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TASTE FOR SCIENCE, ACADEMIC BOUNDARY SPANNING AND INVENTIVE PERFORMANCE OF SCIENTISTS AND ENGINEERS IN INDUSTRY

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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 individual traits and the nature of 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 impactful patents. Academic boundary spanning, proxied by scientific publications co-authored with academic scientists, mediates the effect of taste for science, but only partly and only on impact-weighted inventive output. For novelty of inventive output, we find no mediation through academic boundary spanning. Individuals with a strong taste for salary collaborate less with academic scientists, fully mediating the negative effect of taste for salary on impact-weighted inventive output.

JEL Classification: O31

Keywords: taste for science, industry-science links

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

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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 individual traits and the nature of 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 impactful patents. Academic boundary spanning, proxied by scientific publications co-authored with academic scientists, mediates the effect of taste for science, but only partly and only on impact-weighted inventive output. For novelty of inventive output, we find no mediation through academic boundary spanning. Individuals with a strong taste for salary collaborate less with academic scientists, fully mediating the negative effect of taste for salary on impact-weighted inventive output.

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

JEL codes: O310, O320

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1. INTRODUCTION

Prior firm-level research studied why and how firms should access scientific knowledge to improve their innovation performance, and emphasized the importance of recruiting and accommodating academic-boundary spanning individuals to build effective industry-science links (Allen 1977, Tushman & Scanlan 1981, Laursen & Salter 2004, Cassiman et al. 2012). Individuals with academic research experience and a network of former and current academic collaborators are found to improve their firms' search strategy and ultimately firm-level innovation performance (Cockburn & Henderson 1998, Laursen & Salter 2006, Breschi & Catalini 2010, Ejsing et al. 2013). Given that industrial scientists and engineers are the locus of technological invention inside firms, surprisingly little research has looked at what propels these individuals to span the boundary between industry and academia, and drive the innovative performance of their firms (Sauermann & Cohen 2010, Agarwal & Ohyama 2012, Lacetera & Zirulia 2012). The economics of science literature has a long tradition in studying what drives scientists to perform (Dasgupta & David 1994, Stephan 2012). This literature describes that scientists are particularly characterized by a *taste for science* – a preference for intellectual challenge, autonomy, and contribution to society through the diffusion of their acquired knowledge (Merton 1973, Pelz & Andrews 1976).

In this paper, we bridge both streams of literature and demonstrate how a taste for science of scientists currently working in industry – but formerly trained in academia – is important for the rate and nature of their inventive output. We thus follow Sauermann & Cohen (2010) and Lacetera & Zirulia (2012) by looking at individual scientists and engineers within firms as the unit of analysis, and their individual treats that might relate to their inventive performance. We contribute to this line of research by looking not only at the relation between taste for science and the amount of inventive output, but also at the nature of this output. In particular, we study if taste for science relates to frontier pushing rather than incremental inventive output. To this end, we characterize an individual's inventive output along two dimensions: novelty and technological impact (Amabile 2013, Arts & Fleming 2017). In addition, we follow-up on Sauermann and Cohen (2010) to look deeper into why taste for science would matter for the nature of inventive output. In line with the literature on industry science links, we look particularly at whether

individuals with a strong taste for science engage more in academic-boundary spanning (Stern 2004). By collaborating with academics at the bench, industrial scientists and engineers obtain early and privileged access to new scientific knowledge and insights, and can improve their own inventive performance in industry (Cassiman et al. 2012). Academic boundary spanning is therefore a prime candidate for mediating the relation between taste for science and the nature of inventive output.

To tackle these research questions, we use a representative sample of 464 Ph.D. scientists and engineers working in an R&D job in industry from the Belgian wave of the OECD's Careers of Doctorate Holders survey (2013). The survey provides information on individual traits and job characteristics. We manually matched the survey information to patents and publications using secondary sources. We use the disambiguated 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 impact-weighted 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 (Balsmeier et al. 2017, Arts et al. 2017). The Web of Science allows us to collect the scientific publications of the industrial scientists and engineers in our sample which they co-authored with academic scientists. We use this to proxy for academic boundary spanning (e.g., Cockburn & Henderson 1998, Zucker et al. 2002). Furthermore, the matching with patent and publication data allows us to control for unobserved heterogeneity among industrial scientists and engineers using pre-sample – before their current job – measures of inventive and scientific output. As we also know the identity of the employing firm, we can match publications and patent information at the firm level, allowing 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 output. Looking at potential mediators, we find that those with a stronger taste for science co-publish more with academic scientists. Academic boundary spanning is associated with more novel and higher citation-weighted inventive output. It mediates the relation between taste for science and citation-weighted output,

but only partly. Surprisingly, academic boundary spanning does not mediate the relation between taste for science and novel inventive output. Despite the positive relation between academic co-publications and inventive performance, the data also confirm the negative relation between co-publications and salary (Stern 2004). Consistent with this penalty in salary, individuals with a strong taste for salary & career are less involved in academic boundary spanning. Missing this entry ticket to the academic community significantly explains their lower citation-weighted output.

2. INDIVIDUALS' TRAITS AND INVENTIVE PERFORMANCE

We first review the literature on the individual traits of scientists and engineers, their link to inventive performance, and the mechanisms mediating this relation. We close this section by describing how we will contribute to the literature.

2.1. Individual traits of scientists and engineers working in industry

Understanding which individual traits of scientists and engineers in industry shape their inventive efforts is important to predict their performance. For a given innate ability and acquired expertise, any heterogeneity in traits might relate to differences in inventive output.

