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Taste for science and job (mis)match of industrial researchers

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Abstract

An emerging literature tries to understand how scientists? motivations drive their career choices. A major issue studied is how scientists choose to work in industry or academia based on their taste for science versus commercialization. However, selection into industry or academia may still leave substantial heterogeneity among scientists within sectors. In this paper, we investigate how much scientists who selected into industry match their motivations to a fitting environment. Based on survey data of over 400 industrial researchers, we show that mismatches often occur: industrial researchers with predominantly science-like motivations are not employed in more scientific industry jobs where they can interact with the scientific community or publish findings compared to researchers with more commercial motivations. Hybrid researchers in industry, who have a taste for science as well as commercialization, do find better job matches: they are employed more often in jobs where they can interact with the scientific community or publish findings. This acknowledges hybrid researchers? critical role as boundary-spanning gatekeepers within the firm. Time spent on research versus development does not seem to be a job feature that distinguishes between different types of industrial researchers.

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Abstract

An emerging literature tries to understand how scientists' motivations drive their career choices. A major issue studied is how scientists choose to work in industry or academia based on their taste for science versus commercialization. However, selection into industry or academia may still leave substantial heterogeneity among scientists within sectors. In this paper, we investigate how much scientists who selected into industry match their motivations to a fitting environment. Based on survey data of over 400 industrial researchers, we show that mismatches often occur: industrial researchers with predominantly science-like motivations are not employed in more scientific industry jobs where they can interact with the scientific community or publish findings compared to researchers with more commercial motivations. Hybrid researchers in industry, who have a taste for science as well as commercialization, do find better job matches: they are employed more often in jobs where they can interact with the scientific community or publish findings. Traditional scientists in industry work significantly less hours compared to commercially oriented and hybrid scientists. This acknowledges hybrid researchers' critical role as boundary-spanning gatekeepers within the firm.

PRELIMINARY DRAFT – DO NOT CITE OR QUOTE WITHOUT PERMISSION

1. Introduction

Industrial and academic science are often viewed as guided by different organizational goals. Academic science intends to create knowledge, and is thus focused on basic research, offers more freedom to scientists to choose their own topics, and rewards successful research through peer recognition stemming from the publication of research results (Merton, 1973). In contrast, firms are seen as pursuing innovation for financial goals, and therefore characterized by a focus on applied research, less freedom, and limited opportunities for researchers to disclose research results (Agarwal & Ohyama, 2012; Aghion, et al., 2008; Fini & Lacetera, 2010; Lacetera, 2009).

However, empirical work shows that the differences between industrial and academic science are smaller than indicated by the organizational goals perspective. Firms are heterogeneous in their scientific orientation: while many firms focus on oriented research and secrecy, some firms allow researchers to perform basic research, offer freedom in research, and allow for the publication of research results (Vallas & Kleinman, 2008; Hackett, 1990; Stokes, 1997; Shapin, 2004; Copeland, 2007; Sauermann & Stephan, 2012). It is therefore possible for industrial researchers to have more 'scientific' job profiles than is commonly assumed. The findings of Sauermann & Stephan (2012) underline this. They find in their sample (describe shortly): 62% of researchers in industry are allowed to publish findings, 51% is very satisfied with the level of freedom offered by the firm, and 7% are mainly engaged in basic research.

One reason for a firm to take on a stronger scientific orientation is because this has positive effects on the firm's own R&D: engaging in basic research, disclosing results through publication, and interaction with the scientific community in general allows firms to buy a "ticket of admission" to scientific discoveries, resulting in higher R&D productivity and thus more innovation (Cohen & Levinthal, 1990; Rosenberg, 1990; Stern, 2004). Collaboration with external scientists is important: the success of biotechnology firms has been linked to their engagement of star scientists (Zucker, et al., 1998), and studies of pharmaceuticals and biotechnology found a positive link between collaboration with external scientists, internal science orientation, and higher research productivity (Cockburn & Henderson, 1998; Cockburn, et al., 2000; Gittelman & Kogut, 2003; Gambardella, 1995; Powell, et al., 1996; Zucker, et al., 2002).

While firms are heterogeneous in their scientific orientation, also scientists are heterogeneous in their scientific orientation: in the degree up to which they share a "taste for science" (a preference for basic research, independence, publishing, and peer recognition) as well as the degree up to which they value pecuniary rewards (Stern, 2004; Roach & Sauermann, 2010; Merton, 1973; Dasgupta & David, 1994; Sauermann & Roach, 2012).

If scientists differ in their scientific orientation, this heterogeneity should matter for organizing the academic labour market. Scientists should try to find a working environment that fits as closely as possible to their preferences (Sauermann & Stephan, 2012; Shapin, 2004; Agarwal & Ohyama, 2012; Sauermann & Roach, 2012). This has been explored in the case of sector choice: scientists who have a lower taste for science and more concern for salary prefer employment in industry than those who prefer to work in academia (Roach & Sauermann, 2010; Agarwal & Ohyama, 2012).

Sorting of scientists into academia versus industry is not perfect. Researchers working in industry still strongly differ in their taste for science and business, as evidenced by heterogeneity in their willingness to pay (in the form of lower wages) to be able to publish research results (Stern, 2004; Sauermann & Roach, 2011; see also Sauermann & Stephan, 2012). In academia, scientists with a desire to contribute to society are more likely to engage in applied research, while scientists motivated by intellectual challenge engage more in basic research (Sauermann, et al., 2010).

This literature leaves the relation between researcher's motivations and job choice within industry and academia as of yet relatively unexplored. However, given the strong heterogeneity in industrial researchers jobs (as described above), it is important to assess whether the hypothesis holds that scientists match their motivations to their jobs. Motivations have been related to productivity: industrial researchers motivated by intellectual challenge, salary, or a desire for independence, create more patent applications than others (Sauermann & Cohen, 2010). However, they find little evidence that researchers with certain motivations are more or less likely to publish than others. Motivations have been matched with job satisfaction. Sauermann & Stephan (2012) find positive relationships between satisfaction with independence and preference for independence, and between preference for pay and salary. These relationships can be interpreted as good matches: researchers choose to work in jobs where they are satisfied with the dimensions of the jobs that they find most important.

