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

Sam Arts
KU Leuven
Korte Nieuwstraat 33, 2000 Antwerp, Belgium
sam.arts@kuleuven.be

Reinhilde Veugelers
KU Leuven, Bruegel and CEPR
Naamsestraat 69, 3000 Leuven, Belgium
reinhilde.veugelers@kuleuven.be

ABSTRACT

Matching survey data on Ph.D. scientists and engineers currently working in an R&D job in industry with publications and patents, we study the relation between their individual motives and the rate and nature of their inventive output. We find that individuals with a strong taste for science, i.e. motivated by intellectual challenge, autonomy, and contribution to society, create more novel and impactful patents in industry. These individuals are also more involved in academic boundary spanning, proxied by scientific publications co-authored with academic scientists, and this boundary spanning partially mediates the effect of taste for science on novel and impactful inventive output. By contrast, individuals with a strong taste for salary and career collaborate less with academic scientists, fully mediating the negative effect of taste for salary and career on impactful inventive output.

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

JEL codes: O310, O320

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1. INTRODUCTION

Technological change and innovation are traditionally interpreted as the outcome of firms' profit-driven motives to invest in R&D (Nelson, 1959). Yet, individuals working within these firms are the actual locus of knowledge and invention (Zucker et al., 1998; Felin and Hesterly, 2007). Despite the common understanding that technological invention is a key determinant of firm performance, and that individuals are key actors in the invention process, there is surprisingly little research studying which motives drive R&D scientists in industry to perform (Pelz and Andrews 1976, Katz 2004, Sauermann and Cohen, 2010). In contrast to the management literature, the economics of science literature has a long tradition in studying what drives scientists to perform, and emphasizes that scientists are not only driven by a taste for salary and career, but are particularly driven by a taste for science – a desire for intellectual challenge, autonomy, and contribution to society through the diffusion of their knowledge (Merton, 1973, Pelz & Andrews 1976, Stephan 2012).

In this paper, we contribute to the thin literature which looks at individual R&D scientists within firms and studies how individual motives relate to their inventive performance (Lacetera and Zirulia 2012, Sauermann and Cohen 2010). Bridging the economics of science and management literature, we contribute to the literature in different ways. First, we apply factor analysis to study the relation among different motives and measure latent variables "taste for science" and "taste for salary and career". Second, we match the survey data with secondary patent data to study how individual-level heterogeneity in tastes relates to heterogeneity not only in the rate but also in the nature of inventive output. Recognizing the large spectrum of inventions, it is important to characterize the nature of inventive output in terms of novelty and impact. Third, we look deeper into the mechanisms for why motives would matter for inventive output. We identify and test mediation through amount of effort as measured by the number of hours worked, and through type of effort, characterized by the share of time spent on research (rather than on development or other tasks), and by participation in the academic community. In line with the by now large literature establishing that academic boundary spanning allows firms to better search and absorb external knowledge (e.g. Allen &

Cohen 1969, Liu & Stuart 2010, Simeth and Raffo 2013, Cassiman et al. 2018), we are particularly interested to see whether individuals with a strong taste for science engage more in academic-boundary spanning, and whether this higher involvement mediates the relationship between taste for science and inventive output, particularly the novelty and impact of that output.

To tackle these research questions, we use survey data from 464 R&D scientists working in industry from the Belgian wave of the OECD's Careers of Doctorate Holders survey. We use exploratory factor analysis on the initial motives to choose a career as (R&D) scientist, and obtain two latent variables: *taste for science*, which correlates with motives for intellectual challenge, autonomy, and contribution to society; and *taste for salary and career*, which correlates with motives for salary, extralegal benefits, career advancement and job security. Next, we match each individual to publications and patents using secondary data from the Web of Science and the disambiguated inventor database (Li et al., 2014). We measure impact-weighted inventive output by calculating citation-weighted patents created during their current job (Trajtenberg, 1990), and novelty of inventive output by counting the number of unique stemmed keywords in the title, abstract, and claims of the patents which appear for the first time in history (Arts et al. 2019). To measure involvement in academic boundary spanning, we calculate the number of publications co-authored with academic scientists (Cockburn and Henderson, 1998).

We find that R&D scientists with a stronger taste for science create more, more novel, and more impactful patents. As such, taste for science relates not just to more inventive output, but particularly to more novel and impactful output. Neither the number of hours worked nor the share of time spent on research mediates the relationship between motives and performance. Yet, we find strong support for the mediating role of academic boundary spanning. We show that R&D scientists who collaborate with academics create more novel and impactful patents, and that individuals with a stronger taste for science are more involved in such academic boundary spanning (Zucker et al., 2002; Stern 2004). Academic boundary spanning partially mediates the relation between taste for science and impactful inventive output. Thus, R&D scientists with a stronger taste for science outperform, partially because they keep close working

relationships with academic scientists, which presumably gives them early access to new scientific knowledge and discoveries which they can translate into more impactful and valuable inventions in industry. By contrast, individuals with a strong taste for salary & career are less involved in academic boundary spanning, which fully mediates the negative relation we find between taste for salary & career and impactful inventive output.