The economics of science literature has extensively studied the traits distinguishing scientists (Stephan 2012, Dasgupta & David 1994). This literature characterizes scientists by their 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 & Andrews 1976, Katz 2004). Roach & Sauermann (2010) confirm that PhDs with a strong taste for science prefer a job in academia while those with a strong taste for salary prefer a job in industry (Roach & Sauermann 2010). Still, empirical evidence shows that there remains a large heterogeneity in traits among scientists working in industry (Agarwal & Ohyama 2012, Sauermann & Cohen 2010). Even among individuals working in industry, there are still profiles with a strong taste for science and a weak taste for salary, for instance witnessed by a willingness of some of them to trade off salary in return for the freedom to interact with the academic community and publish (Stern 2004).

Prior innovation management literature has looked at the organizational practices that firms (should) deploy to motivate their researchers (Vallas & Kleinman 2008, Stokes 2011, Stern 2004, Shapin 2004, Sauermann & Stephan 2012). Because not all industrial scientists and engineers have a strong taste for salary, firms' ability to use standard monetary incentives to direct scientists and engineers' effort and performance is limited. Moreover, using bureaucratic controls to stimulate effort and performance might jeopardize the autonomy which industrial scientists and engineers with a taste for science care about. To be able to attract and accommodate individuals with a high taste for science, firms should offer R&D scientists the freedom to develop their own research ideas, to interact with the external academic community, and to disseminate and exchange findings.

Despite the emphasis in the innovation literature on the importance of individuals and their characteristics for understanding firms' innovative performance, there is very little empirical research studying the link between the traits of industrial scientists and engineers and their inventive output. As far as we know, Sauermann & Cohen (2010) remains the only study showing – for a sample of Ph.D. scientists and engineers working in U.S. industry – that individuals motivated by intellectual challenge, salary, and independence create more patents, while those motivated by job security and responsibility create less patents.

2.2. Mediators in the relationship between traits and inventive performance

Individual traits matter for inventive performance because they affect the amount and type of effort exerted (Vroom 1964). Different traits might relate to differences in the amount of effort and – as a result – increase or decrease inventive output (Lazear 1997). Industrial scientists and engineers motivated by intellectual challenge and independence might spend more time at work, particularly if they have more freedom in choosing R&D projects which they find intellectually inspiring (Lacetera 2009). Individuals motivated by salary or career advancement might potentially work more hours when it enables them to earn a higher salary or climb the corporate ladder. However, Sauermann & Cohen (2010) found that controlling for the

number of hours worked did not affect the relation between motives and inventive performance, suggesting that hours worked is not a mediator.

Traits might also relate to inventive performance through soliciting different types of effort. Conditional on a given number of hours worked, industrial scientists and engineers with different traits might allocate their time to other activities, which differently affect their inventive output. Individuals with a strong taste for science might spend more time on upstream research rather than on downstream development or other tasks (Agarwal & Ohyama 2012). Individuals with a strong taste for science might also interact more with the broader academic community, being motivated by the recognition from academic peers and contribution to the advancement of science and diffusion of knowledge (Stern 2004).

Mediation through effort devoted to research rather than development, and effort devoted to academic boundary spanning activities, remain empirically unexplored. Sauermann & Cohen (2010) attempted to address the latter with a crude proxy, namely attendance or not of professional meetings. Admittedly, this proxy only imperfectly captures engagement in academic boundary spanning activities. They did not find any support for such attendance to affect inventive output.

2.3. Our research: Taste for science, academic boundary spanning and the nature of inventive output

While the existing literature and the scant empirical evidence describe the importance of individuals' taste for science for their inventive performance in industry, it remains unclear how taste for science affects not only the rate but also the nature of inventive output, and which mediators can explain the relationship between taste for science and the nature of inventive output. Our research addresses this gap in the literature. We are particularly interested in testing whether taste for science matters, not just for the sheer volume of inventive output, but whether taste for science relates to a higher *novelty* of inventive output, and output with a higher technological *impact* (Amabile 2013, Arts & Fleming 2017).

We further study how taste for science might matter for affecting the nature of inventive output. As mediating mechanisms, we look at the quantity of effort (i.e. do individuals with a stronger taste for science

work more hours, and therefore generate more inventive output). But more importantly, we look at the type of effort (i.e. do individuals with a stronger taste for science engage in different types of effort, and therefore have a more novel and impactful inventive output). To this end, we first look at how much effort is devoted to research. Individuals with a strong taste for science might spend more *time on upstream research* rather than on downstream development or other tasks. Upstream research is arguably more intellectually challenging and provides more scope for independent thinking. Being more engaged in upstream research might allow the individual to push the frontiers of knowledge into new and unexplored territories, and therefore result in more novel inventive output. Downstream development is presumably more routinized, structured and results in more incremental inventions. Inventions originating from upstream research also tend to have a bigger technological impact as they provide more opportunities for follow-up inventions (Verhoeven et al. 2016). Nevertheless, upstream research is also characterized by a high degree of experimentation and a high uncertainty about eventual impact (Aghion et al 2008). Because such exploratory projects typically have more uncertain outcomes, the potential for more novel inventions might simultaneously be associated with a higher probability of failure and an – on average – less (impactful) inventive output (Arts & Fleming 2017).