We contribute to this topic by investigating in more detail the relation between industrial researchers' motivations and the sets of job characteristics they work in. Our main hypothesis is that once researchers choose to be employed in industry, they seek to match their motivations to a fitting set of job characteristics (in line with the literature cited above). Thus, we expect researchers with a higher taste for science to choose more science-like jobs in industry, where they can spend more time on basic research, interact with the scientific community, and disclose research results through publication. Researchers with a higher taste for business should be more willing to trade these off for wage.

We test this using Belgian data from the Careers of Doctorate Holders survey (Federaal Wetenschapsbeleid, 2006).

Our results single out ‘hybrid’ researchers (researchers with combine a taste for science with a taste for business) (Gittelman & Kogut, 2003; Sauermann & Roach, 2012). Hybrid scientists, along with traditional scientists are more likely to sort into academia. they choose more often to be employed in science-like positions in industry where they interact with the scientific community and publish findings. This reinforces the importance of hybrid scientists as boundary-spanning gatekeepers for firms: not only are they interested in basic as well as in applied research (Gittelman & Kogut, 2003), they actively engage with the scientific community. We also find that ‘traditional’ researchers, who have a taste for science but not for business, are employed in equally science-like positions as ‘commercial’ researchers (who have a taste for business but not for science). This indicates a mismatch: many of the researchers who would be interested in partaking in interaction with the community and publishing do not end up in jobs where they do so, and many scientists who are less interested in these activities end up in jobs where they do. Contrary to our expectations, we do not observe differences in the nature of research activities (research versus development) across different motivations.

These findings, first, contribute to the understanding of the role of researchers’ motivations in determining job choice. While work has explored the choice between industry and academia (Roach & Sauermann, 2010) as well as the choice between basic and applied science (Agarwal & Ohyama, 2012), there is still a gap in the literature concerning researchers’ exact choice of job characteristics. By considering job characteristics such as contact with the scientific community, we contribute to filling this gap. Second, we contribute to understanding the job characteristics of hybrid researchers. The importance of hybrid researchers has been acknowledged in industrial as well as in academic research, but few works have studied their characteristics and activities (exceptions are Sauermann & Roach (2012) and Gittelman & Kogut (2003)). We show that, in firms, hybrid researchers reach out significantly more to the scientific community, confirming their role as 'boundary-spanning gatekeepers' for the organization (Gittelman & Kogut, 2003).

The remainder of this paper is structured as follows. In §2, we describe our data, measures, and present descriptive results. In §3 we test whether the observations in the previous part hold in a multivariate setting. §4 concludes.

2. Data and descriptive analysis

We employ the Belgian part of the OECD's Careers of Doctorate Holders survey (Federaal Wetenschapsbeleid, 2006). This survey sampled the population of Belgian doctorate holders (response rate : 17%) in 2005 on a broad array of topics, including motivations, scientific performance, employment, and education. Since most questions related to the variables of interest are measured over the period 2003-2005, we select only those researchers who are employed at their current position for at least three years. Including only those who answered all relevant questions, we retain a sample of 411 industrial researchers and 474 academic scientists employed in natural sciences, engineering, medicine, and agricultural sciences. In the remainder of the analysis, we focus on the 411 industrial researchers. However, we employ the academic sample in selection models in the multivariate analysis.

Variables of interest

Preferences

Preferences are measured through the survey question: 'why did you choose for a career in research?', which is followed by seven binary indicators: 'intellectual challenge', 'salary', 'career prospects', 'job security', 'work circumstances', 'independence', and 'contribution to society' (named respectively MOTIV_CHALLENGE, MOTIV_SALARY, MOTIV_CAREER, MOTIV_SECURITY, MOTIV_WORKCIRC, MOTIV_INDEPENDENCE, MOTIV_CONTRIBUTION; see table 8 for summary statistics). We confirm previous observations of differences in motivations between industrial researchers and academic scientists (Roach & Sauermann, 2010): scientists in academia are significantly more often motivated by independence and contribution to society than industrial researchers, who are more often motivated by salary and career possibilities. In line with previous literature (Sauermann & Roach, 2012) we employ exploratory factor analysis to discern underlying factors (Table 1). We choose the solution using Varimax rotation for interpretability. We find two uncorrelated[1] underlying factors with Eigenvalue larger than 1. The first loads positively with motivation through salary, career progression and job security. Since these are all extrinsic rewards of the scientific profession, we name this factor "taste for business". The other factor correlates positively with motivation through intellectual challenge, independence, and contribution to society. Since these motivations are all related to classical aspects of science (Aghion, et al., 2008; Stephan & Levin, 1992), and in the light of previous findings (Roach & Sauermann, 2010; Sauermann & Roach, 2012), we name this factor "taste for science". We normalize both factors for interpretability (TASTE_SCIENCE_NORM and TASTE_BUSINESS_NORM).

We create four categories of researchers' motivations, defining "having" a taste for science (or business) as scoring higher than average on that factor. Sauermann & Roach (2012) categorizes researchers with a taste for science but no taste for business as 'traditional', since they conform to the traditional view of the intrinsically motivated scientist. Researchers with a taste for business but no taste for science are called 'commercial', and those with both motivations are

[1] Varimax rotation forces these factors to be uncorrelated. However, when applying oblique rotation (oblimin(0)), the solution yields two weakly correlated factors (correlation<0.20), with weaker interpretability than the orthogonal solution. Therefore, we choose the solution using Varimax rotation for interpretability.

labeled ‘hybrid’. The last group, those with weak taste for science or business, are called ‘other types’.

--- Table 1 here ---

Table 2 shows the different motivation profiles in industry and academia. In line with earlier observations (Sauermann & Roach, 2012), we find substantial shares of researchers in each category: 41% of researchers in our sample are ‘traditional’, 16% is ‘commercial’, and 15% is ‘hybrid’. Traditional scientists are more prevalent in academia, while commercial researchers are mainly found in industry, confirming previously found selection effects (Roach & Sauermann, 2010). Hybrid researchers are more likely to be in the academic sector. The summary statistics confirm that industrial researchers on average have lower taste for science and higher taste for business than academic scientists (table 8).

--- Table 2 here ---

We also observe significant heterogeneity among motivations: 31% of academics do not have a strong taste for science, and 25% have a high taste for business. Likewise, 63% of industrial researchers have a low taste for business (42% have a high taste for science). This confirms previous findings regarding heterogeneity among researchers’ motivations within industry and academia (Stern, 2004; Sauermann & Roach, 2011; Sauermann, et al., 2010).