2. INDIVIDUAL MOTIVES AND INVENTIVE PERFORMANCE

2.1. Motives of R&D scientists in industry

The economics of science literature has characterized scientists by their *taste for science*, i.e., their desire for intellectual challenge, autonomy, and contribution to society through the diffusion of their acquired knowledge, and by their *taste for salary and career* (Katz, 2004; Merton, 1973; Pelz and Andrews, 1976; Stephan, 2012). Roach and Sauermann (2010) confirm that PhD students with a strong taste for science prefer a job in academia while those with a strong taste for salary prefer a job in industry. Still, there remains a large heterogeneity in motives among R&D scientists in industry (Agarwal and Ohyama, 2012). For instance, Stern (2004) shows that R&D scientists in industry can still have a strong taste for science and a relatively weak taste for salary, as witnessed by their willingness to trade off salary in return for the freedom to participate in the academic community and publish. Yet, we know little on how and particularly why motives affect inventive performance. Sauermann & Cohen (2010) remains the only study showing – for a sample of science & engineering PhDs 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[1]. In the next section, we identify different potential mechanisms explaining why and how taste for science and taste for salary and career matter for the rate and nature of individual inventive output, and conclude on their overall expected effect.

2.2. Mediators of the relationship between motives and inventive performance

In order to improve our understanding of why motives matter for inventive performance, we study different potential mediators. Motives matter for performance because they affect both the *amount* and the *type of*

effort exerted by the individual, and because the amount and type of effort will affect the rate and nature of inventive performance (Vroom, 1964).

First, different motives might relate to different *amounts of effort* and – as a result – influence inventive output. Inventive output is arguably a function of the amount of time spent at work. Therefore, we hypothesize that the number of working hours mediates the relation between motives and performance. Individuals with a stronger taste for science might outperform their peers because they spend more hours at work. This is particularly the case if they can work on R&D projects which are intellectually challenging, and in case they have sufficient autonomy and can contribute to the advancement of science and technology (Lacetera, 2009). Individuals with a strong motivation for salary and career advancement might have a higher inventive performance than their peers because they work more hours, arguably in order to earn a higher salary or climb the corporate ladder.

Besides affecting the amount of effort, motives might also influence inventive performance through soliciting different *types of effort*. Conditional on the number of hours worked, R&D scientists with a strong taste for science might allocate their time to different activities and these different activities might lead to a different rate and nature of inventive output. In particular, they might spend more time on upstream research rather than on downstream development or on other tasks such as management of R&D projects (Agarwal and Ohyama, 2012). Research is arguably more intellectually challenging and provides a greater opportunity for autonomy. Spending a larger share of their time on research allows the individual to push the frontiers of knowledge and technology into new and unexplored areas, and may therefore result in not only more but particularly more novel and impactful inventions (Aghion and Howitt, 1996). Downstream development is presumably more narrowly focused, routinized, and results in more incremental and less impactful inventions. Thus, we hypothesize that individuals with a strong taste for science spend a larger share of their time on research (rather than on development or other tasks), and thus are more likely to create more inventive output, especially more novel and impactful output. By contrast, we hypothesize that individuals with a strong taste for salary and career create less and particularly less novel and impactful inventions

because they spend less time on conducting research and more time on development or on the management of R&D projects.

Besides spending more time on conducting research in the corporate R&D lab, individuals with a strong taste for science might also participate more actively in the academic community as they can find an environment more tuned to intellectual challenges, independence and contributions to the advancement of knowledge (Merton, 1973; Sauermann and Roach, 2014). By collaborating with academic scientists, R&D employees obtain close access to the frontier of scientific knowledge, which they can translate into more novel and impactful inventions in industry (Cassiman et al., 2018; Liu and Stuart, 2010; Tushman, 1977). Thus, we hypothesize that individuals with a strong taste for science engage more in academic boundary spanning and this academic boundary spanning will lead to more, especially more novel, higher impact inventions.[2] Yet, at the same time, as shown by Stern (2004), R&D scientists in industry often need to pay for the freedom to participate in the academic community and publish by accepting a lower salary. Therefore, we hypothesize that individuals with a stronger taste for salary and career engage less in academic boundary spanning and – as a result – will produce less, especially less novel and impactful inventions.

Overall, we predict that taste for science will positively relate to inventive performance. Driven by their motives for intellectual challenge, independence and contributing to society, we expect R&D scientists with a strong taste for science to work more hours, to spend a larger share of their time on research, and to more actively engage in collaboration with academic scientists, and therefore develop more novel and high impact inventions.

By contrast, for taste for salary and career we have opposite predictions for different mediators. On the one hand, a motivation for salary and career advancement might trigger people to work more hours, and therefore perform better. On the other hand, we expect these people to spend less time on conducting research and collaborating with academic scientists, and therefore to create less novel and impactful output. Thus, the overall net effect of taste for salary and career on the rate and nature of inventive performance remains an empirical question.