Besides spending more effort on upstream research, individuals with a strong taste for science might spend more effort interacting with the broader academic community, as they are more motivated by recognition from academic peers and from contributing to the advancement of knowledge (Tushman 1977, Tushman and Scanlan 1981). A by now large literature on industry science links has established that *academic boundary spanning* allows firms to better source and absorb external knowledge developed in academe, which enhances the effectiveness of downstream R&D (e.g. Allen & Cohen 1969, Cohen & Levinthal 1990, Liu & Stuart 2010, Salter & Laursen 2006, Cassiman et al. 2008). New scientific knowledge is often difficult to access and absorb and requires hands-on involvement through close interaction with academic scientists (Jensen & Thursby 2001, Zucker et al. 2002). Individuals who interact more with the academic community obtain early and privileged access to novel scientific insights, which

they can translate in more novel and impactful inventions. Thus, academic boundary spanning may mediate the effect of taste for science on the nature of inventive output of the individual scientist.

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 OECD, Eurostat, and the 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 contains information on individuals' initial motives to choose for a Ph.D. and career as scientist or engineer. In addition, the survey includes information on the job of the Ph.D. holders at the end of 2005. The survey was launched in 2006, addressed the full population of Ph.D. holders in Belgium, and had a response rate of 20%.

We use a subsample of 464 individuals who obtained a Ph.D. in science or engineering (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 patents and publications from secondary sources. To collect publication data, we used the Web of Science database. To collect patent data, we use the disambiguated inventor database to match each individual to a unique inventor if any (Li

[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.

et al., 2014)[2]. We also collect the patents of the employing firms. We use PATSTAT to collect patent-family corrected citation data[3].

3.2. Measures

(i) Outcome variables: nature of inventive output

We are interested not only in the relation between taste for science and the amount of inventive output, but specifically at the nature of this output. To test whether taste for science relates to frontier pushing rather than incremental inventive output, we characterize an individual's inventive output along two dimensions: novelty and technological impact. To measure the novelty of inventive output, we count the number of unique words in the title, abstract, and claims of the patents, which appear for the first time in the full patent corpus: *New words.* To calculate the measure, all words in the title, abstract, and claims, are tokenized for all U.S. patents back to 1975. Numbers are not taken into account and all patents before 1980 are used to establish a baseline (Balsmeier et al. 2017, Arts et al. 2017). To measure the technological impact of inventive output, we follow Trajtenberg (1990) and calculate the number of citation-weighted patents: *Citation-weighted patents*. Citations refer to how often the patent served as prior art for subsequent patents, which proxies for the technological impact of the invention and correlates with the private economic value of the invention (Harhoff et al. 1999). We take into account all patents filed between the starting date of the job and January 1 2006, the reference date of the survey.

(ii) Taste for science and taste for salary & career

[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. The fact that we use US patents to measure inventive output might result in bias because not all firms might be filing patents at the USPTO. This bias in unlikely to be important. First, our results are robust for the subsample of individuals working in firms with at least one US patent. Second, we use PATSTAT to manually search for non-US patents assigned to the 80 firms in our sample without any US patents. We find non-US patents for only 15 of these firms (19% of the sample of firms without US patents). Our findings remain robust if we exclude the scientists and engineers who work for these companies which exclusively have non-US patents. Finally, our results remain robust for firm fixed effects (cf infra), which control for firm-level patenting strategies. In the firm fixed effects models, we study the effects of tastes and academic boundary spanning among scientists and engineers working in the same firm.

[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.

To measure taste for science, we use the survey question *"Why did you choose a career in research?"*. Respondents could indicate any number of motives from a list. We apply exploratory factor analysis to examine the relation among different motives (Sauermann and Roach 2012)[4]. 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

The first latent variable correlates with motives for salary, extralegal benefits, and – to a smaller extent – career advancement and job security. We label this first variable as *taste for salary & career*. The second latent variable 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). We therefore label this second variable as *taste for science.* We calculate taste for science and taste for salary & career using the regression scoring method and normalize the measures for ease of interpretability.[5]

In line with prior research, we treat motives for pursuing a career in research as pre-determined, exogenously given, and stable over time (e.g., Amabile et al. 1994). Sauermann and Cohen (2010: 2142), using a survey targeting the same individuals at different points in time, confirm that the motives to choose a research career are very stable over time and not affected by changes in their inventive performance. In our study, the question on motives to choose a research career appears in the survey right after questions on education and before any job-related questions.

(iii) ***Mediating variables: quantity and nature of effort***

[4] In the factor analysis, we retain the full sample of scientists and engineers currently employed in industry or academia (n=1,114). Our main findings are robust to using only the sample of industrial scientists and engineers in the factor analysis.

[5] In line with Roach & Sauermann (2010), we also find in our sample that individuals with a low taste for science or a high taste for salary & career are more likely to work in industry, while those with a high taste for science or a low taste for salary & career are more likely to work in academia (T-test for difference in taste for science: t= -10.9055, Pr(|T| > |t|) = 0.0000. T-test for difference in taste for salary & career: t= 4.2777, Pr(|T| > |t|) = 0.0000). Still, there remains a large heterogeneity in tastes among scientists and engineers working in industry, which is the heterogeneity we will exploit in the analysis.

To study how taste for science affects the nature of inventive performance, we look at both the quantity and nature of effort. To measure the quantity of effort, the survey provides self-reported *hours worked* on average on a weekly basis. To measure the nature of effort, we use the self-reported share of time spent on performing, guiding, or interpreting *research* in their current job. To further capture the nature of effort, we look at academic boundary spanning. In line with prior firm-level research, we use *co-publications* with academic scientists to measure academic boundary spanning (e.g., Cockburn and Henderson 1998, Zucker et al. 2002, Gittelman and Kogut 2003). It is a much more involved form of interaction with the academic community than reading scientific publications or attending professional meetings[6]. We calculate for each 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[7].

