WOS publications co-authored with university scientists during current job	2.02	6.52	0.00	75.00
Zero co-publications	Binary: zero WOS publications co-authored with university scientists during current job	0.60		0.00	1.00
Research	Share of time spent on research	29.75	28.06	0.00	100.00
Hours worked	Average number of hours worked per week	49.50	7.94	38.00	80.00
Pre-sample ability controls					
Pre sample patents (citation weighted)	Number of citation-weighted patents before current job	2.47	14.62	0.00	211.00
Pre sample publications	Number of WOS publications before current job	1.80	5.06	0.00	74.00
Pre sample publication citations	Average number of citations per WOS publication before current job	1.37	3.16	0.00	38.17
Ph.D. scholarship	Binary: Ph.D. funded by scholarship	0.62		0.00	1.00
Time to Ph.D.	Time to finish Ph.D. relative to peers	0.97	0.28	0.02	2.63
Ph.D. abroad	Binary: Ph.D. obtained from foreign university	0.11		0.00	1.00
Other controls					
Job tenure	Number of years in current job	9.98	7.92	1.00	37.00
Job tenure>10	Binary: longer than 10 years in current job	0.30	0.46	0.00	1.00
Age	Age at the end of 2015	42.05	8.51	27.00	65.00
Female		0.19		0.00	1.00
Belgian		0.88		0.00	1.00
Married	Binary: married or officially cohabiting	0.86		0.00	1.00
Children	Number of children	1.61	1.33	0.00	6.00
Ph.D. natural science		0.61		0.00	1.00
Ph.D. agricultural sciences		0.03		0.00	1.00
Ph.D. medical sciences		0.07		0.00	1.00
Ph.D. engineering and technology		0.29		0.00	1.00
Firm patents	Number of patents assigned to the firm from 2003-2005, log transformed	3.23	3.05	0.00	10.90
Firm zero patents	Binary: zero patents assigned to the firm from 2003-2005	0.29		0.00	1.00
Firm co-publications	Number of WOS publications by firm employees co-authored with university scientists, from 2003-2005, log transformed	1.04	1.47	0.00	5.47
Firm zero co-publications	Binary: zero WOS publications by firm employees co-authored with university scientists, from 2003-2005	0.57		0.00	1.00
Firm name missing	Binary: firm name missing	0.09		0.00	1.00
Salary	Annual base salary in EURO in 2015, log transformed (n=410)	11.09	0.44	9.83	12.61

Notes: Taste for science and taste for salary & career are calculated and normalized based on the full sample of scientists and engineers currently employed in industry or academe (n=1,114). Publication data sourced from Thomson Reuters Web of Science. Patent data sourced from the U.S. inventor patent database (Li et al., 2014).

TABLE 3: Summary Statistics for Subsamples of Industrial Scientists and Engineers (n=464)

	Inventive performance					Mediators			
	Patents		Citation-weighted patents	New words		Co-publications		Research	Hours worked
	Mean	Binary	Mean	Mean	Binary	Mean	Binary	Mean	Mean
Taste for science									
Larger than median	1.37	0.22	14.71	3.18	0.17	2.52	0.43	33.37	49.10
Smaller than median	0.51	0.19	4.52	0.70	0.12	1.75	0.39	27.77	49.72
Taste for salary & career									
Larger than median	1.10	0.22	9.57	3.79	0.17	1.28	0.38	29.94	50.55
Smaller than median	0.73	0.20	7.71	0.96	0.12	2.23	0.41	29.69	49.20
Co-publications									
Larger than median	1.20	0.26	12.86	2.76	0.17	5.02	1.00	31.40	49.35
Smaller than median	0.55	0.16	4.92	0.78	0.11	0.00	0.00	28.63	49.60
Research									
Larger than median	0.95	0.22	9.66	2.07	0.14	2.22	0.42	46.96	49.70
Smaller than median	0.60	0.18	5.82	0.85	0.12	1.74	0.38	4.02	49.20
Hours worked									
Larger than median	1.13	0.24	11.60	2.28	0.17	2.34	0.39	29.08	55.10
Smaller than median	0.42	0.16	3.91	0.72	0.10	1.64	0.42	30.55	42.72