3. DATA AND METHODS

3.1. Sample and Data Collection

Our main data source 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 an insight in the careers of individuals with a Ph.D. degree. The survey contains questions on their motives to choose a career as (R&D) scientist. In addition, the survey contained questions on their current job and employer. The survey was launched in 2006, addressed the full population of individuals with a Ph.D. degree in Belgium, and had a response rate of 20%[3]. We use a subsample of 464 individuals who obtained a Ph.D. in science or engineering (disregarding social sciences and humanities), who are full-time employed as R&D scientist in industry at the end of 2005, who answered the relevant survey questions and who agreed to share their information. For each R&D scientist and each firm, we trace all publications and patents from secondary sources, the Web of Science and the disambiguated inventor database respectively (Li et al., 2014)[45].

3.2. Measures

(i) Taste for science and taste for salary and career

To measure motives, we use the survey question *"Why did you initially choose a career in research?"*. This question aimed to probe the individual about their motives at the start of their career, immediately after obtaining a PhD degree. This is why the question appeared right after questions on education and before any job-related questions. Respondents indicate any number of motives from a list. Each motive is measured as a binary variable. We apply exploratory factor analysis to examine the relation among the different motives[6]. Table A.I in the appendix shows the results. Both the screeplot and the Kaiser criterion suggest the existence of two latent variables, which jointly explain 87% of the variance in motives. 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 and career*. The second latent variable strongly correlates with motives for intellectual challenge, autonomy, and – to a smaller extent – contribution to society. We label this second variable as *taste for science.* We calculate taste for science and

taste for salary and career using the regression scoring method and normalize the measures for ease of interpretability. For each individual, we obtain both a score for taste for science and a score for taste for salary and career. In the regressions, we estimate the effect of taste for science while controlling for taste for salary and career and vice versa. In line with prior research, we treat motives for pursuing a career as R&D scientist as pre-determined and stable over time (e.g., Amabile et al., 1994; Sauermann and Cohen, 2010)[7].

(ii) Outcome variables

The majority of all inventions are incremental in nature and have little impact. Only a handful of inventions are truly novel and impactful. To capture this heterogeneity, we measure both the amount, novelty and impact of the inventive output of each R&D scientist. We take into account all patents listing the individual as inventor, and filed between the starting date of the individual's job and January 1 2006, the reference date of the survey. To measure the novelty of inventive output, we calculate *new words* as the total number of unique stemmed keywords in the title, abstract, and claims of the patents which appear for the first time in the U.S. patent database. To calculate the measure, we concatenate title, abstract, and claims, lowercase all text, tokenize words, and remove punctuation, words composed of numbers only, one-digit words, words which appear in only one patent, natural stop words, and frequently occurring non-technical keywords (Arts et al., 2018). The remaining keywords are stemmed. Next, we identify the first patent in history with stemmed keywords[8]. To measure impact-weighted inventive output, we follow Trajtenberg (1990) and calculate *citation-weighted patents*. Using fractional counts of patents, citations or new words to account for the number of inventors listed on a patent does not change any of our findings.

(iii) Mediating variables: hours worked, time spent on research and academic boundary spanning

To measure the amount of effort, we use the self-reported number of *hours worked* on average on a weekly basis. To measure the type of effort, we use the self-reported share of working hours spent on conducting *research*, and the number of *co-publications* with academic scientists as a measure of academic boundary

spanning (e.g., Cockburn and Henderson, 1998; Gittelman and Kogut, 2003; Zucker et al., 2002). We take into account all co-publications in the Web of Science published between the starting date of the current job and January 1 2006 [910].

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

It is crucial to control for individual ability and skills, which might correlate with motives, mediators and inventive performance. For example, the returns from working more hours or from spending more time on research or academic boundary spanning will be higher for individuals with stronger ability and skills. As such, the smartest people, who might also have a higher taste for science, might work more hours, and spend more time on research or on academic boundary spanning and be more productive. Companies might assign their most productive people to the most promising R&D projects, and stimulate them to work on research and to collaborate with academic scientists. As such, the estimated coefficients of both motives and mediators might suffer from an upward skill bias. To control for ability, skills, and other unobserved individual-level heterogeneity, we include pre-sample values of the outcome variables (Blundell et al., 1999). *Pre sample patents* measures the number of citation-weighted patents of the R&D scientist filed before the current job, *pre sample publications* counts the number of publications published before the current job, and *pre sample publication citations* measures the average number of citations received by the pre-sample publications within three years. In addition, *PhD. scholarship* indicates whether their Ph.D. was funded by a scholarship, which select on prior academic achievement and ability. The Flemish Science Foundation for instance uses applicants' class rank as one of the criteria to grant PhD scholarships. These fellowships are the main source for individual grants for PhD students in Belgium. We also include *time to PhD* measured as the time needed to complete the Ph.D. relative to peers within the same field, and *Ph.D. abroad.* Virtually all respondents who obtained a Ph.D. abroad studied at a university that is higher ranked than any Belgian university. We also include a battery of additional individual-level control variables related to civil status and field of expertise (see Table I).