Job characteristics

In this part, we characterize industrial researchers’ job characteristics and relate these to their motivations. Previous literature has focused on heterogeneity in the right to publish (Stern, 2004; Sauermann & Roach, 2011), researchers’ main engagement as ‘basic’ or ‘applied’ (Agarwal & Ohyama, 2012) and both factors’ impact on earnings. Sauermann & Stephan (2012) identify four dimensions of heterogeneity amongst research positions. First, the nature of the work: research can be basic or applied in focus. Second, the characteristics of the workplace: research positions differ in the degree of independence and salaries they offer to workers. Third, disclosure of research results: while some positions allow the researcher to disclose research results through publications, most do not. Last, worker characteristics: motivations are heterogeneous among researchers within industry and academia. We build on this framework, contributing by, first, analyzing detailed information about researchers' research and development activities; second, reporting measures on industrial researchers engagement in the scientific community; and third, by analyzing the correlations among these dimensions.

Table 8 reports the average self-reported share of time spent on research (RES_SHARE) and development (DEV_SHARE) of industrial researchers. On average, an industrial researcher spends 35% of his time on activities related to research, and 38% of his time on development. However, strong variance exists among these factors (Table 3). A significant share of researchers does not spend time on research at all (23%), and most who do spend less than half of their time on it (40%). A third spends more than half – but not all – of their time on research, and 7% is full-time engaged in research. We find a similar distribution of time spent on development activities. 24% of industrial researchers in our sample does not engage in development at all, while 5% spends all of their time on development activities. Approximately a third of industrial researchers spend less than half of their time on development, and 37% spends more than half but not all of their time. Figure 1 plots the share of time spent on research versus development.

--- Figure 1 here ---

--- Table 3 here ---

Next, we focus on industrial researchers' opportunities to engage in the scientific community, which is important for firms in order to build absorptive capacity (Gittelman & Kogut, 2003). Sauermann & Cohen (2010) find that industrial researchers who interact in the scientific community through professional meetings (73% of their sample) to be more productive than others. We report two (self-reported) measures. The first indicates whether or not the researcher cooperated with international research groups (INT_COOP). While we do not know the nature of the actors involved in these collaborations (e.g. other firms, or scientific institutes), we can assume that firms which allow their personnel to engage in this behavior to take a more open stance towards R&D than firms who do not. 45% of the researchers in the sample indicates to have cooperated with international research groups in the three years prior to the survey date. Our second measure of engagement is whether or not the researcher mentored Master or Ph.D. students (MENTOR). Researchers who do this are likely to keep direct ties with the university to which the students are affiliated, and to have more opportunities for further interaction. As with the previous measure, employers who allow their personnel to do this are likely to be more open towards the scientific community than others. 22% of industrial researchers in the sample reports having done this in the last three years.

Next, we consider the researchers' opportunity to disclose research results through publication. While many researchers value publishing for its contribution to scientific progress and because of its value for career progression and reputation (Sauermann & Roach, 2011), firms have a negative incentive to allow publishing since it hampers the appropriation of research results. On the other hand, publishing builds firm's 'scientific credibility', creating opportunities to cooperate with scientific actors (Cohen & Levinthal, 1990; Rosenberg, 1990). Allowing researchers to publish also allows the firm to attract more able researchers who would otherwise demand large monetary compensation in order to give up publishing (Stern, 2004; Sauermann & Roach, 2011). A large share of the industrial researchers in the sample indicates to having published at least one paper in the last three years (See table 8; PUBLICATION: 36%).

Another important employer characteristic is wage. Industrial researchers in our sample earn on average 76.395 EUR, compared to 60.533 EUR for academic scientists. In the analysis, we consider wage differences between researchers with different motivations.

Finally, we consider the amount of effort exerted by the researcher, in the form of the self-reported average amount of hours worked (HOURS_WORKED). Specifically, we are interested in whether researchers with certain motivational profiles expend more efforts than others. On average, researchers in industry report working 49 hours per week.

These job characteristics are not independent from each other; rather, the researcher chooses a set of job characteristics in which to work. Table 4 shows correlations between job attributes. Observe that while INT_COOP, MENTOR, and PUBLICATION are all correlated, RES_SHARE and DEV_SHARE are less correlated with these activities. While we might expect only more basic researchers to engage in disclosure or interaction, we find no negative correlation these activities and DEV_SHARE (we do find some positive correlation between these activities and RES_SHARE). WAGE and HOURS_WORKED also appear to be uncorrelated with the other job attributes. There is an expected positive correlation between effort and wage. We apply exploratory factor analysis on these variables in order to discern underlying trends. When including WAGE and HOURS_WORKED, these are each assigned their own factor with low cross-loadings. Because the solution without these variables yields better interpretability, we choose to treat them as independent and exclude them from the factor analysis. This makes intuitive sense: the other variables represent activities the researcher can choose to engage in, while wage and effort are not. The analysis return two factors with eigenvalue greater than 1 (Varimax rotation)[2]. The first factor correlates strongly with INT_COOP, MENTOR, and PUBLICATION, and weakly with RES_SHARE. We name this factor "SCIENCE", as positions which score higher on this dimension have more science-like attributes: interaction with the scientific community, disclosure through publication, and (weakly) more time spent on research. The second factor correlates negatively with RES_SHARE and positively with DEV_SHARE. Therefore, we name this factor 'APPLIED'.

--- Table 4 here ---

--- Table 5 here ---

Figure 2 plots the scores on the two factors. Creating a 2-dimensional grid based on higher-than-average or lower-than-average scores on SCIENCE and APPLIED, we observe that all combinations are approximately equality prevalent. 30% of researchers are mostly engaged in research activities (i.e., below-average score on APPLIED) with a low score on SCIENCE, while 25% of the researchers who score lower than average on APPLIED score higher than average on SCIENCE. 21% of those who score higher on APPLIED score low on SCIENCE, and 25% of the researchers who score above average on APPLIED score above average on SCIENCE.

One implication of this analysis is that the nature of the researchers' activities does not appear to be systematically related to interactions with the scientific world or disclosure: many scientists who spend most time on development do pursue these activities. On the other hand, spending more time on research does not guarantee disclosure or the freedom to interact with external actors. Rather, when describing researchers' job characteristics, the nature of the research on the one hand and opportunity to engage in the scientific community on the other (whether through disclosure or through direct interaction) could be thought of as separate dimensions.

