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The effect of self-monitoring on academics? engagement with industry

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Abstract

According to self-monitoring theory, individuals differ in the extent to which they are willing and able to monitor and control their self-expression in social situations. Using data from a survey administered to 6,000 academics in physical sciences faculties in UK universities, this paper suggests that high self-monitoring individuals collaborate more with industry than their low self-monitoring colleagues, across a variety of channels of interaction. Furthermore, the influence of self-monitoring on researchers? collaboration activities is moderated by both individual and environmental characteristics. For high-status researchers who have already achieved high levels of visibility outside academia, the influence of their self-monitoring score is less pronounced. This applies also to academics who are extrinsically motivated in their jobs and who value tangible benefits. Individuals who operate in an environment that is very supportive of industrial engagement need to rely less on their self-monitoring profiles since opportunities are readily available to everyone.

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THE EFFECT OF SELF-MONITORING ON ACADEMICS' ENGAGEMENT WITH INDUSTRY

INTRODUCTION

In his seminal work on the behavioural patterns of scientists, Merton (1969) states that James Watson's personal account of the discovery of the DNA was destined to be a marker in the history of scientists' behaviour. The public was struck by the revelation that scientists were human after all – perhaps too human, since they were portrayed by their fellow scientist, Watson, as displaying overly human characteristics of jealousy, stupidity, competitiveness and ambition. A closer look at the history of science shows that revelations of this sort abound. From the numerous accounts of Newton's obsessive need to establish his scientific priority against Leibniz in the invention of calculus, to anecdotes about Cavendish's pathological shyness, which meant he could communicate with his female servants only through written notes. So, scientists are characterized by very human traits and driven by similar motives to non-scientists.

Since the publication of Merton's article, the psychology of science moved away from the myth of scientists as over-rational, objective and methodical individuals and the focus now is on systematically analysing scientists' personal attributes and how they affect their behaviours. These efforts, however, tend to concentrate on scientists' performance of scientific research, and only a few works include other activities researchers engage in.

Since the 1980s, universities have had pressure on them to contribute to national economic development and growth (Feller, 1990). Alongside the traditional missions of teaching and research, a "third mission" has emerged (Etzkowitz et al., 2000). Universities are becoming more entrepreneurial and are asking their researchers to be active in knowledge transfer and technology commercialization. This new set of activities, however, may not be embraced in the same way by all academics, even among those working in the same institution. The literature shows that individuals' alignment with universities' third mission depends on the incentives and the support mechanisms in place (Owen-Smith and Powell, 2001), and also more importantly, on the characteristics of individual researchers (Klofsten and Jones-Evans, 2000). Besides demographic elements and characteristics related to scientific productivity, scholars have started to analyse the impact of psychological characteristics on the willingness of academics to participate in academic entrepreneurship (Clarysse et al., 2011, Jain et al., 2009).

In this paper I seek to expand analysis of the role of individuals' psychological characteristics in encouraging academics to collaborate with industry, focusing on the specific trait of self-monitoring. Self-monitoring is the individual's active construction of the public self to achieve social ends (Gangestad and Snyder, 2000). This concept is interesting in the context of university-industry interaction because it relates to how individuals react when faced with different (and ambiguous) tasks and environments, as in the case of university researchers engaging in collaborative activities with private firms.

I use data on a large-scale sample of UK academic researchers working in the physical and engineering sciences. I combine data from multiple sources, including a survey, the records of the UK's largest research council and other public records. First, I explore the effect of self-monitoring on individual behaviour and then extend the analysis to understand the contingencies that affect this relationship. My results suggest that high self-monitoring academics tend to engage more with industry than their low self-monitoring colleagues. However, certain individual and environmental characteristics have the potential to mitigate this effect. In particular, the influence of self-monitoring is lower for academics whose visibility outside the university is high or those driven by extrinsic motivations. Moreover, when the environment is especially favourable to collaboration with industry, high levels of self-monitoring are less relevant for determining individual engagement with private companies.