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

It is most important to control for the scientific and technological ability and experience of the individual. Individuals with a strong taste for science may also have a strong record of scientific or inventive output. Moreover, individuals with a higher ability or experience might work more hours, spend more time on research, and engage more in academic boundary spanning, because of the higher expected returns. The returns from participating in the academic community will be higher for individuals with stronger scientific skills (Dasgupta & David 1994). These individuals 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). Moreover, companies might assign their best people to the most promising R&D projects, and stimulate them to work on research rather than development projects, and to collaborate with academic scientists. As such, the estimated effect of both taste for science, hours worked, share of time spent on research, and academic co-publications might suffer from an upward skill bias.

[6] A potential concern is that co-publications could be interpreted as an alternative measure of inventive output in case individuals would not only patent but also publish their inventions. It is unlikely that this would bias our results given the small fraction of patent-publication pairs found in prior studies (e.g., Magerman et al. 2015).

[7] The large majority (85%) of WOS publications in our sample 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.

We include the pre-sample value of the outcome variable as a control for technical expertise and other unobserved individual-specific heterogeneity (e.g., Blundell et al. 1999). The variable *pre sample patents* measures the number of citation-weighted patents filed before the current job. Similarly, to correct for scientific expertise, we include the number of publications published before the current job (*pre sample publications)* and the average number of citations received by these publications within three years *(pre sample publication citations)*. In addition, we include *PhD. scholarship*: a binary measure indicating whether their Ph.D. was funded by a government or private scholarship, which select on prior academic achievement and perceived ability; *Time to PhD* is a variable measuring the time needed to complete their Ph.D. relative to peers within the same field, which is expected to be shorter for more able individuals; *PhD. abroad* is 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 that is higher ranked than any Belgian university.

Besides controlling for scientific and technical ability and experience, we include a number of additional individual-level control variables. *Job tenure* measures the number of years the person has been in their job at the end of 2005; As we have only access to publication data from 1996 onwards, we capture only those publications of the last 10 years. We therefore include *Job tenure>10,* a binary measure equal to one when job tenure is longer than 10 years. We also include *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* is a binary measure equal to one for females; *Belgian* is a binary measure indicating whether the individual has the Belgian nationality; *Married* is a binary measure indicating whether the person is married or officially cohabiting; *Children* measures the number of children.

We also include a series of dummies to control for differences between scientific fields: *Ph.D. in natural science*, *Ph.D. in agricultural sciences*, *Ph.D. in medical sciences*, or *Ph.D. in engineering and technology*.

Next to individual-level and scientific field controls, it is also important to include firm-level controls, as the inventive output of industrial scientists and engineers is also driven by the characteristics

of the employing firm. Productive individuals are likely to join productive firms. Particularly, individuals with a high taste for science might join firms with higher scientific and innovative capacity. To control for this, we include a measure for the inventive capacity of the employing firms by the extent to which they patent: *Firm patents* measures the number of granted patents filed by the firm between the beginning of 2003 until the end of 2005. We measure the scientific capacity of the firms by the extent to which they collaborate with academic scientists and publish in scientific journals. *Firm co-publications* measures the number of publications co-authored by the firm's employees and academic scientists between the beginning of 2003 until the end of 2005[8]. A small number of individuals did not fill in the name of the firm. 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. For firms which have more than one employee in our survey, we can include firm fixed effects (i.e. 61 firms and 240 individuals). Firm fixed effects control for any remaining unobserved firm-level heterogeneity that might affect the relationship between taste for science and individual inventive output.

Table A.1 in appendix provides a description and summary statistics for all variables. It illustrates the high variance among industrial scientists and engineers in *taste for science* and *taste for salary & career*, and the large skew in both co-publications and inventive performance. Table A.2 in appendix shows the correlation matrix among our main variables.

3.3. Specification and Estimation Method

Our main equation of interest is the relationship between individual *i*'s *taste for science* and the nature of his or her inventive output P_{if} (*citation-weighted patents* and *new words*) created since the beginning of his or her current job in firm *f* until the end of 2005.

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

[8] Not all firms have patents and co-publications in the observation window. But, 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.

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. 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).

As we also want to unravel why taste for science might impact the nature of inventive output, we examine explicitly the role of mediators, using 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 check the effects of tastes on the potential mediators: time spent on research, academic co-publications and hours worked. 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 assess 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 the mediation results and calculate the direct, indirect, and total effects of taste for science and taste for salary & career on inventive output, 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, see Kaplan and Vakili (2015) for a similar approach).

3.4. Social Desirability and Common Method Bias

The use of survey data can introduce two common types of bias. A first type of potential bias results from using a common method to measure outcome, mediator and explanatory variables (Podsakoff et al. 2003). Our analysis is unlikely to suffer from this common method bias because information on motives, academic boundary spanning, and inventive output are collected from three separate sources. Second, 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 performance. This type of bias is unlikely in our case because the measures for academic boundary-spanning and inventive output are collected from other sources than the survey. Moreover, the survey question on motives is proximally separated from job-related questions, reducing the likelihood that respondents adapted their responses to provide a desirable explanation for their performance or collaboration with academic scientists.

4. RESULTS

4.1. Descriptive Results

Table 2 illustrates our main research questions with descriptive statistics. Individuals with a strong *taste for science* (above the median value) are not more likely to patent, but create significantly more patents, particularly more *citation-weighted patents*, and have more *new words* in their patents. Individuals with a strong *taste for salary & career* (above the median value) do not create significantly more patents or citation-weighted patents, but surprisingly have a higher number of new words. This may be driven by individuals that combine a high taste for salary & career with a high taste for science or other individual characteristics that drive novelty of inventive output. The econometric analysis in section 4.2 will allow to correct for this.