[2] As in the previous analysis, applying oblique rotation yields weakly correlated factors (<0.20). Therefore, we choose the solution using Varimax rotation for interpretability.

--- Table 6 here ---

--- Figure 2 here ---

Do preferences and job attributes match?

We now assess whether researchers with different motivation profiles choose to pursue jobs with different characteristics in industry. We expect researchers with a higher taste for science compared to their taste for business ('traditional' researchers) to choose for jobs where they can interact more with the scientific community, publish more often, and spend more time on basic research. Researchers with a higher taste for business compared to their taste for science ('commercial researchers') should be more willing to trade off these characteristics for higher wage. For hybrid researchers, the trade-off could go both ways.

Table 7 provides summary statistics by type of researcher. We observe statistically significant differences across the four groups in INT_COOP, MENTOR, SCIENCE, WAGE, and HOURS_WORKED. More specifically, we observe that hybrid researchers cooperate more often with international research groups (INT_COOP), more often mentor students (MENTOR), and score higher on the aggregate index SCIENCE. Contrary to our expectations, traditional researchers are not more likely than commercial or 'other' researchers to publish or to interact with the scientific community. This could potentially indicate a 'mismatch' for this group, especially considering that traditional researchers earn less than others (68625 versus approximately 79000). Traditional researchers also exert less efforts than others (HOURS_WORKED) We observe no significant differences across time spent on research or development across different groups of researchers.

We additionally provide summary statistics by higher or lower than average taste for science. We observe expected lower earnings for researchers with a higher taste for science. This might (partly) be explained by the observed lower number of hours worked. While we do observe more cases of interaction with the scientific community and publishing, these differences are not statistically significant. We do observe weakly significantly higher scores on SCIENCE for those with a higher taste for science. Researchers with a higher taste for business score higher on SCIENCE. They earn more than others. Again, we do not observe differences in the nature of research activities across higher or lower taste for science or business[3].

These observations lead to the preliminary conclusion that many researchers in industry do not achieve a match between motivations and job characteristics: many researchers with a strong taste for science do not interact with the scientific community or and do not publish research findings. Only researchers with strong taste for science as well as business manage to have more science-like job characteristics in industry. In the next part, we confirm these findings in a multivariate setting.

3. Multivariate analysis

a. Specification

In this part we confirm these findings in a multivariate setting, where we control for various researcher characteristics.

We first estimate the researchers' scores on SCIENCE, APPLIED, WAGE (of which we take the natural logarithm in the regressions), and HOURS_WORKED. In order to ensure the robustness of our results, we verify the individual effects of INT_COOP, MENTOR, RES_SHARE, DEV_SHARE, and PUBLICATION. Our main variable of interest is the motivational profile of the researcher, for which we employ three dummy indicators: TRADITIONAL, COMMERCIAL, and HYBRID (base category: 'OTHER') For the continuous dependent variables (SCIENCE, APPLIED, HOURS_WORKED, RES_SHARE,

[3] We should note here that even though this analysis does not take selection effects into account (e.g. industrial scientists have, on average, a stronger taste for business and a weaker taste for science), these results are not affected in any significant way by setting the average within industry as the point of comparison for the motivation categories. In the multivariate analysis, we show that our results hold even controlling for selection.

DEV_SHARE) we estimate a linear regression model with robust standard errors. For the regressions with binary dependent variables (INT_COOP, MENTOR, PUBLICATION), we specify a Probit model.

Control variables include demographics (AGE, GENDER), ability, and scientific domain. We include a squared term for age (AGE2) to account for quadratic effects. We control for ability through a dummy indicator which takes value 1 if the researcher funded his Ph.D. studies with a government or private scholarship, since – especially in Belgium – these select strongly on the applicant's previous academic performance (see also Agarwal & Ohyama, 2012) (SCHOLARSHIP). Additionally, we control for job-specific expertise through the number of years spent in the current job (T_CJ). Lastly, we control for the researchers' broad scientific field with three dummy variables representing engineering (ENGINEERING), medical (MEDICAL), and agricultural (AGRICULTURAL) sciences (base category: natural sciences). In the regression with WAGE as dependent variable, we further control for effort through HOURS_WORKED.

As a robustness check, we present results using TASTE_SCIENCE_NORM, TASTE_BUSINESS_NORM and their interaction (I) as explanatory variables. Additionally, we present results correcting for researchers' selection into industry. For this we employ Heckman selection models, where we first estimate the researchers' probability of choosing to work in industry and then estimate job characteristics given that choice. To achieve identification we do not include the field dummies in the regression equations.

b. Results

Table 9 presents the first set of regression results. Columns 1 through 4 estimate models for SCIENCE, APPLIED, WAGE and HOURS_WORKED using categorical motivation profiles. We observe that hybrid researchers score significantly higher on SCIENCE than others (column 1). Note that researchers score lower on SCIENCE as they grow older. We observe no significant differences in

APPLIED across motivation profiles, confirming our observations in the descriptive analysis (column 2). Once controlling for researcher characteristics, we observe no significant differences in wage among across different motivations (column 4). However, since we only observe outcome wages, these observations do not necessarily contradict the earlier findings based on reservation wages by Stern (2004) and Sauermann & Roach (2012). As expected, wage increases with age and tenure, and effort. In terms of effort, we see that traditional researchers tend to work fewer hours than others. These results thus confirm our observation that hybrid researchers more often choose to work in more science-oriented positions. These hybrid researchers do not trade off wage to pursue these activities, which might indicate the value of these interactions for the firm. On the other hand, hybrid researchers' research is not different of a different nature, in the sense that they do not spend more or less time performing research or development.

Columns 5 to 8 present the same regressions using TASTE_SCIENCE_NORM, TASTE_BUSINESS_NORM, and their interaction I. We find that SCIENCE increases with taste for business as well with taste for science, but their interaction is not significant. We also observe a weak positive effect of taste for business on wage. Researchers with a higher taste for science exert less effort in industry, but the interaction is positive: they exert more effort as taste for business increases together with taste for science.

--- Table 9 here ---

Table 10 presents the same regressions correcting for selection into industry. We observe that traditional researchers and hybrid researchers are less likely to go to industry, and commercial researchers are more likely to do so. However, as the Mills' Lambda is not statistically significant, selection bias appears not to be very important in this specific situation. The interpretation of the results does not change critically in this specification.