THE PSYCHOLOGY OF SCIENCE

Compared to research on other occupations, there is a relative lack of work on the psychological attributes of scientists. Mahoney (Mahoney, 1979, p.349) states tat towards the end of the 1970s "in terms of behaviour patterns, affect, and even some intellectual matters, we know more about alcoholics, Christians, and criminals than we do about the psychology of the scientist". Research in this area has increased since that time but, except for the work of Feist (1998, 2006), it has remained fragmented. In other disciplines, such as philosophy, history and sociology, the origins of science, and the development of scientific processes and values have been investigated. However, as stated by Feist (2006, p. x), "a complete understanding of scientific thought and behaviour requires a psychological perspective". Study of the psychology of science should be aimed at explaining how scientific thought and behaviour are the outcomes of a person's unique personality traits and social influences.

Science is often associated with a set of norms, values and rule of behaviour which positions it somewhat apart from other realms of human endeavour. It is believed that the scientific community is ruled by norms of universalism, disinterestedness, originality, organized scepticism, communalism and conviction that the discoveries generated through publicly funded research should be placed in the public domain (Merton, 1973). This set of norms determines the rules of conduct of scientists and, in exchange for adherence to these principles, researchers are granted freedom of enquiry and are rewarded with peer esteem, promotions, research grants and scientific prizes. This social structure and historical recollections of the lives of former great scientists have contributed to creating an image of the "ideal" scientist as objective, rational, open-minded, of utmost integrity and intelligence, and willing to share research results with the scientific community. Indeed, as Knickerbocker (1927, p. vii) suggests, "the history of science is as inspiring in its human values as are the legends of the saints".

Archival data and empirical research have challenged most of these absolute characteristics. History shows that scientists' perceptions of reality, far from being completely objective, are influenced by their theoretical expectations. Several eminent scientists have displayed dogmatic faith in their theories, even in the face of contradictory data (Weimer, 1979). Albert Einstein said that he would have rejected the data before he would have rejected his theory of relativity. Far from being neutral about their investigations, scientists derive much of their motivation and professional satisfaction from their emotional involvement in their work. This is particularly relevant in the scientific profession where initiative, persistence and endurance seem to be as (if not more) important than intelligence in determining scientific performance (Reilly, 1976, Zuckerman, 1970). The rules of behaviour in science remain very relevant as the pursuit of a career in research involves long training and socialization processes through which academic norms become inextricably linked to researchers' identity roles (Jain, George and Maltarich, 2009, Van Maanen and Schein, 1977).

In recognizing the human nature of scientists, the literature proposes a set of characteristics, which, on average, differentiate scientists from non-scientists. Scientists have been observed to be more introverted than individuals in other occupations (Feist, 1998, Wilson and Jackson, 1994). Scientific work requires inductive and deductive reasoning, creative thinking and reflection - activities best performed alone, without the distractions of interacting with other people, which produces the tendency for scientists to be less sociable, gregarious and expressive than people in other professions. This reasoning, based on logic and facts, makes rational decision making an important feature of the scientist: in his meta-analysis Feist (1998) shows that scientists score higher than non-scientists on scales measuring tough-mindedness. On the other hand, given the uncertain nature of research, scientists also appear to be more inclined towards innovative thinking, more open-minded and more non-conformist (Feist, 1998, Lounsbury et al., 2012). As these characteristics are part of personality, and traits and personality are fairly stable over time, it is possible to assume that individuals do not manifest these features because of their profession, but rather that they are rather selected into the specific job because of these characteristics.

ACADEMIC ENGAGEMENT AND SELF MONITORING

Researchers in universities traditionally performed the dual role of education and research. Since the Second World War, we have observed increased professionalization of research in academia, characterized by intense competition between scientists on the one side and extreme specialization of skills on the other. This “modern competitive science” (as Watson in his personal account of the discovery of DNA describes it) has resulted in changes to some of the crucial characteristics of academic research: because of specialization, teams have become increasingly important; because of the decline in public funding, scientists in public organizations are being compelled to augment their research budgets by funding from other sources.