Insert Table 2 here

When looking at the mediating variables, they all positively correlate with inventive output (see also the correlation matrix in Table A.2). This particularly holds for academic boundary spanning. Industrial scientists and engineers with co-publications above the median create more patents, but particularly more *citation-weighted patents* and *new words*. Individuals spending a large share of their time on research are also more productive, but none of the differences is statistically significant. Individuals who work more hours create more patents, more *citation-weighted patents* and *new words*.

Concerning the relation between traits and mediators, we find that individuals with a *strong taste for science* do not work more hours on average, confirming Sauermann & Cohen's (2010) finding that the higher inventive performance is not driven by an increased quantity of effort. However, they spend a larger share of their time on research and co-publish more with academic scientists. The latter difference is only significant at p=0.11. Industrial scientists and engineers with a strong *taste for salary & career* work more hours, but engage less in academic boundary spanning.

4.2. Regression Analysis

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

The regressions reported in Table 3, corresponding with model (1), confirm that industrial scientists and engineers with a stronger *taste for science* have a higher citation-weighted and more novel inventive output. Importantly, these results are not driven by a selection into patenting. Taste for science has no significant effect on the likelihood to patent (column 1). Thus, taste for science does not seem to make a difference in whether or not the individual will patent, but in being a prolific inventor with more novel and impactful inventions. The effects are substantial: a one standard deviation higher score on taste for science relates to a 66% higher patent count, a 82% higher citation-weighted patent count, and a 102% higher new word count. The numbers suggest a higher impact on the nature of inventive output than on the mere quantity of inventive output (cf infra). 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 number of (citation-weighted) patents. A one standard deviation higher score on taste for salary & career is associated with a 26% lower patent count and a 32% lower citation-weighted patent count. In the econometric analysis, taste for salary & career does not significantly relate to novel output.

It is particularly important to control for individual ability and experience. 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 short period, perform better in their current job in industry. The firm-level controls for innovation performance are also significant.

Insert Table 3 here

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

As a *first step* to understand the mechanisms mediating the relation between traits and inventive performance, we test whether taste for science and taste for salary & career significantly relate to the three mediators: co-publications, time spent on research and total hours worked. Table 4 shows that individuals with a high taste for science do not work more hours. However, they spend a larger share of their time on research and they engage more in academic boundary spanning, as measured by the number of co-publications. A one standard deviation higher score on taste for science implies 22% more time spent on research and a 34% higher co-publication count. Those with a high taste for salary & career do not work significantly more hours or spend more time on research, but they engage significantly less in academic boundary spanning. A one standard deviation higher score on taste for salary & career is associated with 28% fewer co-publications. 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 4).

To further explore why individuals with a strong taste for salary & career are less engaged in co-publishing with academics, we analyze in Table A.3 in appendix the relationship between co-publications and salary. In line with Stern (2004), we find a significant negative relation between co-publications and annual base salary, controlling for individual ability and experience. This negative correlation is consistent with Stern's 2004 finding that industrial scientists and engineers need to "pay" to co-publish with academic scientists, in the form of accepting a lower salary[9]. This "paying" to co-publish could explain why individuals with a strong taste for salary would engage less in academic boundary spanning, as they care more about the associated wage loss.

Insert Table 4 here

[9] Marginal effects indicate that a standard deviation increase in co-publications implies a 3% lower 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.

The *second step* in the mediation analysis is to establish that the mediators significantly affect inventive performance while controlling for taste for science and taste for salary & career. As shown in columns 2-4 in Table 5, a standard deviation increase in hours worked, share of time spent on research and co-publications, implies respectively a 32%, 36% and 25% increase in citation-weighted patents. If we include the three mediators together (column 5), only co-publications remains significant. As shown in columns 7-10 of Table 5, co-publications and hours worked significantly affect the number of new words while time spent on research has no effect, confirming the descriptive statistics (cf supra). A standard deviation increase in hours worked and co-publications implies a 33% and 20% increase in new words respectively. In line with the findings for citation-weighted patents, only co-publications remains significant if we jointly include the three mediators (column 10). Together, the results confirm the positive effect of quantity of effort on inventive performance (Sauermann and Cohen 2010). However, the nature of this effort – particularly academic boundary spanning – seems to matter more for performance, particularly for citation-weighted patents.

Insert Table 5 here

The *third and final step* of the mediation analysis is to test 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 5, the effect of taste for science on citation-weighted patents decreases significantly after including the mediators[10]. Especially the inclusion of co-publications reduces 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 now implies a 43% higher citation-weighted patent count compared to a 82% higher citation-weighted patent count in the model excluding the mediators. Although we find support for mediation through boundary spanning activities, this mediation is only partial, as the effect of taste for science remains significant after inclusion of the mediators.

[10] 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, academic boundary spanning fully mediates the negative effect of taste for salary & career on citation-weighted patents[11]. The 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 individuals with a stronger taste for salary & career perform worse in generating citation-weighted patents because they engage less in academic boundary spanning. Once controlled for their lesser involvement in boundary spanning, those with a strong taste for salary & career are no longer significantly underperforming.

For novelty of inventive output, we find contrary to our expectations, no support for mediation through the quantity or nature of effort. Although individuals with a high taste for science engage more in academic boundary spanning, and boundary spanning relates to a more novel inventive output, boundary spanning does not mediate the relation between taste for science and novel inventive output. This suggests that taste for science has an innate effect on novelty not mediated by the quantity and nature of effort, or that other mediators are at play not captured in our analysis.