--- Table 10 here ---

As an additional check, we regress the motivation profiles on the individual elements of SCIENCE and APPLIED (table 11). Analog to the previous findings, we find no differences across motivation profiles in RES_SHARE and DEV_SHARE. As researchers in industry grow older, they tend to spend less time performing research, but time spent on development proves difficult to explain using researcher characteristics. Hybrid researchers are more likely to cooperate in international research projects (INT_COOP), to mentor students (MENTOR), or to publish (PUBLISH). The latter two become less prevalent with age. Women are more likely to publish in industry than men.

--- Table 11 here ---

In conclusion, these regressions confirm our inferences from the descriptive analysis: hybrid researchers in industry engage more often than others with the scientific community and publish more often than others, but do not spend more time performing research or development.

4. Preliminary conclusions, limitations, and future research

In this paper, we investigate the fit between industrial researchers' motivations and job characteristics. While the literature on researchers' 'taste for science' has established selection into industry and academia (Roach & Sauermann, 2010), researchers within industry are still strongly heterogeneous in their motivations (Stern, 2004; Agarwal & Ohyama, 2012; Sauermann & Stephan, 2012; Sauermann & Roach, 2011). We contribute by this by testing whether researchers with different motivations manage to find jobs suited to their tastes within industry.

We hypothesize that researchers with a strong ‘taste for science’ (motivation trough intellectual challenge, independence, or contribution to society) should seek to find jobs which allow for disclosure of research results, interaction with the scientific community, and basic research. At the same time, researchers with a strong ‘taste for business’ (motivation through salary, career prospects, or job security) should be more willing to trade these off for higher wage. We test these hypotheses using survey data on over 400 industrial researchers from the Belgian part of the Careers of Doctorate Holders survey.

Our findings are as follows. First, we confirm earlier observations about heterogeneity in researchers’ motivations within industry and academia. Second, we show heterogeneity among industrial researchers’ job profiles, considering the nature of research (time spent on research and development), engagement in the scientific community (cooperation with international research groups and mentoring of graduate and Ph.D. students), and disclosure through scientific publications. Third, we test the hypothesis that researchers try to match their motivations to job attributes within industry. We find that ‘hybrid’ researchers, those with a strong taste for science as well as business, engage more often in interaction with the scientific community and publish more often than others. However, their activities are not more focused on research or development than those of other researchers. This underlines the critical role of hybrid researchers as boundary-spanning gatekeepers in the firm. R&D managers should be aware of the importance of attracting hybrid researchers when they want to build their organization’s absorptive capacity through publishing and interactions with the scientific community. Traditional researchers are typically mismatched in industry, as they do not find more science-like environments to work in than researchers with commercial motivations.

This study is not without limitations. Since our data is cross-sectional in nature, we cannot formally establish causality: socialization in the workplace might drive differences in motivations. However, since our analyses mainly consider researchers within industry, this is less likely to drive our results than when analysing the choice between more explicitly distinguished environments such as industry and academia. Second, we have to draw conclusions from observed behaviour, not from intentions. This limits our findings somewhat, since we cannot observe which researchers had the opportunity to engage in certain behaviours but chose not to do so.

Having established that many researchers in industry do not find jobs to fit their motivations, the question remains how much a (mis)match affects the researcher. To investigate this, future research will consider how much 'job match' affects the researcher's willingness to expend efforts, the researcher's satisfaction with pecuniary and nonpecuniary rewards stemming from his work, and the researcher's (scientific) productivity. A second issue for future research is whether the issues found here exist in the academic sector: do commercially motivated researchers who choose to work in academia match to find a job profile suiting their tastes?