TABLE 4: Regression of Inventive Performance on Motives

	(1) Citation-weighted patents	(2) Citation-weighted patents	(3) Citation-weighted patents	(4) New words	(5) New words	(6) New words
Taste for science	0.546***		0.612**	0.656***		0.718***
	(0.202)		(0.249)	(0.201)		(0.223)
Taste for salary & career		-1.005	-0.802*		-0.095	-0.302
		(0.754)	(0.423)		(0.535)	(0.348)
Age	0.046	0.056	0.039	-0.022	-0.012	-0.024
	(0.045)	(0.044)	(0.039)	(0.027)	(0.028)	(0.026)
Age^2	-0.005*	-0.006*	-0.005*	0.004**	0.004*	0.005**
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Female	-0.227	-0.179	-0.085	-0.409	-0.391	-0.285
	(0.452)	(0.473)	(0.420)	(0.704)	(0.597)	(0.585)
Belgian	0.363	-0.000	0.137	0.610	0.406	0.539
	(0.666)	(0.521)	(0.512)	(0.669)	(0.683)	(0.649)
Married	0.207	0.087	0.173	-1.147**	-1.455**	-1.098**
	(0.546)	(0.578)	(0.511)	(0.488)	(0.588)	(0.472)
Children	0.061	0.112	0.055	-0.045	0.039	-0.055
	(0.146)	(0.151)	(0.131)	(0.217)	(0.197)	(0.206)
Pre sample patents	0.023***	0.024***	0.022***	0.013**	0.015**	0.012**
	(0.005)	(0.005)	(0.004)	(0.006)	(0.007)	(0.006)
Pre sample publications	-0.009	0.008	0.003	-0.126	-0.142	-0.112
	(0.032)	(0.028)	(0.030)	(0.129)	(0.137)	(0.122)
Pre sample publication citations	-0.055	-0.024	-0.043	-0.208	-0.167	-0.208
	(0.040)	(0.052)	(0.046)	(0.156)	(0.146)	(0.158)
Ph.D. scholarship	1.021**	1.031***	0.984**	0.290	0.557	0.256
	(0.429)	(0.392)	(0.410)	(0.418)	(0.406)	(0.418)
Time to Ph.D.	-1.637*	-1.334*	-1.651*	-0.544	-0.399	-0.622
	(0.889)	(0.802)	(0.883)	(0.703)	(0.693)	(0.695)
Ph.D. abroad	-0.995	-1.030	-1.032	0.411	0.326	0.360
	(0.671)	(0.714)	(0.679)	(0.593)	(0.572)	(0.568)
Firm patents	0.230**	0.236**	0.232**	0.271***	0.238***	0.278***
	(0.115)	(0.101)	(0.098)	(0.083)	(0.080)	(0.084)
Firm co-publications	-0.243	-0.226	-0.216	-0.371**	-0.352	-0.365*
	(0.205)	(0.189)	(0.180)	(0.184)	(0.218)	(0.187)
Firm name missing	0.871**	0.736**	0.799**	-1.763***	-2.369***	-1.739***
	(0.416)	(0.354)	(0.358)	(0.481)	(0.540)	(0.473)
Job tenure>10	0.148	0.206	0.318	-0.945	-0.945*	-0.884
	(0.395)	(0.423)	(0.402)	(0.575)	(0.546)	(0.589)
Constant	-0.789	-0.858	-0.759	-3.091***	-2.979***	-3.102***
	(1.374)	(1.414)	(1.386)	(0.960)	(0.911)	(0.972)
Log likelihood	-5649.884	-5741.403	-5383.628	-1220.869	-1323.293	-1212.691

Notes: The sample include 464 industrial scientists and engineers. Models are estimated with Poisson quasi-maximum likelihood, the models are estimated with exposure to account for differences in job tenure, all models include Ph.D. field fixed effects, robust standard errors in brackets, clustered at firm level, *** p<0.01, ** p<0.05, * p<0.1

TABLE 5: Regression of Co-publications, Time Spent on Research, and Hours Worked as Potential Mediators