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. As illustrated in Table 6, the total effect of taste for science on citation-weighted patent output is significant. This total effect is composed of a significant positive direct effect and a significant positive indirect effect through academic boundary spanning. The bootstrapping therefore confirms the robustness of the direct effect of taste for science on citation-weighted patents and the positive indirect effect through academic boundary spanning. As the indirect effect is much smaller, it also confirms that mediation is only partial. The total effect of taste for salary & career on citation-weighted

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

patents is negative but not significant at the 5% level[12]. While the direct effect is negative and insignificant, the indirect effect through academic boundary spanning is significantly negative, confirming that individuals with a strong taste for salary & career have a lower citation-weighted patent output because they are less involved in academic boundary spanning.

Insert Table 6 here

4.3. Robustness Checks

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 1 of Table A.4, 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).

Because citation-weighted patents capture both the quantity and technological impact of patents, we further check any differential effect on quantity versus technological impact by separately studying the effect on the number of patents and on the number of citations in columns 2-3 and 4-5 of Table A.2 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%. Furthermore, the mediation effect through academic boundary spanning is only significant for citations[13] and not for number of patents as outcome. Overall, these findings suggests that the effect of taste for science, both directly and indirectly through academic boundary spanning, is more pronounced for the impact than for the quantity of inventive output.

As illustrated in Table A.2 columns 6-9, we obtain consistent results using two alternative measures for the quality of inventive output: total number of claims of all patents filed during current job, and total

[12] Also in the results reported supra in Table 3, the negative effect of taste for salary & career on citation-weighted patent count was only significant at the 10% level.
[13] Coefficient taste for science in column (4) versus (5): chi2(1)= 2.81; p-value of one sided test = 0.0468;Coefficient taste for salary and career in column (4) versus (5): chi2(1)= 3.00; p-value of one sided test = 0.0416.

number of times maintenance fees are paid for all patents filed during current job. Findings also remain consistent if we use the number of new pairwise subclass combinations appearing in all patents filed during current job as an alternative measure of the novelty of inventive output (Arts and Fleming 2017) (see columns 10-11 in Table A.4).

Finally, to further control for firm specific effects driving our results, particularly to control for any unobserved firm-level heterogeneity which is not captured by any of our firm-level control variables, we include firm fixed effects, which we can do for firms with at least two surveyed employees. As illustrated in Table A.5 in appendix, our findings remain consistent if we include binary firm indicators for firms with at least two surveyed employees. Our findings also remain robust to the inclusion of industry fixed effects (results not shown).

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 drives these individuals to perform. In this paper, we show how their taste for science matters not only for the quantity but also, and especially, for the nature of their inventive output within firms. Matching survey data with publication and patent information, we find that industrial scientist and engineers with a strong taste for science have a more novel and higher impact-weighted inventive output, while those with a strong taste for salary & career have a lower impact-weighted inventive output. Looking at potential mediators for the link between taste for science and inventive performance, we find that individuals with a strong taste for science engage more in academic boundary spanning – measured by publications co-authored with academic scientists. Active collaboration with academics is associated with a more novel and impactful output, and mediates the relation between taste for science and impact-weighted inventive output, but only partly. 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 are less involved in academic boundary spanning, arguably because of the tradeoff between co-publishing and

salary, for which we also find empirical evidence. Their lower inclination to collaborate with academic scientists fully mediates their lower impact-weighted inventive output.

Our paper makes several contributions to the literature. First, we contribute to the thin innovation management literature studying individual scientists and engineers within firms by providing evidence on how and why taste for science relates to the quantity but particularly the nature of inventive output (Pelz & Andrews 1976, Sauermann & Cohen 2010, Lacetera & Zirulia 2012). Most new inventions only introduce an incremental rather than a radical change with respect to prior art and have little impact (Scherer and Harhoff 2000). Only a few inventions are truly novel and have a big impact. We show how taste for taste matters particularly for driving not just the amount of inventive output but also and even more so the novelty and impact of that output.

Our results also contribute to the literature that studies the micro foundations of how scientific research in academia translates into innovation in industry (e.g., Jaffe 1989). Prior research 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 some of the employees in the firm may have stronger incentives or ability to interact with the academic community. Studying individual scientists and engineers within firms provides a more granular insight in the mechanism of how academic science translates into applied research and innovation in industry (Liu and Stuart 2010). Our findings confirm that individuals with a strong taste for science are most likely to engage in academic boundary spanning and that this academic boundary spanning at least partly explains their higher impact-weighted inventive performance. It does however not explain their higher novel inventive performance.

Finally, our results are also informative for the literature that looks at how to attract and accommodate scientists in industry (e.g., Vallas & Kleinman 2008) and for firms 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 & 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. Firms' policies of paying a lower salary in return for the freedom to participate in the scientific community and publish is arguably 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 impactful inventions.

Our study has several limitations. First, although the survey and secondary sources provide information on a range of traits and potential mediators, there might be other traits and mediators for which we miss information. In particular, the desire for peer recognition is not included in the survey while it is a typically discussed trait for scientists (Merton 1973). As none of the considered mechanisms mediate the effect of taste for science on novelty of inventive output and only partly mediate the effect on impact-weighted output, there might be other mediating mechanisms not captured in our study. Second, we remain reluctant to interpret causal relations between traits, mediators, and performance. Although prior research illustrates that taste for science and taste for salary & career are stable over time and not affected by changes in performance (Sauermann and Cohen 2010), we only have one wave of survey data, so we cannot rule out the possibility that tastes changed due to socialization in the job or due to a change in performance. Finally, although the study focuses on the scientist level, the firm environment obviously matters for individual performance. Although our analysis tries to control for these firm effects, it nevertheless remains a line of further research to study in more detail how firm effects may matter for shaping the relation between individuals' traits and their performance. A larger panel of firms and individuals within the same firm would allow to study in more detail the matching between individuals and firms. Future firm-level

research could also study how academic boundary spanning individuals might generate intra-firm spillovers, driving follow-on inventions within the firm.