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Figures

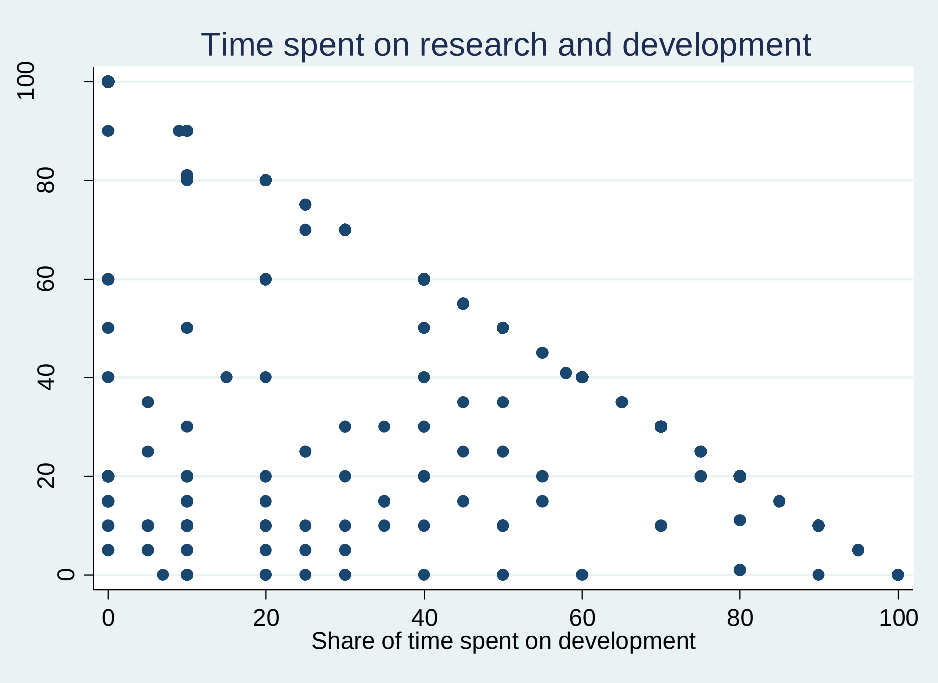

Figure 1: Time spent on research and development

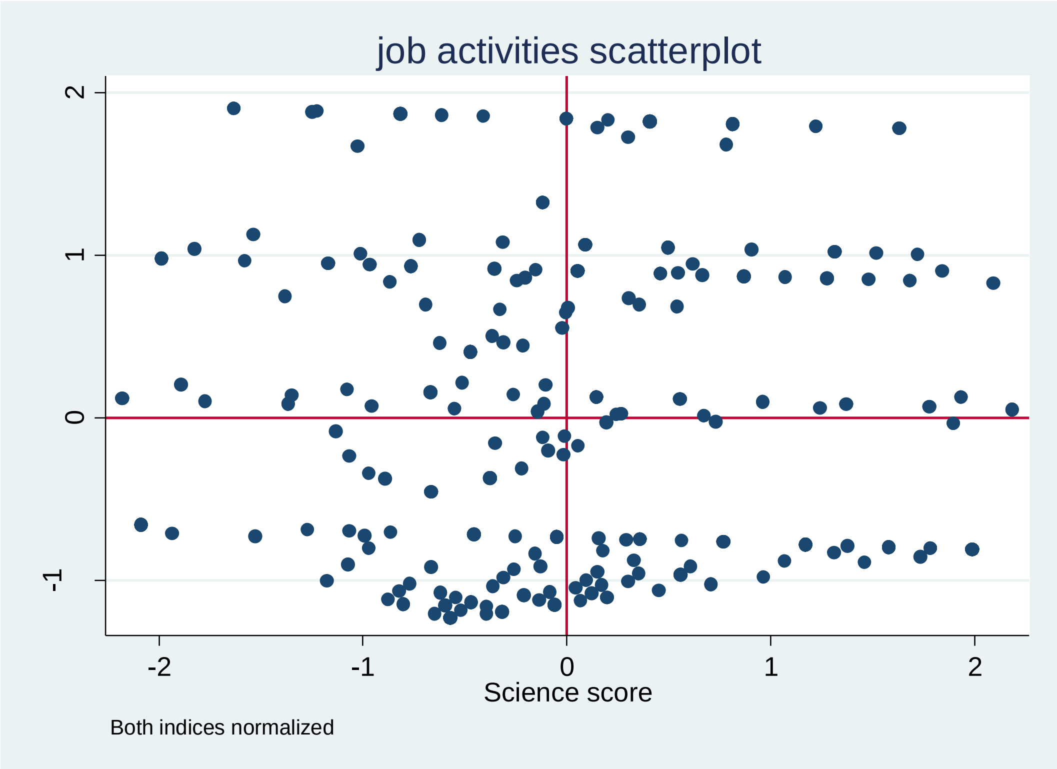

Figure 2: Job activities scatterplot

Tables

Table 1: Motivations factor analysis

	Taste for Business	Taste for Science	Uniqueness
MOTIV_CHALLENGE	-0.09	**0.54**	0.69
MOTIV_SALARY	**0.66**	-0.09	0.56
MOTIV_CAREER	**0.58**	-0.02	0.67
MOTIV_WORKCIRC	0.27	0.29	0.84
MOTIV_SECURITY	**0.70**	0.18	0.47
MOTIV_INDEPENDENCE	0.06	**0.67**	0.53
MOTIV_CONTRIBUTION	0.26	**0.43**	0.75
Eigenvalue	1.4	1.05	

Note: results rotated with Varimax rotation. Factor loadings > 0.4 are listed in **bold.**

Table 2: Motivations distribution

Motivation category	Total (885)	Industrial (411)	Academic (474)
Other	249 (28%)	136 (33%)	113 (24%)
Traditional	366 (41%)	123 (30%)	243 (50%)
Commercial	138 (16%)	104 (26%)	34 (7%)
Hybrid	132 (15%)	48 (12%)	84 (18%)

Table 3: Distribution of research activities

Share of time spent on	Research	Development
0%	95 (23%)	100 (24%)
1%-49%	163 (40%)	138 (34%)
50%-99%	125 (30%)	153 (37%)
100%	28 (7%)	20 (5%)
Total	411 (100%)	411 (100%)

Table 4: Correlations between job attributes

	1	2	3	4	5	6	7
1 INT_COOP	1.00						
2 MENTOR	0.42	1.00					
3 RES_SHARE	0.29	0.19	1.00				
4 DEV_SHARE	0.01	0.00	-0.20	1.00			
5 PUBLICATION	0.48	0.33	0.29	-0.07	1.00		
6 WAGE	0.05	0.02	0.03	-0.09	-0.06	1.00	
7 HOURS_WORKED	0.08	0.08	0.00	-0.03	-0.06	0.43	1.00

Table 5: Job attributes factor analysis

	SCIENCE	APPLIED	Uniqueness
INT_COOP	**0.82**	0.01	0.32
MENTOR	**0.72**	0.08	0.47
RES_SHARE	**0.46**	**-0.58**	0.46
DEV_SHARE	0.07	**0.89**	0.20
PUBLICATION	**0.75**	-0.14	0.42
Eigenvalue	1.97	1.15	

Note: results rotated with Varimax rotation. Factor loadings > 0.4 are listed in **bold.**

Table 6: Job Attribute Distribution

SCIENCE	APPLIED	Number of obs
< mean	< mean	122 (30%)
> mean	< mean	101 (25%)
< mean	> mean	86 (21%)
> mean	> mean	102 (25%)
Total		411 (100%)

Table 7: Motivation profile by job characteristics

MOTIVATION CATEGORY	INT_COOP	MENTOR	RES_SHARE	DEV_SHARE	PUBLICATION	SCIENCE	APPLIED	WAGE	HOURS_WORKED
Other	0.40	0.17	34.49	35.29	0.34	-0.13	-0.08	79415	49.83
	0.49	0.38	33.26	32.55	0.47	0.99	1.04	33732.6	8.69
Traditional	0.42	0.21	35.02	38.88	0.37	-0.03	0.02	**68625**	**47.09**
	0.50	0.41	30.37	30.53	0.48	1.00	1.01	24386	7.21
Commercial	0.45	0.23	32.70	38.53	0.35	-0.01	0.06	80859	48.40
	0.50	0.42	28.86	31.19	0.48	0.97	0.97	38221	7.63
Hybrid	**0.67**	**0.38**	38.96	39.79	**0.48**	**0.45**	0.07	78083	49.15
	0.48	0.49	27.44	28.82	0.50	0.98	0.93	35413	7.50
#	***	**	.	.	.	***	.	**	**
Low taste for science	0.42	0.20	33.71	36.70	0.34	-0.08	-0.02	80040	49.21
	0.49	0.40	31.38	31.94	0.48	0.98	1.01	35677	8.26
High taste for science	0.49	0.26	36.13	39.13	0.40	**0.11**	0.03	**71278**	**47.67**
	0.50	0.44	29.55	29.98	0.49	1.02	0.98	28136	7.33
##	.	.	.	.	.	*	.	***	**
Low taste for business	0.41	0.19	34.74	37.00	0.35	-0.08	-0.04	74290	48.53
	0.49	0.39	31.86	31.60	0.48	1.00	1.03	30096	8.12
High taste for business	**0.52**	**0.28**	34.68	38.93	0.39	**0.13**	0.06	**79982**	48.64
	0.50	0.45	28.48	30.37	0.49	0.99	0.95	37263	7.57
##	**	**	.	.	.	**	.	*	.