	(1) Co-publ.	(2) Co-publ.	(3) Co-publ.	(4) Research	(5) Research	(6) Research	(7) Hours worked	(8) Hours worked	(9) Hours worked
Taste for science	0.311***		0.297***	0.201***		0.201***	-0.006		-0.006
	(0.096)		(0.106)	(0.039)		(0.039)	(0.007)		(0.007)
Taste for salary & career		-0.849**	-0.664**		-0.115	-0.097		-0.013	-0.014
		(0.381)	(0.279)		(0.103)	(0.088)		(0.013)	(0.013)
Job tenure				0.026**	0.024**	0.027**	0.001	0.001	0.001
				(0.011)	(0.011)	(0.012)	(0.002)	(0.002)	(0.002)
Age	-0.034*	-0.035*	-0.039**	-0.017*	-0.015*	-0.018**	0.001	0.001	0.001
	(0.020)	(0.020)	(0.019)	(0.009)	(0.009)	(0.009)	(0.001)	(0.001)	(0.001)
Age^2	-0.002	-0.002	-0.002	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Female	-0.116	-0.173	-0.125	0.311***	0.268***	0.303***	-0.036	-0.036	-0.037*
	(0.217)	(0.200)	(0.206)	(0.101)	(0.103)	(0.102)	(0.022)	(0.022)	(0.022)
Belgian	0.396	0.239	0.308	0.001	-0.070	-0.012	-0.009	-0.009	-0.011
	(0.809)	(0.841)	(0.821)	(0.185)	(0.165)	(0.185)	(0.030)	(0.029)	(0.029)
Married	0.445	0.479*	0.469*	0.090	0.101	0.097	0.045**	0.046**	0.046**
	(0.273)	(0.276)	(0.269)	(0.152)	(0.161)	(0.151)	(0.020)	(0.020)	(0.020)
Children	0.001	0.016	0.001	-0.008	0.001	-0.009	0.008	0.007	0.007
	(0.101)	(0.112)	(0.103)	(0.034)	(0.035)	(0.035)	(0.006)	(0.006)	(0.006)
Pre sample patents	-0.036***	-0.018*	-0.024**	-0.007	-0.006	-0.007	0.000	0.000	0.000
	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)
Pre sample publications	0.061***	0.059***	0.059***	0.000	0.002	0.001	-0.000	0.000	0.000
	(0.009)	(0.009)	(0.009)	(0.013)	(0.014)	(0.014)	(0.002)	(0.002)	(0.002)
Pre sample publication citations	-0.005	0.013	0.004	-0.016	-0.011	-0.016	0.003*	0.003*	0.003*
	(0.023)	(0.021)	(0.021)	(0.016)	(0.016)	(0.016)	(0.002)	(0.002)	(0.002)
Ph.D. scholarship	0.063	0.106	0.105	0.147	0.149	0.151	-0.008	-0.007	-0.007
	(0.232)	(0.234)	(0.229)	(0.100)	(0.101)	(0.100)	(0.014)	(0.014)	(0.014)
Time to Ph.D.	0.394	0.372	0.350	0.047	0.062	0.038	-0.019	-0.021	-0.021
	(0.385)	(0.397)	(0.393)	(0.171)	(0.169)	(0.174)	(0.029)	(0.029)	(0.029)
Ph.D. abroad	0.149	0.136	0.144	-0.062	-0.095	-0.065	0.012	0.013	0.012
	(0.677)	(0.719)	(0.711)	(0.182)	(0.174)	(0.184)	(0.030)	(0.030)	(0.030)
Firm patents	0.002	0.023	0.018	-0.007	-0.003	-0.005	-0.002	-0.002	-0.002
	(0.095)	(0.092)	(0.093)	(0.019)	(0.020)	(0.019)	(0.003)	(0.003)	(0.003)
Firm co-publications	-0.129	-0.136	-0.123	-0.025	-0.029	-0.025	-0.001	-0.001	-0.001
	(0.138)	(0.136)	(0.136)	(0.039)	(0.043)	(0.040)	(0.004)	(0.004)	(0.004)
Firm name missing	0.104	0.097	0.112	0.060	0.016	0.056	0.013	0.014	0.013
	(0.276)	(0.260)	(0.270)	(0.075)	(0.075)	(0.075)	(0.013)	(0.013)	(0.013)
Job tenure>10	-0.517	-0.439	-0.434	-0.219	-0.203	-0.216	0.063**	0.064**	0.064**
	(0.340)	(0.350)	(0.351)	(0.184)	(0.191)	(0.185)	(0.030)	(0.030)	(0.030)
Constant	-2.184***	-2.357***	-2.339***	2.962***	2.983***	2.947***	3.895***	3.894***	3.893***
	(0.744)	(0.784)	(0.786)	(0.308)	(0.290)	(0.310)	(0.054)	(0.054)	(0.054)
Log likelihood	-1454.903	-1445.265	-1419.648	-7095.467	-7321.256	-7080.141	-1579.407	-1579.307	-1578.932