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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 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**				
Smaller than median	**0.55**	**0.16**	**4.92**	**0.78**	**0.11**				
Research									
Larger than median	0.95	0.22	9.66	2.07	0.14				
Smaller than median	0.60	0.18	5.82	0.85	0.12				
Hours worked									
Larger than median	**1.13**	**0.24**	**11.60**	**2.28**	**0.17**				
Smaller than median	**0.42**	**0.16**	**3.91**	**0.72**	**0.10**				

Notes: differences significant at 0.05 in bold

TABLE 3: Regression of Inventive Performance on Motives

	(1) Patents>0	(2) Patents	(3) Citation-weighted patents	(4) New words
Taste for science	0.156	0.517***	0.612**	0.718***
	(0.120)	(0.166)	(0.249)	(0.223)
Taste for salary & career	-0.186	-0.625**	-0.802*	-0.302
	(0.304)	(0.313)	(0.423)	(0.348)
Age	0.026	0.007	0.039	-0.024
	(0.021)	(0.025)	(0.039)	(0.026)
Age2	-0.005***	-0.003	-0.005*	0.005**
	(0.002)	(0.003)	(0.003)	(0.002)
Female	-0.445	-0.372	-0.085	-0.285
	(0.328)	(0.342)	(0.420)	(0.585)
Belgian	0.358	-0.117	0.137	0.539
	(0.582)	(0.429)	(0.512)	(0.649)
Married	0.099	-0.179	0.173	-1.098**
	(0.431)	(0.487)	(0.511)	(0.472)
Children	-0.109	0.077	0.055	-0.055
	(0.134)	(0.129)	(0.131)	(0.206)
Pre sample patents	0.038**	0.016***	0.022***	0.012**
	(0.016)	(0.004)	(0.004)	(0.006)
Pre sample publications	-0.025	0.026	0.003	-0.112
	(0.034)	(0.018)	(0.030)	(0.122)
Pre sample publication citations	0.046	-0.020	-0.043	-0.208
	(0.050)	(0.041)	(0.046)	(0.158)
Ph.D. scholarship	0.406	0.494*	0.984**	0.256
	(0.276)	(0.294)	(0.410)	(0.418)
Time to Ph.D.	-0.183	-0.892*	-1.651*	-0.622
	(0.428)	(0.507)	(0.883)	(0.695)
Ph.D. abroad	-0.057	-0.363	-1.032	0.360
	(0.601)	(0.465)	(0.679)	(0.568)
Firm patents	-0.000	0.156**	0.232**	0.278***
	(0.058)	(0.072)	(0.098)	(0.084)
Firm co-publications	0.022	-0.125	-0.216	-0.365*
	(0.109)	(0.148)	(0.180)	(0.187)
Firm name missing	-0.423*	-0.064	0.799**	-1.739***
	(0.233)	(0.256)	(0.358)	(0.473)
Job tenure>10	0.856***	0.051	0.318	-0.884
	(0.331)	(0.333)	(0.402)	(0.589)
Constant	-2.080**	-2.772***	-0.759	-3.102***
	(0.954)	(0.891)	(1.386)	(0.972)
Log likelihood	-205.321	-627.439	-5383.628	-1212.691

Notes: The sample includes 464 industrial scientists and engineers. All models except (1) are estimated with Poisson quasi-maximum likelihood, the models are estimated with exposure to account for differences in job tenure. Model (1) estimated with logit. 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 4: 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 includes 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 5: 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)
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 includes 464 industrial scientists and engineers. Models are estimated with Poisson quasi-maximum likelihood, estimated with exposure to account for differences in job tenure. All models include controls for age, age^2, female, Belgian, married, children, pre sample patents, pre sample publications, pre sample publication citations, Ph.D. scholarship, time to Ph.D., Ph.D. abroad, firm patents, firm co-publications, firm name missing, job tenure>10, and 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: 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.

TABLE A.1: 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 A.2: 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

APPENDIX A.3: 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.4: Robustness Checks

	(1) Citation-weighted patents <=75	(2) Patents	(3) Patents	(4) Citations	(5) Citations	(6) Claims	(7) Claims	(8) Renewals	(9) Renewals	(10) New subclass combinations	(11) New subclass combinations
Taste for science	0.404***	0.517***	0.366***	0.624**	0.382*	0.480***	0.312**	0.713***	0.560***	1.562*	1.518*
	(0.155)	(0.166)	(0.134)	(0.261)	(0.215)	(0.180)	(0.151)	(0.181)	(0.146)	(0.797)	(0.811)
Taste for salary & career	-0.097	-0.625**	-0.362	-0.817*	-0.369	-0.658**	-0.318	-0.717**	-0.455*	-1.637	-1.104
	(0.268)	(0.313)	(0.279)	(0.432)	(0.383)	(0.293)	(0.223)	(0.308)	(0.256)	(1.528)	(1.252)
Co-publications	0.036***		0.025***		0.032***		0.029***		0.022***		0.065***
	(0.012)		(0.007)		(0.008)		(0.006)		(0.006)		(0.020)
Research	-0.014**		0.006		0.007		0.006		0.005		0.014
	(0.006)		(0.006)		(0.008)		(0.005)		(0.007)		(0.014)
Hours worked	-0.016		0.025*		0.021		0.032**		0.024*		0.009
	(0.025)		(0.013)		(0.016)		(0.015)		(0.014)		(0.051)
Log likelihood	-2062.684	-627.439	-573.685	-4898.233	-4121.614	-8433.706	-7269.139	-780.751	-720.398	-76.693	-63.132