Note: #: Stars indicate p-value of anova test across the four categories. ##: Stars indicate p-value of t-test between the two groups *: p<0.1, **p<0.05, ***: p<0.01. Groups significantly different at p<0.1 printed in **bold**. Standard deviations printed in italics.

Table 8: Summary statistics

	Industry (411 obs)		Academia (474 obs)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	P-value t-test
MOTIV_CHALLENGE	0.90	0.30	0.91	0.28	.
MOTIV_SALARY	0.13	0.34	0.03	0.16	***
MOTIV_CAREER	0.28	0.45	0.17	0.38	***
MOTIV_SECURITY	0.07	0.26	0.10	0.30	.
MOTIV_WORKCIRC	0.25	0.43	0.28	0.45	.
MOTIV_INDEPENDENCE	0.43	0.50	0.70	0.46	***
MOTIV_CONTRIBUTION	0.10	0.30	0.21	0.41	***
TASTE_SCIENCE_NORM	-0.30	0.96	0.26	0.96	***
TASTE_BUSINESS_NORM	0.11	1.09	-0.09	0.91	***
RES_SHARE	34.72	30.62	51.46	33.15	***
DEV_SHARE	37.71	31.13	7.70	15.12	***
INT_COOP	0.45	0.50	0.88	0.33	***
MENTOR	0.22	0.42	0.91	0.28	***
PUBLICATION	0.36	0.48	0.91	0.28	***
WAGE	76395	32999	60533	20369	***
HOURS_WORKED	48.57	7.91	53.03	9.62	***
AGE	43.47	7.11	46.62	9.39	***
GENDER	0.17	0.38	0.18	0.38	.
SCHOLARSHIP	0.61	0.49	0.52	0.50	***
T_CJ	10.27	7.01	14.04	10.65	***
NATURAL SCIENCES	0.67	0.47	0.58	0.49	***
ENGINEERING	0.24	0.43	0.21	0.41	.
MEDICAL	0.05	0.23	0.15	0.36	***
AGRICULTURAL	0.04	0.20	0.06	0.24	.

Note: stars indicate p-value of t-test with unequal variances. *:p<0.10, **:p<0.05, ***:p<0.01

Table 9: Regression results 1

	(1) SCIENCE	(2) APPLIED	(3) LN(WAGE)	(4) HOURS WORKED	(5) SCIENCE	(6) APPLIED	(7) LN(WAGE)	(8) HOURS_WORKED
TRADITIONAL SCI.	0.0957	0.0646	-0.0209	-2.7661***				
	(0.1226)	(0.1270)	(0.0382)	(0.9551)				
COMMERCIAL SCI.	0.0578	0.1352	0.0421	-1.1593				
	(0.1277)	(0.1307)	(0.03595)	(0.9743)				
HYBRID SCI.	0.5549***	0.1331	-0.0077	-1.0926				
	(0.1701)	(0.1608)	(0.0470)	(1.2316)				
TASTE_SCIENCE_NORM					0.1588***	-0.0030	-0.0190	-1.1561***
					(0.0506)	(0.0539)	(0.0155)	(0.4256)
TASTE_BUSINESS_NORM					0.1315***	-0.0018	0.0232**	0.3190
					(0.0450)	(0.0451)	(0.0117)	(0.3197)
I					-0.0066	0.0180	0.0033	0.9862***
					(0.0380)	(0.0508)	(0.0111)	(0.2768)
AGE	-0.2245***	0.0934	0.0680***	1.4364***	-0.2236***	0.0828	0.0655***	1.4077***
	(0.0795)	(0.0729)	(0.0245)	(0.5354)	(0.0804)	(0.0720)	(0.0240)	(0.5323)
AGE2	0.0022**	-0.0013	-0.0006**	-0.0145**	0.0022**	-0.0012	-0.0005*	-0.0142**
	(0.0009)	(0.0008)	(0.0002)	(0.0060)	(0.0009)	(0.0008)	(0.0003)	(0.0059)
GENDER	0.1461	-0.2320	0.0034	-4.0646***	0.1247	-0.2411	0.0030	-3.8613***
	(0.1354)	(0.1458)	(0.0350)	(1.1331)	(0.1316)	(0.1476)	(0.0350)	(1.1287)
SCHOLARSHIP	0.0278	0.0412	0.0181	-0.7176	0.0129	0.0511	0.0206	-0.6343
	(0.1027)	(0.0997)	(0.0291)	(0.7735)	(0.1020)	(0.0999)	(0.0291)	(0.7669)
T_CJ	0.0136	0.0158	0.0153***	0.0696	0.0121	0.0167*	0.0149***	0.0628
	(0.0106)	(0.0100)	(0.0040)	(0.0898)	(0.0108)	(0.0100)	(0.0040)	(0.0897)
ENGINEERING	-0.0519	0.1788	-0.0075	1.7787*	-0.0694	0.1694	-0.0016	1.7912*
	(0.1190)	(0.1298)	(0.0335)	(0.9365)	(0.1192)	(0.1300)	(0.0342)	(0.9355)
MEDICAL	-0.0905	0.0476	0.0444	2.1673	-0.0727	0.0632	0.0500	1.8558
	(0.2212)	(0.2404)	(0.0938)	(1.9960)	(0.2140)	(0.2406)	(0.0938)	(1.9474)
AGRICULTURAL	0.1945	0.2141	-0.2113**	4.8981**	0.2057	0.2191	-0.2128**	4.8864**
	(0.2274)	(0.2224)	(0.0850)	(1.9668)	(0.2472)	(0.2277)	(0.0842)	(1.9810)
HOURS_WORKED			0.0188***				0.0186***	
			(0.0018)				(0.0019)	
CONSTANT	5.1314***	-1.8569	-8.2328**	15.2906	5.2457***	-1.5365	8.2906***	14.3565
	(1.7780)	(1.6613)	(0.5361)	(11.9577)	(1.7919)	(1.6288)	(0.5216)	(11.9317)
N	411	411	411	411	411	411	411	411
R-sq	0.063	0.035	0.50	0.128	0.075	0.032	0.483	0.139