The inventive performance of R&D scientists might also be driven by the characteristics of the employing firm. Individuals with certain motives might join more innovative firms or firms with stronger links to the academic community. To control for this potential bias, we include *firm patents* as the number of granted patents filed by the firm between the beginning of 2003 until the end of 2005, and *firm co-publications* as the number of publications co-authored by the firm's employees and academic scientists between the beginning of 2003 until the end of 2005[11]. For the small number of individuals who did not fill in the name of the firm, firm patents and co-publications is set at zero, and the binary indicator *firm name missing* is set at one. Finally, as a robustness check, we include firm fixed-effects for firms with at least two respondents (i.e., 61 firms and 240 R&D scientists), which control for any remaining unobserved firm-level heterogeneity. Table I provides a description and summary statistics for all variables.

INSERT TABLE I ABOUT HERE

3.3. Specification and Estimation Method

Our main equation of interest is the relationship between individual *i*'s motives and the size and nature of *i*'s inventive performance P_{if} (*patents*, *citation-weighted patents* and *new words*) created since the beginning of *i*'s current job in firm *f* until the end of 2005.

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

Given that our outcome variables are non-negative integers, we estimate the regressions using Poisson quasi-maximum likelihood (PQML). We cluster standard errors 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).

To unravel why motives influence inventive output, we use the mediation analysis procedure of Baron and Kenny (1986). First, we predict the main effects of motives on inventive performance,

corresponding with model (1) above. Second, we check the effect of motives on the potential mediators: *research*, *co-publications* and *hours worked*. Third, we re-estimate model (1) but include the mediator variables, corresponding with model (2) below.

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

To test for mediation, we assess whether the coefficients of taste for science and taste for salary and career in model (2) are smaller compared to the coefficients in model (1) using seemingly unrelated estimation (*suest* command in Stata). In addition, we use nonparametric bootstrapping with 1,000 replications to test the robustness of the mediation results (Preacher and Hayes, 2008).

3.4. Potential Bias Survey Data

The use of survey data can introduce different types of bias (Moorman and Podsakoff, 1992; Podsakoff et al., 2003). First, common method bias is unlikely in our case because information on motives, academic boundary spanning, and inventive output are collected from three separate sources. Second, social desirability bias might cause individuals to list those motives which they believe to be socially desirable. This type of bias is also unlikely because the measures for academic boundary spanning and inventive output are collected from secondary sources, and because the survey question on motives appears in the beginning of the survey and is proximally separated from job-related questions. This reduces the likelihood that respondents adapted their responses to provide a desirable explanation for their performance or collaboration with academic scientists. Third, the retrospective nature of the questions on motives might potentially introduce bias because individuals might respond differently compared to asking PhD candidates about to enter the job market (Sauermann and Roach, 2014). Yet, Roach and Sauermann (2017) find that motives of R&D scientists are relatively stable over time.

4. RESULTS

4.1. Descriptive Statistics

As shown in Table II, individuals with a strong *taste for science* (above the median) are not more likely to patent, but create significantly more patents, particularly more impactful patents. They are also more likely to have a novel patent (containing new words). Concerning the relation between motives and mediators, we find that individuals with a strong *taste for science* do not work more hours, but spend a larger share of their time on research and engage more in academic boundary spanning[12].All mediator variables positively correlate with inventive output. This particularly holds for academic boundary spanning: R&D scientists with more co-publications with academic scientists (above the median) create more patents, but particularly more novel and impactful patents.

INSERT TABLE II ABOUT HERE

4.2. Regressions

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

The results from the regressions, reported in Table III, confirm that R&D scientists with a stronger *taste for science* create sizably more, more novel, and more impactful inventions. A one standard deviation higher score on *taste for science* relates to a 66% higher patent count, a 83% higher citation-weighted patent count, and a 67% higher new word count. Importantly, these results are not driven by selection into patenting, as illustrated in column 1. These results confirm a positive relation not only between *taste for science* and the amount of inventive output, but also with the novelty and the impact of that output. 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 related to a 23% lower patent count and a 27% lower citation-weighted patent count. *Taste for salary & career* does not significantly relate to novelty of inventive output.

It is particularly important to control for individual ability and skills, and for firm-level innovation capacity. Individuals with a higher pre-sample citation-weighted patent count, whose Ph.D. was funded by a scholarship, who finished their Ph.D. in a relatively short period, or who work for more innovative firms, display a stronger inventive performance in their current job.

INSERT TABLE III ABOUT 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 motives and 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 hours worked. As shown in Table IV, individuals with a stronger *taste for science* do not work more hours, but spend a larger share of their time on research, and engage more in academic boundary spanning. A one standard deviation higher score on *taste for science* implies 22% more time spent on research and a 36% higher co-publication count. Those with a stronger *taste for salary & career* do not work more hours or spend more time on research, but engage 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 publications is important because those with a stronger pre-sample scientific track record collaborate more with academic scientists in their current job in industry (result not shown).