Notes: The sample include 464 industrial scientists and engineers. Models are estimated with Poisson quasi-maximum likelihood, models (1), (2), and (3) are estimated with exposure to account for differences in job tenure, all models include Ph.D. field fixed effects, robust standard errors in brackets, clustered at firm level, *** p<0.01, ** p<0.05, * p<0.1

TABLE 6: Mediation of Motives by Co-publications, Time Spent on Research, and Hours Worked

	(1) Citation-weighted patents	(2) Citation-weighted patents	(3) Citation-weighted patents	(4) Citation-weighted patents	(5) Citation-weighted patents	(6) New words	(7) New words	(8) New words	(9) New words	(10) New words
Taste for science	0.612**	0.461**	0.508**	0.595**	0.380*	0.718***	0.634***	0.672***	0.721***	0.610***
	(0.249)	(0.215)	(0.247)	(0.243)	(0.204)	(0.223)	(0.209)	(0.229)	(0.221)	(0.217)
Taste for salary & career	-0.802*	-0.388	-0.829*	-0.741*	-0.373	-0.302	-0.103	-0.305	-0.243	-0.065
	(0.423)	(0.361)	(0.425)	(0.404)	(0.373)	(0.348)	(0.335)	(0.364)	(0.336)	(0.337)
Co-publications		0.034***			0.031***		0.028***			0.025***
		(0.007)			(0.008)		(0.008)			(0.009)
Research			0.011*		0.007			0.006		0.003
			(0.006)		(0.008)			(0.007)		(0.007)
Hours worked				0.035**	0.022				0.036*	0.025
				(0.015)	(0.015)				(0.019)	(0.020)
Age	0.039	0.010	0.046	0.024	0.005	-0.024	-0.028	-0.020	-0.035	-0.034
	(0.039)	(0.029)	(0.040)	(0.034)	(0.028)	(0.026)	(0.026)	(0.030)	(0.026)	(0.028)
Age^2	-0.005*	-0.004	-0.005*	-0.004	-0.003	0.005**	0.005**	0.004**	0.005**	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.085	-0.082	-0.191	-0.148	-0.166	-0.285	-0.344	-0.296	-0.263	-0.326
	(0.420)	(0.399)	(0.483)	(0.404)	(0.439)	(0.585)	(0.591)	(0.601)	(0.568)	(0.599)
Belgian	0.137	-0.024	0.058	-0.055	-0.164	0.539	0.605	0.533	0.382	0.486
	(0.512)	(0.451)	(0.538)	(0.476)	(0.456)	(0.649)	(0.719)	(0.632)	(0.598)	(0.675)
Married	0.173	-0.095	0.012	-0.038	-0.243	-1.098**	-1.225***	-1.090**	-1.242**	-1.317***
	(0.511)	(0.484)	(0.466)	(0.498)	(0.477)	(0.472)	(0.453)	(0.449)	(0.494)	(0.473)
Children	0.055	-0.079	0.090	0.039	-0.063	-0.055	-0.169	-0.037	-0.073	-0.162
	(0.131)	(0.110)	(0.140)	(0.128)	(0.125)	(0.206)	(0.228)	(0.214)	(0.195)	(0.229)
Pre sample patents	0.022***	0.020***	0.024***	0.022***	0.022***	0.012**	0.012**	0.013**	0.012**	0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Pre sample publications	0.003	-0.025	0.004	0.008	-0.017	-0.112	-0.122	-0.098	-0.086	-0.100
	(0.030)	(0.032)	(0.030)	(0.027)	(0.029)	(0.122)	(0.132)	(0.119)	(0.111)	(0.124)
Pre sample publication citations	-0.043	-0.061	-0.033	-0.044	-0.051	-0.208	-0.258	-0.205	-0.210	-0.251
	(0.046)	(0.058)	(0.053)	(0.041)	(0.057)	(0.158)	(0.167)	(0.157)	(0.151)	(0.158)
Ph.D. scholarship	0.984**	1.010**	0.964**	0.921**	0.949**	0.256	0.284	0.263	0.259	0.283
	(0.410)	(0.436)	(0.392)	(0.384)	(0.407)	(0.418)	(0.455)	(0.425)	(0.400)	(0.441)
Time to Ph.D.	-1.651*	-1.415	-1.514*	-1.589*	-1.286	-0.622	-0.352	-0.634	-0.560	-0.307
	(0.883)	(0.906)	(0.773)	(0.864)	(0.814)	(0.695)	(0.631)	(0.675)	(0.647)	(0.609)
Ph.D. abroad	-1.032	-0.855	-0.933	-1.156*	-0.855	0.360	0.644	0.364	0.293	0.586
	(0.679)	(0.645)	(0.703)	(0.670)	(0.633)	(0.568)	(0.525)	(0.559)	(0.552)	(0.506)
Firm patents	0.232**	0.109**	0.220**	0.232**	0.111*	0.278***	0.230***	0.268***	0.268***	0.219***
	(0.098)	(0.054)	(0.091)	(0.090)	(0.057)	(0.084)	(0.084)	(0.078)	(0.074)	(0.073)
Firm co-publications	-0.216	0.001	-0.236	-0.219	-0.021	-0.365*	-0.297	-0.357**	-0.350**	-0.282
	(0.180)	(0.132)	(0.170)	(0.172)	(0.127)	(0.187)	(0.192)	(0.179)	(0.175)	(0.181)
Firm name missing	0.799**	0.652**	0.593*	0.788**	0.571*	-1.739***	-2.000***	-1.799***	-1.934***	-2.158***
	(0.358)	(0.309)	(0.318)	(0.351)	(0.298)	(0.473)	(0.485)	(0.461)	(0.506)	(0.547)
Job tenure>10	0.318	0.238	0.274	0.286	0.216	-0.884	-1.062	-0.884	-0.841	-1.016
	(0.402)	(0.442)	(0.424)	(0.413)	(0.461)	(0.589)	(0.649)	(0.598)	(0.581)	(0.639)
Constant	-0.759	0.064	-1.103	-2.218	-1.164	-3.102***	-2.965***	-3.269***	-4.688***	-4.188***
	(1.386)	(1.229)	(1.345)	(1.593)	(1.422)	(0.972)	(0.930)	(1.004)	(1.392)	(1.381)
Log likelihood	-5383.628	-4656.485	-5205.093	-5268.610	-4548.289	-1212.691	-1156.376	-1205.659	-1193.241	-1145.243