Linear regression results. Robust standard errors in parentheses.
Stars indicate level of statistics: * p<0.10, ** p<0.05, *** p<0.05

Table 10: Regression results 2

	(1)		(2)		(3)		(4)	
	SCIENCE	SELECTION	APPLIED	SELECTION	LN (WAGE)	SELECTION	HOURS_WORKED	SELECTION
TRADITIONAL SCI.	0.1437	-0.6374***	-0.0281	-0.6374***	0.0363	-0.6676***	-4.1370***	-0.6374***
	(0.1923)	(0.1105)	(0.1963)	(0.1105)	(0.0621)	(0.1127)	(1.5093)	(0.1105)
COMMERCIAL SCI.	0.0192	0.6241***	0.1986	0.6241***	0.0079	0.5912***	-0.1333	0.6241***
	(0.1656)	(0.1498)	(0.1694)	(0.1498)	(0.0499)	(0.1520)	(1.3115)	(0.1498)
HYBRID SCI.	0.5992***	-0.4714***	0.0653	-0.4714***	0.0229	-0.4680***	-2.0634	-0.4714***
	(0.1934)	(0.1449)	(0.1975)	(0.1449)	(0.0589)	(0.1468)	(1.5214)	(0.1449)
AGE	-0.2422**	0.2845***	0.1404	0.2845***	0.0361	0.3331***	2.1378***	0.2845***
	(0.1005)	(0.0610)	(0.1025)	(0.0610)	(0.0334)	(0.0630)	(0.7869)	(0.0610)
AGE2	0.0025**	-0.0033***	-0.0018	-0.0033***	-0.0002	-0.0038***	-0.0226**	-0.0033***
	(0.0011)	(0.0007)	(0.0012)	(0.0007)	(0.0004)	(0.0007)	(0.0089)	(0.0007)
GENDER	0.1644	-0.1746	-0.2895**	-0.1746	0.0304	-0.2951**	-4.7646***	-0.1746
	(0.1337)	(0.1230)	(0.1368)	(0.1230)	(0.0453)	(0.1268)	(1.0594)	(0.1230)
SCHOLARSHIP	0.0159	0.1499	0.0669	0.1499	-0.0017	0.1471	-0.4887	0.1499
	(0.1113)	(0.0927)	(0.1138)	(0.0927)	(0.0335)	(0.0942)	(0.8791)	(0.0927)
T_CJ	0.0143	-0.0136	0.0125	-0.0136	0.0168***	-0.0113	0.0182	-0.0136
	(0.0112)	(0.0084)	(0.0114)	(0.0084)	(0.0033)	(0.0086)	(0.0877)	(0.0084)
ENGINEERING		-0.0239		-0.0239		0.0196		-0.0239
		(0.1143)		(0.1143)		(0.1163)		(0.1143)
MEDICAL		-0.8555***		-0.8555***		-0.7420***		-0.8555***
		(0.1672)		(0.1672)		(0.1727)		(0.1672)
AGRICULTURAL		-0.3774*		-0.3774*		-0.2775		-0.3774*
		(0.2095)		(0.2095)		(0.2121)		(0.2095)
HOURS_WORKED					0.0212***	-0.0336***		
					(0.0032)	(0.0056)		
_CONS	5.5432**	-5.5716***	-2.9001	-5.5716***	8.8860***	-5.0606***	-0.5701	-5.5716***
	(2.3439)	(1.3841)	(2.3919)	(1.3841)	(0.6935)	(1.4157)	(18.3604)	(1.3841)
MILLS LAMBDA	-0.1322		0.2550		-0.1461		3.5491	
	(0.3819)		(0.3893)		(0.1261)		(2.9782)	
N	885		885		885		885	

Heckman regression results. Stars indicate level of statistics: * p<0.10, ** p<0.05, *** p<0.01

Table 11: Regression results 3

	(1) RES_SHARE	(2) DEV_SHARE	(3) INT_COOP	(4) MENTOR	(5) PUBLICATION
TRADITIONAL SCI.	0.7976	2.3910	0.0794	0.1348	0.0846
	(3.8615)	(3.9431)	(0.1595)	(0.1832)	(0.1652)
COMMERCIAL SCI.	-2.6399	2.7970	0.0964	0.1628	-0.0371
	(4.0281)	(4.1940)	(0.1696)	(0.1923)	(0.1734)
HYBRID SCI.	4.3415	3.7554	0.6652***	0.6109***	0.4144*
	(4.9117)	(5.0613)	(0.2188)	(0.2309)	(0.2183)
AGE	-5.1184**	1.9159	-0.1339	-0.2932***	-0.2593***
	(2.3216)	(2.2183)	(0.1013)	(0.1080)	(0.1000)
AGE2	0.0554**	-0.0296	0.0012	0.0029**	0.0027**
	(0.0263)	(0.0242)	(0.0011)	(0.0012)	(0.0011)
GENDER	4.9883	-5.8810	-0.0427	0.1338	0.4263**
	(4.4988)	(4.3741)	(0.1726)	(0.1897)	(0.1725)
SCHOLARSHIP	0.6216	1.9826	-0.0419	0.0570	0.0590
	(3.0438)	(3.1839)	(0.1314)	(0.1451)	(0.1357)
T_CJ	0.1843	0.5348	0.0237	0.0300*	-0.0151
	(0.3353)	(0.3390)	(0.0148)	(0.0160)	(0.0150)
ENGINEERING	-3.9088	3.8426	-0.1543	0.2430	-0.2241
	(3.6776)	(3.9779)	(0.1573)	(0.1698)	(0.1611)
MEDICAL	-7.9172	-2.0408	-0.0559	-0.1737	0.0625
	(7.4980)	(7.4397)	(0.2916)	(0.3536)	(0.2917)
AGRICULTURAL	-19.6172***	-5.5561	0.3713	0.4383	0.3394
	(6.5350)	(9.0555)	(0.3211)	(0.3537)	(0.3232)
CONSTANT	148.5873**	3.7170	2.9922	5.6919**	5.6297**
	(51.7505)	(50.3703)	(2.2799)	(2.4106)	(2.2515)
N	411	411	411	411	411
(pseudo-)R-sq	0.044	0.030	0.032	0.019	0.047

(1), (2): Linear regression results. (3-5): Probit regression results.
Robust standard errors in parentheses. Stars indicate level of statistics: * p<0.10, ** p<0.05, *** p<0.01