To further explore why individuals with a strong taste for salary and career are less engaged in co-publishing with academics, we analyze in Table A.II in appendix the relation between co-publications and salary. We find a significant negative correlation, controlling for amongst others individual ability and skills. This negative correlation is consistent with Stern's (2004) finding that R&D scientists in industry need to "pay" for the freedom to participate in the academic community and publish, in the form of accepting a lower salary. This result is consistent with individuals with a strong taste for salary engaging less in

academic boundary spanning. However, notice that we do not observe the actual agreement between scientists and their employer, and what R&D scientists get in return or have to pay for the freedom to collaborate with academics and publish (Stern, 2004; Sauermann and Roach, 2014).

INSERT TABLE IV ABOUT HERE

The ***second step*** in the mediation analysis is to establish that the mediators significantly affect inventive performance while controlling for motives. As shown in columns 2-4 in Table V, a standard deviation increase in hours worked, share of time spent on research, and co-publications with academics, implies a 28%, 31% and 23% increase in citation-weighted patents respectively. If we include the three mediators together (column 5), only co-publications with academics remains significant. As shown in columns 7-10 of Table V, co-publications significantly affects the novelty of inventive output while hours worked and time spent on research have no effect. A standard deviation increase in co-publications implies a 31% increase in novelty of output. Together, the results identify academic boundary spanning as a key determinant of the rate and nature of inventive output of R&D scientists in industry.

INSERT TABLE V ABOUT 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 V, the effect of *taste for science* on citation-weighted patents decreases significantly after including the mediators[13]. Especially the inclusion of co-publications with academics reduces the effect of *taste for science*. A one standard deviation higher score on *taste for science* now implies a 45% higher citation-weighted patent count compared to a 83% higher citation-weighted patent count in the model excluding the mediators. Similarly, the effect of *taste for science* on the novelty of output decreases

significantly after including the mediators (columns 6-10 of Table V).[14] A one standard deviation higher score on *taste for science* now implies a 41% higher new word count compared to a 67% higher new word 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. These findings illustrate that R&D scientists with a stronger *taste for science* create more novel and impactful inventions in industry partially because they more actively engage in collaboration with academic scientists.

Interestingly, academic boundary spanning fully mediates the negative effect of *taste for salary & career* on citation-weighted patents[15]. The negative coefficient of *taste for salary & career*, 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* have a lower citation-weighted patent output because they engage less in academic boundary spanning.

4.3. Robustness Checks

We use nonparametric bootstrapping with 1,000 replications to test the significance of the indirect effect of motives through academic boundary spanning (Preacher and Hayes, 2008). In line with our results using the traditional mediation analysis procedure, we find that co-publications partially mediates the positive relation between *taste for science* and citation-weighted patents[16], and fully mediates the negative relation between *taste for salary & career* and citation-weighted patents[17]. The indirect effect of *taste for science* on new words through co-publications is only significant at p=0.14[18].

A source of potential bias in our results relates to the non-random selection of individuals into certain firms. In addition to controlling for job and firm level characteristics, we test the robustness of our findings to the inclusion of firm fixed-effects. We can do this for firms with at least two surveyed R&D scientists. The within-firm analysis exploits the heterogeneity in motives, hours worked, share of time spent on research, and academic boundary spanning among R&D scientists working within the same firm. As

shown in Table A.III, our findings remain robust to the inclusion of firm fixed effects. This result illustrates that our findings are unlikely to be driven by a selection of scientists into certain firms.

Although we control for ability, skills and other unobserved individual-level heterogeneity using pre-sample values of scientific and inventive performance, the results might be driven by a few very productive R&D scientists. Yet, the main results remain after dropping the most productive individuals with a citation-weighted patent count above 75 (see Column 1 in Table A.IV in the appendix).

Because citation-weighted patents capture both the quantity and impact of patents, we further check any differential effect on quantity versus impact by separately studying the number of patents and the number of citations. Results are robust to using either measure of performance. The mediation effects through academic boundary spanning are significant for both the number of patents[19] and citations[20] (columns 2-5 in Table A.IV). Comparing the results on patents and citations shows that tastes have a stronger effect on impact than on quantity. A standard deviation increase in taste for science relates to 66% more patents and 85% more citations. A standard deviation increase in taste for salary and career relates to 23% fewer patents and 27% fewer citations. But these differences are not statistically significant.

Finally, our findings remain robust if we use alternative measures for the impact and novelty of inventive output. As alternative measures for the impact or value of a patent, we use the number of claims and the number of times maintenance fees are paid by the patent owner (columns 6-9 in Table A.IV). As an alternative measure for the novelty of a patent, we use the number of new pairwise subclass combinations appearing for the first time in the entire patent database (Arts and Fleming, 2018) (columns 10-11 in Table A.IV).