Notes: The sample include 464 industrial scientists and engineers. Models are estimated with Poisson quasi-maximum likelihood, estimated with exposure to account for differences in job tenure and include Ph.D. field fixed effects, robust standard errors in brackets, clustered at firm level,
*** p<0.01, ** p<0.05, * p<0.1

TABLE 7: Effects of Motives on Citation-Weighted Patents

	Coef.	Bias.	Bootstrap std. err.	[95% bias-corrected conf. interval]	
Taste for science					
Direct effect	0.3798	-0.0912	0.1968	0.0943	0.8566
Indirect effect via co-publications	0.0093	0.0018	0.0059	0.0006	0.0204
Indirect effect via research	0.0015	-0.0007	0.0021	-0.0030	0.0052
Total indirect effect	0.0108	0.0011	0.0057	0.0018	0.0222
Total effect	0.3905	-0.0901	0.1964	0.1072	0.8793
Taste for salary & career					
Direct effect	-0.3733	0.0528	0.4706	-1.8154	0.3105
Indirect effect via co-publications	-0.0208	-0.0078	0.0153	-0.0435	-0.0002
Indirect effect via research	-0.0007	0.0004	0.0015	-0.0045	0.0013
Total indirect effect	-0.0215	-0.0073	0.0150	-0.0438	-0.0003
Total effect	-0.3949	0.0455	0.4681	-1.8256	0.2883

Notes: Based on non-parametric bootstrapping with 5,000 replications (with replacement). Model is estimated with generalized structured equation model (Poisson quasi maximum likelihood). The indirect effects are calculated by multiplying the effect of the taste on the mediator with the effect of the mediator on citation-weighted patents. The total indirect effects are calculated by adding the individual indirect effects. The total effect of the taste is calculated by adding the direct effect of the taste with the total indirect effect of the taste.