This shift has become especially marked since the 1980s, and we have witnessed increased pressures on universities to act as engines of economic growth (Feller, 1990) and the subsequent institutionalization of academic entrepreneurship and commercialization of university research (Geuna and Muscio, 2009). Academic researchers increasingly are expected to interact with industry; however, as university career systems continue to be dominated by the old paradigm of exclusively rewarding scientific productivity expressed as published papers , scientists’ training seldom provides the skills required to collaborate with private companies and, for some scientists, the logics and modus operandi of industry can conflict with their own values of freedom of enquiry, openness and dissemination.

Researchers who engage in technology transfer or in entrepreneurial activities need to acquire a new set of often unfamiliar skills. While increased team size in science means that academics are often required to manage large laboratories, collaboration with industry entails new issues related to the coordination of complex projects involving different stakeholders, and mediation between different working cultures and the establishment of fruitful dialogue. Much managerial work involves communicating with others (Gronn, 1983), performing a variety of different roles (Mintzberg, 1973) and relating to the needs of large numbers of different people (Kotter, 1982). When collaborating with firms, academics need to bridge across two domains and adapt to the logic that prevails in industry. They need to be proactive in looking for possible partners and must have the skills to manage and negotiate projects involving multiple actors. These activities may require different personal characteristics from those usually associated with the scientific profession. As highlighted in the previous section, scientists tend to be more introverted, reflective, tough-minded and unsociable than non-scientists. On the other hand, collaboration may require skills closer to those possessed by successful managers, who tend to be extroverted, comfortable with team working and able to relate to different audiences (Barrick and Mount, 1991).

Performance in the work environment undoubtedly is affected by many personality variables (Barrick and Mount, 1991): among these, self-monitoring theory provides compelling arguments for linking individual differences in self-monitoring with a range of job outcomes relevant in the context of university-industry collaboration (Baron, 1989, Caldwell and O'Reilly, 1982, Deluga, 1991, Jenkins, 1993, Kilduff, 1992, Kilduff and Day, 1994). Self-monitoring is the individual’s active construction of the public self to achieve social ends: according to this theory, individuals differ in the extent to which they are willing and able to monitor and control their self-expression in social situations (Gangestad and Snyder, 2000). In social situations, high self-monitoring individuals question: “who does this situation want me to be and how can I be that person?”, while low self-monitoring individuals ask “who am I and how can I be me in this situation?” (Mehra et al., 2001). Following Sir Isaiah Berlin’s famous metaphor (Berlin, 1953), high self-monitors are like foxes, pursuing many different objectives and presenting the right image to the right audience, while low self-monitors are like hedgehogs, relating everything to a single central vision and being always true to themselves. An interesting characteristic of self monitoring is that it seems to remain constant over time: as Jenkins (1993, p.84) notes “research suggests that self-monitoring is a stable personality trait throughout one’s lifespan”. Support for this claim comes from different sources: first of all, observations on monozygotic and dizygotic twins show that the latent causal variable corresponding to self-monitoring has a biological basis (Gangestad and Snyder, 1985, Snyder and Gangestad, 1986). Additional support comes from studies that test the construct over longer periods of time (Snyder, 1987).

High self-monitoring individuals show a desire to project positive images of themselves in order to impress others and, therefore, are motivated to pursue behaviours that will help them to be accepted or to gain status (Gangestad and Snyder, 2000, Turnley and Bolino, 2001). On the other hand, low self-monitoring individuals behave in ways that are consistent with their core values and beliefs, insisting on being themselves despite social expectations (Gangestad and Snyder, 2000). As a consequence of their social ambition, high self-monitors tend to perform better than low self-monitors in boundary-spanning activities that require individuals to be sensitive to different social cues (Caldwell and O'Reilly, 1982).