5. DISCUSSION AND CONCLUSION

Our paper contributes to the thin literature studying individual R&D scientists within firms, and analyzing how their motives relate to the rate and nature of their inventive output (e.g., Pelz and Andrews, 1976; Sauermann and Cohen, 2010). First, we apply factor analysis to uncover the relation between different

motives, and identify two latent variables – *taste for science* and *taste for salary and career* – which explain roughly 90% of the variance in motives. Second, controlling for individual and firm ability and other unobserved heterogeneity, we are the first to show how *taste for taste* matters not just for producing more inventions, but also for more novel and impactful inventions. Third, we study whether amount and type of effort mediate the relation between motives and performance. We are the first to show the important role of academic boundary spanning as mediator. Employees with a stronger taste for science engage more in academic boundary spanning, and this collaboration results in more novel and impactful inventions in industry. These collaborations mediate the positive relation between taste for science and inventive performance, but only partly so. For individuals with a higher taste for salary and career, their lesser involvement in academic boundary spanning fully mediates their lower impact-weighted inventive output. Our data further suggests that the freedom to participate in the academic community and publish indeed comes at the cost of a lower salary (Stern, 2004). This finding presumably explains why individuals with a strong taste for salary and career engage less in academic boundary spanning and – as a result – underperform.

Our results on individual employees contributes to the more extensive firm-level literature that studies how firms can benefit from science for their innovation performance. This line of firm-level research illustrates the importance of co-publications with academic scientists for firm-level innovation (e.g., Cockburn and Henderson, 1998), but overlooked that different employees inside the same firm have different incentives and abilities to interact with the academic community. Assuming homogeneity among all employees might bias the firm-level estimates (Felin and Hesterly, 2007; Hicks, 1995). Studying individual R&D scientists within firms provides a more granular insight in the mechanism of how academic science translates into innovation, and allows us to control for individual ability, skills, and motives. Our findings show that involvement in academic boundary spanning positively influences the novelty and impact of output. Yet, involvement differs according to profiles. Individuals with a stronger *taste for science* and those who have a stronger scientific track record before their current job in industry tend to collaborate more

with academics while employed in industry, while those with a strong *taste for salary and career* collaborate less with academic scientists.

Our study has several limitations. First, a larger sample would allow us to obtain more robust results, particularly on any differential effects on the rate versus the nature of inventive output. Next, there might be other motives, such as peer recognition, for which we miss information. Also, due to high collinearity in motives, we cannot identify the impact of individual motives instead of the two latent variables *taste for science* and *taste for salary & career*. Motives for intellectual challenge for instance largely co-occur with motives for autonomy, and motives for salary essentially co-occur with motives for extralegal benefits. Furthermore, their might be mediators we missed, particularly as the mediators we included are only able to partially explain the relation between taste for science and inventive performance. More detailed information on the type of projects and activities would be helpful. For instance, the amount of time spent on more basic versus more applied research will arguably have a different effect on the rate and nature of inventive output. Finally, scientists do not randomly sort into firms and jobs, which might lead to selection bias. Although we control for individual- and firm-specific effects, amongst others using pre-sample values of the outcome measures and firm fixed-effects, we cannot fully rule out selection bias, nor unobserved correlated heterogeneity. For this reason, our findings should be interpreted as correlations and not causal relations and call for further research on the matching of employees and employers.

Our finding that R&D scientists with a stronger *taste for science* generate more, more novel and more impactful inventions, even after controlling for ability, number of hours worked, time spent on research and academic boundary spanning, has important implications. To be able to attract and accommodate the most creative and productive people, firms should offer working conditions that fit their motivations: sufficient freedom to work autonomously on projects which they find intellectually challenging, opportunities to interact with the academic community, and to disseminate and exchange findings. Our results suggest that bench-level collaboration with academics is an important source of external knowledge and driver of individual inventive performance. Firms' policies to allow – or even

stimulate – R&D employees to interact with the academic community should thus pay off in terms of fostering innovation. By contrast, some firms pay lower salaries in return for the freedom to participate in the academic community and publish (Stern, 2004), which is presumably counterproductive in terms of fostering innovation. This will particularly restrain employees who care most about monetary rewards, i.e. with a high *taste for salary & career*, to engage in academic boundary spanning, thereby limiting their inventive performance. Of course, such policies might be driven by other managerial considerations, such as an increased risk of knowledge spillovers and appropriability concerns (Simeth & Raffo, 2013). Future work should develop and test these ideas in a new setting with stronger identification.