APPENDIX

TABLE A.1: Salary

	(1) Salary (ln)
Co-publications	-0.005**
	(0.002)
Research	-0.000
	(0.001)
Hours worked	0.014***
	(0.002)
Job tenure	0.022***
	(0.005)
Age	0.022***
	(0.004)
Age^2	-0.001***
	(0.000)
Female	0.048
	(0.037)
Belgian	0.181**
	(0.083)
Married	0.054
	(0.042)
Children	0.026*
	(0.013)
Pre sample patents	0.000
	(0.001)
Pre sample publications	0.005**
	(0.002)
Pre sample publication citations	-0.004
	(0.004)
Ph.D. scholarship	-0.002
	(0.035)
Time to Ph.D.	-0.087*
	(0.051)
Ph.D. abroad	0.087
	(0.072)
Firm patents	0.008
	(0.006)
Firm co-publications	0.009
	(0.012)
Firm name missing	-0.090***
	(0.029)
Job tenure>10	-0.111*
	(0.061)
Constant	10.108***
	(0.158)
R-squared	0.581

Notes: The sample includes 410 industrial scientists and engineers. Ph.D. field fixed effects are included. Model is estimated with OLS, robust standard errors in brackets, clustered at firm level, *** p<0.01, ** p<0.05, * p<0.1

TABLE A.2: Firm Fixed Effects

	(1) Co-publications	(2) Research	(3) Hours worked	(4) Citation-weighted patents	(5) Citation-weighted patents	(6) New words	(7) New words
Taste for science	0.216***	0.253***	0.046*	0.611***	0.751***	0.790***	1.034***
	(0.077)	(0.094)	(0.025)	(0.118)	(0.133)	(0.156)	(0.218)
Taste for salary & career	-0.671***	-0.373**	-0.193***	-0.013	0.161	0.081	0.483
	(0.142)	(0.185)	(0.053)	(0.503)	(0.466)	(0.318)	(0.451)
Co-publications					0.150***		0.122***
					(0.050)		(0.033)
Research					-0.005		-0.013*
					(0.007)		(0.008)
Hours worked					-0.002		-0.077
					(0.034)		(0.049)
Age	-0.059***	-0.034*	-0.048***	-0.023	-0.014	-0.041	-0.010
	(0.015)	(0.018)	(0.008)	(0.036)	(0.028)	(0.061)	(0.073)
Age^2	-0.002*	0.000	0.002***	-0.010***	-0.010***	-0.007*	-0.010*
	(0.001)	(0.001)	(0.000)	(0.003)	(0.002)	(0.004)	(0.006)
Female	-0.678***	0.218	0.101	-0.151	0.580	-0.005	0.265
	(0.183)	(0.159)	(0.084)	(0.822)	(0.641)	(0.803)	(0.512)
Belgian	0.980**	0.386	-0.120	-0.065	0.804	2.612*	1.714
	(0.431)	(0.390)	(0.174)	(1.245)	(1.248)	(1.527)	(1.176)
Married	-0.342	-0.474	0.015	1.251**	1.576***	2.598***	3.101***
	(0.231)	(0.331)	(0.121)	(0.609)	(0.440)	(0.742)	(0.818)
Children	0.022	-0.050	0.017	-0.280	-0.413**	-0.610**	-0.691**
	(0.065)	(0.070)	(0.020)	(0.176)	(0.183)	(0.280)	(0.280)
Pre sample patents	-0.035***	-0.013	-0.001	0.014*	0.020***	-0.002	0.003
	(0.012)	(0.010)	(0.001)	(0.008)	(0.007)	(0.009)	(0.006)
Pre sample publications	0.052***	0.039***	0.025***	-0.164	-0.196	0.299	0.316
	(0.015)	(0.015)	(0.008)	(0.159)	(0.179)	(0.279)	(0.210)
Pre sample publication citations	-0.026	-0.048	-0.015	-0.185	-0.138	-0.615	-0.604
	(0.034)	(0.049)	(0.019)	(0.283)	(0.295)	(0.392)	(0.387)
Ph.D. scholarship	-0.131	0.093	-0.053	0.136	-0.059	-0.053	-0.442
	(0.168)	(0.161)	(0.050)	(0.929)	(0.691)	(0.670)	(0.517)
Time to Ph.D.	-0.322	-0.217	-0.102	-2.690***	-2.429***	-1.703***	-1.255**
	(0.278)	(0.231)	(0.137)	(0.814)	(0.607)	(0.620)	(0.581)
Ph.D. abroad	1.087***	0.632*	0.185	1.091	1.456	5.291**	4.561***
	(0.368)	(0.365)	(0.138)	(0.985)	(1.315)	(2.213)	(1.526)
Job tenure>10	-0.510**	-0.788***	-0.605***	0.070	-0.211	-0.486	-0.495
	(0.216)	(0.244)	(0.094)	(0.837)	(0.682)	(0.560)	(0.546)
Number of observations	205	234	240	143	143	125	125
Log likelihood	-363.896	-3559.541	-1525.072	-1725.865	-1506.732	-203.325	-189.250