Notes: The sample includes 464 industrial scientists and engineers. *Claims* is the total number of claims of all granted patents filed during current job. *Renewals* is the total number of times maintenance fees are paid for of all granted patents filed during current job. *New subclass combinations* is the number of pairwise subclass combinations in the granted patents of the individual that appear for the first time in the patent database. Models are estimated with Poisson quasi-maximum likelihood, all models are estimated with exposure to account for differences in job tenure. All models include controls for age, age^2, female, Belgian, married, children, pre sample patents, pre sample publications, pre sample publication citations, Ph.D. scholarship, time to Ph.D., Ph.D. abroad, firm patents, firm co-publications, firm name missing, job tenure>10, and Ph.D. field fixed effects. Robust standard errors in brackets, clustered at firm level, *** p<0.01, ** p<0.05, * p<0.1

APPENDIX A.5: Firm Fixed Effects

	(1) Co-publ.	(2) Research	(3) Hours worked	(4) Citation-weighted patents	(5) Citation-weighted patents	(6) New words	(7) New words
Taste for science	0.263**	0.156***	-0.011	0.698***	0.414**	0.807***	0.703***
	(0.112)	(0.044)	(0.008)	(0.219)	(0.182)	(0.202)	(0.162)
Taste for salary & career	-0.709***	-0.113	-0.010	-0.482*	-0.115	-0.206	-0.081
	(0.218)	(0.087)	(0.015)	(0.263)	(0.285)	(0.224)	(0.238)
Co-publications					0.035***		0.025**
					(0.009)		(0.010)
Research					0.002		-0.002
					(0.005)		(0.007)
Hours worked					0.034**		0.038*
					(0.015)		(0.023)
Age	-0.034*	-0.009	0.002	0.036	0.002	-0.047	-0.059
	(0.018)	(0.008)	(0.001)	(0.033)	(0.026)	(0.032)	(0.036)
Age^2	-0.002	-0.000	-0.000***	-0.005*	-0.004	0.007***	0.008***
	(0.002)	(0.001)	(0.000)	(0.003)	(0.003)	(0.002)	(0.003)
Female	-0.537**	0.164	-0.046*	-0.344	-0.395	-0.517	-0.655
	(0.238)	(0.125)	(0.025)	(0.545)	(0.389)	(0.639)	(0.604)
Belgian	0.048	-0.036	-0.027	-0.632	-0.636	0.442	0.528
	(0.761)	(0.200)	(0.031)	(0.525)	(0.485)	(0.768)	(0.736)
Married	0.336	0.035	0.043**	0.317	-0.098	-0.828*	-1.080**
	(0.309)	(0.169)	(0.022)	(0.531)	(0.565)	(0.442)	(0.444)
Children	0.080	-0.018	0.012*	0.053	-0.152	-0.083	-0.255
	(0.127)	(0.039)	(0.006)	(0.146)	(0.173)	(0.232)	(0.260)
Pre sample patents	-0.034***	-0.010**	0.001	0.019***	0.019***	0.004	0.004
	(0.009)	(0.004)	(0.000)	(0.006)	(0.004)	(0.008)	(0.008)
Pre sample publications	0.048***	0.006	-0.002*	-0.023	-0.026	-0.084	-0.097
	(0.009)	(0.010)	(0.001)	(0.036)	(0.029)	(0.144)	(0.173)
Pre sample publication citations	0.015	-0.025	0.004**	-0.003	-0.058	-0.364*	-0.454**
	(0.027)	(0.019)	(0.002)	(0.074)	(0.076)	(0.192)	(0.214)
Ph.D. scholarship	0.104	0.225**	-0.016	0.764*	0.896*	0.013	0.175
	(0.273)	(0.101)	(0.015)	(0.441)	(0.467)	(0.467)	(0.478)
Time to Ph.D.	0.346	0.088	-0.015	-1.115	-0.833	0.055	0.316
	(0.339)	(0.183)	(0.032)	(0.776)	(0.660)	(0.467)	(0.401)
Ph.D. abroad	-0.144	0.078	-0.001	-1.332*	-0.725	0.766	1.246
	(0.736)	(0.198)	(0.034)	(0.728)	(0.569)	(0.735)	(0.773)
Firm patents	0.070	-0.001	0.000	0.349***	0.200***	0.412***	0.361***
	(0.111)	(0.026)	(0.004)	(0.076)	(0.055)	(0.085)	(0.081)
Firm co-publications	-0.013	-0.003	-0.003	-0.472	-0.415	-0.561	-0.676
	(0.148)	(0.087)	(0.011)	(0.295)	(0.345)	(0.363)	(0.491)
Firm name missing	0.015	0.102	0.003	1.077*	1.035***	-1.293***	-1.824***
	(0.348)	(0.093)	(0.015)	(0.641)	(0.346)	(0.483)	(0.606)
Job tenure>10	-0.394	0.134	0.066***	0.302	0.017	-1.014**	-1.312***
	(0.356)	(0.141)	(0.022)	(0.439)	(0.460)	(0.504)	(0.489)
Constant	-2.039**	3.214***	3.913***	-0.644	-1.640	-4.644***	-6.498***
	(0.806)	(0.339)	(0.057)	(1.120)	(1.514)	(1.119)	(1.565)
Log likelihood	-1183.069	-6062.211	-1538.076	-3584.655	-2985.406	-758.346	-710.098

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