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Table I: Summary Statistics for R&D scientists (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 stemmed keywords in the title, abstract, or claims, appearing for the first time in a U.S. patent, found in the granted patents filed during current job	0.69	4.59	0.00	79.00
Motives					
Taste for science	Latent variable obtained from factor analysis, standardized	-0.19	0.98	-1.65	1.88
Taste for salary and 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 (publication data is collected from 1996 onwards)	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 and career are calculated and normalized based on the full sample of (R&D) scientists 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 II: Summary Statistics for Subsamples of R&D scientists (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**	0.84	**0.13**	2.52	0.43	**33.37**	49.10
Smaller than median	**0.51**	0.19	**4.52**	0.60	**0.07**	1.75	0.39	**27.77**	49.72
Taste for salary and career									
Larger than median	1.10	0.22	9.57	0.86	**0.15**	1.28	0.38	29.94	**50.55**
Smaller than median	0.73	0.20	7.71	0.64	**0.08**	2.23	0.41	29.69	**49.20**
Co-publications									
Larger than median	**1.20**	**0.26**	**12.86**	**1.21**	0.12				
Smaller than median	**0.55**	**0.16**	**4.92**	**0.33**	0.08				
Research									
Larger than median	0.95	0.22	9.66	0.90	0.10				
Smaller than median	0.60	0.18	5.82	0.37	0.08				
Hours worked									
Larger than median	**1.13**	**0.24**	**11.60**	1.00	**0.12**				
Smaller than median	**0.42**	**0.16**	**3.91**	0.31	**0.06**				

Notes: differences significant at 0.05 in bold

Table III: 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**	0.522***
	(0.120)	(0.166)	(0.249)	(0.186)
Taste for salary and career	-0.186	-0.625**	-0.802*	-0.379
	(0.304)	(0.313)	(0.423)	(0.433)
Age	0.026	0.007	0.039	-0.060
	(0.021)	(0.025)	(0.039)	(0.054)
Age2	-0.005***	-0.003	-0.005*	-0.001
	(0.002)	(0.003)	(0.003)	(0.004)
Female	-0.445	-0.372	-0.085	-0.725
	(0.328)	(0.342)	(0.420)	(0.599)
Belgian	0.358	-0.117	0.137	0.170
	(0.582)	(0.429)	(0.512)	(0.525)
Married	0.099	-0.179	0.173	0.526
	(0.431)	(0.487)	(0.511)	(0.774)
Children	-0.109	0.077	0.055	-0.091
	(0.134)	(0.129)	(0.131)	(0.204)
Pre sample patents	0.038**	0.016***	0.022***	0.010
	(0.016)	(0.004)	(0.004)	(0.006)
Pre sample publications	-0.025	0.026	0.003	-0.307
	(0.034)	(0.018)	(0.030)	(0.201)
Pre sample publication citations	0.046	-0.020	-0.043	-0.031
	(0.050)	(0.041)	(0.046)	(0.127)
Ph.D. scholarship	0.406	0.494*	0.984**	0.345
	(0.276)	(0.294)	(0.410)	(0.440)
Time to Ph.D.	-0.183	-0.892*	-1.651*	-0.581
	(0.428)	(0.507)	(0.883)	(0.630)
Ph.D. abroad	-0.057	-0.363	-1.032	-0.099
	(0.601)	(0.465)	(0.679)	(0.624)
Firm patents	-0.000	0.156**	0.232**	-0.030
	(0.058)	(0.072)	(0.098)	(0.138)
Firm co-publications	0.022	-0.125	-0.216	0.089
	(0.109)	(0.148)	(0.180)	(0.237)
Firm name missing	-0.423*	-0.064	0.799**	-2.616***
	(0.233)	(0.256)	(0.358)	(0.570)
Job tenure>10	0.856***	0.051	0.318	-0.898**
	(0.331)	(0.333)	(0.402)	(0.436)
Constant	-2.080**	-2.772***	-0.759	-4.239***
	(0.954)	(0.891)	(1.386)	(0.979)
Log likelihood	-205.321	-627.439	-5383.628	-808.353

Notes: The sample includes 464 R&D scientists. All models except (1) are estimated with Poisson quasi-maximum likelihood, and 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 IV: 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 and 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)
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 R&D scientists. 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 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 V: 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*	0.522***	0.457**	0.393*	0.520***	0.351*
	(0.249)	(0.215)	(0.247)	(0.243)	(0.204)	(0.186)	(0.189)	(0.205)	(0.194)	(0.189)
Taste for salary and career	-0.802*	-0.388	-0.829*	-0.741*	-0.373	-0.379	-0.155	-0.317	-0.365	-0.071
	(0.423)	(0.361)	(0.425)	(0.404)	(0.373)	(0.433)	(0.400)	(0.462)	(0.423)	(0.368)
Co-publications		0.034***			0.031***		0.047***			0.044***
		(0.007)			(0.008)		(0.010)			(0.011)
Research			0.011*		0.007			0.013		0.011
			(0.006)		(0.008)			(0.011)		(0.012)
Hours worked				0.035**	0.022				0.019	0.012
				(0.015)	(0.015)				(0.021)	(0.021)
Log likelihood	-5383.628	-4656.485	-5205.093	-5268.610	-4548.289	-808.353	-736.265	-789.798	-805.455	-724.500

Notes: The sample includes 464 industrial R&D scientists. Models are estimated with Poisson quasi-maximum likelihood, and 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

ONLINE APPENDIX

Table A.I: Rotated Factor Loadings and Unique Variances (n=1,114)

Motives	Taste for salary and 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. Motives are measure as binary variables (yes/no).