Notes: The sample include 252 industrial scientists and engineers. Models are estimated with firm-fixed effects Poisson quasi-maximum likelihood, all models are estimated with exposure to account for differences in job tenure and include Ph.D. field fixed effects, robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

TABLE A.3: Robustness Checks

	(1) Patents>0	(2) Citation-weighted patents <=75	(3) Patents	(4) Patents	(5) Citations	(6) Citations
Model	logit	pqml	pqml	pqml	pqml	pqml
Taste for science	0.125	0.404***	0.517***	0.366***	0.624**	0.382*
	(0.127)	(0.155)	(0.166)	(0.134)	(0.261)	(0.215)
Taste for salary & career	-0.048	-0.097	-0.625**	-0.362	-0.817*	-0.369
	(0.284)	(0.268)	(0.313)	(0.279)	(0.432)	(0.383)
Co-publications	0.092*	0.036***		0.025***		0.032***
	(0.055)	(0.012)		(0.007)		(0.008)
Research	-0.000	-0.014**		0.006		0.007
	(0.004)	(0.006)		(0.006)		(0.008)
Hours worked	0.024	-0.016		0.025*		0.021
	(0.017)	(0.025)		(0.013)		(0.016)
Age	0.018	0.023	0.007	-0.011	0.043	0.006
	(0.020)	(0.027)	(0.025)	(0.023)	(0.041)	(0.029)
Age^2	-0.004**	-0.008***	-0.003	-0.002	-0.005*	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Female	-0.365	-0.068	-0.372	-0.421	-0.055	-0.136
	(0.345)	(0.333)	(0.342)	(0.356)	(0.434)	(0.453)
Belgian	0.316	0.110	-0.117	-0.223	0.186	-0.145
	(0.592)	(0.584)	(0.429)	(0.368)	(0.537)	(0.479)
Married	-0.062	0.895**	-0.179	-0.452	0.221	-0.215
	(0.433)	(0.450)	(0.487)	(0.498)	(0.516)	(0.475)
Children	-0.117	-0.405***	0.077	0.015	0.051	-0.074
	(0.144)	(0.097)	(0.129)	(0.139)	(0.133)	(0.126)
Pre sample patents	0.046**	0.012**	0.016***	0.016***	0.023***	0.022***
	(0.020)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
Pre sample publications	-0.073	-0.027*	0.026	0.011	-0.008	-0.030
	(0.046)	(0.016)	(0.018)	(0.017)	(0.040)	(0.040)
Pre sample publication citations	0.048	-0.013	-0.020	-0.024	-0.046	-0.055
	(0.053)	(0.038)	(0.041)	(0.045)	(0.049)	(0.062)
Ph.D. scholarship	0.418	0.887***	0.494*	0.430	1.056**	1.029**
	(0.300)	(0.306)	(0.294)	(0.303)	(0.435)	(0.431)
Time to Ph.D.	-0.312	-1.118**	-0.892*	-0.658	-1.762*	-1.383
	(0.431)	(0.548)	(0.507)	(0.454)	(0.929)	(0.865)
Ph.D. abroad	-0.175	-1.156*	-0.363	-0.254	-1.136	-0.956
	(0.630)	(0.598)	(0.465)	(0.407)	(0.712)	(0.676)
Firm patents	0.007	0.081	0.156**	0.089*	0.242**	0.113*
	(0.060)	(0.053)	(0.072)	(0.047)	(0.101)	(0.059)
Firm co-publications	0.030	-0.016	-0.125	-0.018	-0.228	-0.021
	(0.106)	(0.132)	(0.148)	(0.120)	(0.184)	(0.130)
Firm name missing	-0.495*	0.364	-0.064	-0.225	0.911**	0.669**
	(0.269)	(0.267)	(0.256)	(0.244)	(0.377)	(0.312)
Job tenure>10	0.757**	-0.091	0.051	-0.042	0.356	0.248
	(0.336)	(0.330)	(0.333)	(0.379)	(0.414)	(0.473)
constant	-3.232**	0.234	-2.772***	-3.807***	-0.939	-1.225
	(1.290)	(1.345)	(0.891)	(1.065)	(1.451)	(1.492)
Log likelihood	-195.813	-2062.684	-627.439	-573.685	-4898.233	-4121.614