Table A.II: 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 R&D scientists. 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.III: 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**	0.621***	0.517**
	(0.112)	(0.044)	(0.008)	(0.219)	(0.182)	(0.205)	(0.224)
Taste for salary and career	-0.709***	-0.113	-0.010	-0.482*	-0.115	-0.593	-0.413
	(0.218)	(0.087)	(0.015)	(0.263)	(0.285)	(0.681)	(0.644)
Co-publications					0.035***		0.034***
					(0.009)		(0.011)
Research					0.002		0.010
					(0.005)		(0.012)
Hours worked					0.034**		0.023
					(0.015)		(0.023)
Log likelihood	-1183.069	-6062.211	-1538.076	-3584.655	-2985.406	-537.679	-491.065

Notes: The sample includes 464 R&D scientists. Models are estimated with Poisson quasi-maximum likelihood, estimated with exposure to account for differences in job tenure (except in models 2 and 3). 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, job tenure>10, 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

Table A.IV: Robustness Checks

	(1) Citation-weighted patents	(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 and 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 R&D scientists. Model 1 excludes individuals with citation-weighted patents>75. *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. All models are estimated with Poisson quasi-maximum likelihood and 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

NOTES

[1] Our paper contributes to this prior work by 1) applying factor analysis to measure taste for science versus taste for salary and career, 2) using secondary data sources to measure both the rate and nature of inventive output rather than the self-reported number of patents, and 3) identify and test participation in the academic community as an important mediator of the relationship between the motives and performance of R&D scientists.

[2] Sauermann & Cohen (2010) recognized the importance of involvement in the scientific community as mediating factor, but failed to find a significant mediation effect on the quantity of inventive output. Because of data limitations, they could only consider a crude proxy, attendance or not of professional meetings.

[3] The survey was develop by the OECD, Eurostat, and the UNESCO Institute for Statistics. See Eurostat (2012) or OECD (2012) for more information on the survey. Moortgat and Van Mellaert (2011) discuss the Belgian data collection, including a brief explanation of response rate and representativeness (in Dutch). Due to privacy concerns, the survey was administrated and launched by a Belgian government agency (FOD economie) who used census data to identify the population of individuals who obtained a PhD degree (or enrolled in doctoral studies). Unfortunately, we only received the survey data itself and did not receive access to the census data (on the full population of individuals with a PhD degree, including those who received the survey but did not respond). Therefore, we are unable to formally test for non-response bias ourselves.

[4] We only collect U.S. patents for which disambiguated inventor information is available. This might invoke concerns on a possible bias because not all firms might file patents at the USPTO. This bias in unlikely. First, our results are robust for the subsample of 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%). Our findings remain robust if we exclude firms with exclusively non-US patents. Finally, our results remain robust for firm fixed effects (cf infra), which control for firm-level patenting strategies.

[5] We use PATSTAT to collect patent-family corrected citation data. As such, we make sure to collect all forward citations for all patent families, which include at least one USPTO patent application.

[6] For the factor analysis, we retain the full sample of (R&D) scientists currently employed in industry or academia (n=1,114). The main findings do not change if we only use the industry sample.

[7] Sauermann and Cohen (2010, p. 2142), confirm that motives of R&D scientists are stable over time and not affected by changes in performance.

[8] Examples of stemmed keywords are rfid, oled, html, bluetooth, email, or rnai (Arts et al. 2019; Balsmeier et al. 2018).

[9] 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 simultaneously publish their inventions. This bias is unlikely given that we find only very few patents listing academic scientists as co-inventors while all co-publications list an academic scientist by definition. Moreover, prior studies find only a very small fraction of patent-publication pairs (e.g., Magerman et al. 2015).

[10] Another potential concern is that co-publications confound the effect of academic boundary spanning with the effect of publishing in itself. To investigate this, we collect publications not co-authored with academics and published during the current job and include it as a control variable. All findings for co-publications (with academics) remain robust to the inclusion of this control variable (results not reported). The level of significance and size of the effect of co-publications are only marginally affected. Moreover, we find that publications not co-authored with academics do not significantly mediate the relation between taste for science and citation-weighted patents, nor the relation between taste for salary and career and citation-weighted patents.

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

[12] The latter difference is however only significant at p=0.11

[13] 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.

[14] 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 (6) versus (10): chi2(1)=2.34; p-value of one sided test = 0.0632.

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

[16] Test for the indirect effect of taste for science on citation-weighted patents through co-publications: chi2(1) = 2.75; p-value of one sided test that indirect effect is larger than zero= 0.0485.

[17] Test for the indirect effect of taste for salary and career on citation-weighted patents through co-publications: chi2(1) = 1.97; p-value of one sided test that indirect effect is negative=0.0804.

[18] Test for the indirect effect of taste for science on new words through co-publications: chi2(1) = 1.15; p-value of one sided test that indirect effect is larger than zero= 0.1415.

[19] Coefficient taste for science in column (2) versus (3): chi2(1)=2.46; p-value of one sided test=0.058; Coefficient taste for salary and career in column (2) versus (3): chi2(1)=2.30; p-value of one sided test=0.0649.
[20] 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.