Notes: The sample include 464 industrial scientists and engineers. Models are estimated with Poisson quasi-maximum likelihood, all models are estimated with exposure to account for differences in job tenure and include Ph.D. field fixed effects, robust standard errors in brackets, clustered by firm, *** p<0.01, ** p<0.05, * p<0.1

TABLE A.4: Correlation Table

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(1)	Patents	1.00																						
(2)	Citation-weighted patents	0.93	1.00																					
(3)	New words	0.52	0.35	1.00																				
(4)	Taste for science	0.12	0.09	0.06	1.00																			
(5)	Taste for salary & career	-0.04	-0.04	0.01	-0.02	1.00																		
(6)	Co-publications	0.40	0.42	0.11	0.10	-0.09	1.00																	
(7)	Research	0.07	0.07	0.04	0.17	-0.06	0.05	1.00																
(8)	Hours worked	0.11	0.10	0.02	0.00	-0.02	0.05	-0.02	1.00															
(9)	Pre sample patents (citation weighted)	0.23	0.18	0.04	0.07	0.00	-0.03	-0.07	0.04	1.00														
(10)	Pre sample publications	-0.04	-0.05	-0.04	0.07	0.07	0.25	-0.01	-0.03	0.15	1.00													
(11)	Pre sample publication citations	-0.07	-0.07	-0.05	0.07	0.04	0.06	-0.02	-0.04	-0.02	0.36	1.00												
(12)	Ph.D. scholarship	0.08	0.08	0.05	0.00	0.07	0.02	0.08	-0.02	-0.01	0.02	-0.03	1.00											
(13)	Time to Ph.D.	-0.06	-0.06	-0.02	0.02	-0.10	0.06	0.04	-0.04	-0.05	-0.02	-0.08	-0.09	1.00										
(14)	Ph.D. abroad	0.02	-0.01	-0.01	0.02	0.03	-0.01	-0.02	0.04	0.08	-0.02	-0.01	-0.13	-0.15	1.00									
(15)	Job tenure	0.21	0.19	0.15	-0.03	0.06	0.07	-0.01	0.18	-0.07	-0.25	-0.30	0.03	0.04	-0.05	1.00								
(16)	Job tenure>10	0.20	0.18	0.11	-0.02	0.06	0.01	-0.02	0.21	-0.04	-0.24	-0.29	0.09	0.02	-0.07	0.86	1.00							
(17)	Age	0.15	0.12	0.13	0.02	0.01	0.01	-0.08	0.16	0.09	-0.16	-0.31	-0.04	0.06	0.02	0.74	0.65	1.00						
(18)	Female	-0.07	-0.06	-0.03	-0.08	-0.06	-0.03	0.14	-0.15	-0.06	0.02	0.06	-0.01	0.09	0.05	-0.19	-0.16	-0.20	1.00					
(19)	Belgian	-0.02	0.01	0.01	-0.07	-0.05	0.03	0.00	-0.02	-0.09	0.01	0.03	0.09	0.06	-0.64	0.09	0.11	-0.04	-0.03	1.00				
(20)	Married	0.01	0.02	-0.09	0.06	0.06	0.05	0.02	0.15	0.06	0.02	-0.04	0.08	-0.02	0.05	0.06	0.05	0.06	-0.10	-0.07	1.00			
(21)	Children	0.05	0.05	-0.04	0.10	-0.02	0.06	-0.01	0.18	-0.04	0.00	-0.08	0.01	-0.06	0.07	0.09	0.10	0.12	-0.15	0.03	0.29	1.00		
(22)	Firm patents (log)	0.16	0.13	0.11	0.02	0.13	-0.01	-0.01	-0.01	-0.03	-0.06	0.00	0.07	-0.09	0.07	0.19	0.18	0.08	0.07	-0.01	0.04	0.08	1.00	
(23)	Firm co-publications (log)	0.07	0.04	0.00	-0.02	0.06	-0.04	-0.04	-0.03	0.06	0.04	0.03	-0.05	-0.08	0.05	0.08	0.04	0.03	0.07	0.03	0.01	0.02	0.57	1.00
(24)	Firm name missing	-0.05	-0.02	-0.04	-0.05	-0.06	0.01	0.01	0.03	-0.02	0.00	0.03	-0.02	-0.01	0.05	-0.02	-0.05	-0.01	-0.06	-0.04	-0.04	-0.01	-0.34	-0.23

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