Several studies analyse the impact of self-monitoring in the workplace. High self-monitors are more at ease in social situations and, therefore, are more likely to be employed in management or sales positions (Day and Kilduff, 2003). They seek prestige and, as a consequence, are less well represented in lower-level jobs (Day and Kilduff, 2003, Kilduff and Day, 1994) and tend to get more promotions (Kilduff and Day, 1994). Since they perform well in boundary-spanning roles and are socially ambitious, they are more likely to occupy leadership positions (Zaccaro et al., 1991) and other central positions in organizations (Mehra, Kilduff and Brass, 2001).

In the context of university-industry collaboration, self-monitoring theory provides several elements that may contribute to explaining individual differences in engagement behaviours. High self-monitoring individuals rely more on social cues from others to guide their behaviour than on their own inner attitudes and emotions and, therefore, are more likely than low self-monitors to resolve conflicts through collaboration and compromise (Baron, 1989) and to perform well in boundary-spanning tasks (Caldwell and O'Reilly, 1982). This is an important characteristic for academics who want to collaborate with firms because they must strike a balance between their own values and priorities and the prevalent industry logic. Because they are more sensitive to the external environment, high self-monitoring academics may be able to frame problems so that they are more appealing to different audiences. Low self-monitors, on the other hand, are more interested in self-validation and largely lack the skills required for social interactions: it is more difficult for them to find potential partners for collaboration and to establish connections. Associating with high-profile companies may help academics to improve their images - both inside and outside of academia: since high self-monitors are socially ambitious, they may proactively seek industry partners that are not in their personal network of contacts. In addition, engaging with industry involves not only dealing with industry partners, but also with the university bureaucracy. Because high self-monitors are more motivated to engage in behaviours that will help them to be accepted or to gain status (Gangestad and Snyder, 2000, Turnley and Bolino, 2001) and, at the same time, are more able to adapt to the feedback they receive from the situation they are in, they may have a transactional advantage compared to their low self-monitoring colleagues, in dealing with their universities' regulations and internal politics. Thus,

Hypothesis 1: The position of a researcher on the self-monitoring scale is positively related to his/her individual engagement with industry.

Having established that self-monitoring exerts a significant influence on academics' propensity to work with industry, we need to investigate whether there are individual or environmental characteristics that can attenuate this relationship.

The effects of hierarchies in academia have been investigated by sociologists in the context of their role in generating and reproducing inequality in social outcomes. This process is caused by the fact that an actor's status is often used as a critical lens through which his/her quality is judged. Individual status is often amplified by specific designations, such as those associated with prestigious prizes or affiliations, creating sudden breaking points in an otherwise smooth quality distribution (Azoulay et al., 2011).

The role of scientific status in university-industry collaboration, therefore, is particular important for two reasons. First, when firms are looking for collaborators, they will look for high-quality researchers capable of delivering good quality results. In some cases, firms may be able to identify the right expert, but often they will need to rely on some measure of reputation in order to guide their search for potential collaborators. It is easier for high-status scientists to make contact with external organizations that require their scientific expertise and want to engage in collaborative activities, as the companies involved can infer the academic's scientific quality from his/her status in the field. Second, the status some scientists acquire in the academic system can generate benefits within both the confined professional community of academia and in other fields. For instance, the annual Nobel Prizes are covered by the mainstream media and the cultural capital of Nobel Prize winners is recognized beyond their professional communities.

Thanks to their reputation, high-status academics have access to a large pool of potential partners: because a large share of academic engagement is initiated based on personal contacts (Louis et al., 1989, Van Dierdonck et al., 1990), the number and reach of the scientist's personal connections are crucial for determining his/her collaboration activities. Moreover, since high profile academics are more visible than their colleagues, they will be more likely to be invited by firms to collaborate even without any proactive seeking of engagement opportunities. This privileged position makes other personal characteristics less relevant in determining the researcher's collaborative behaviours. High-status researchers do not need to actively see out potential partners; therefore, they do not need characteristics such as extroversion and expressiveness, which facilitate contact formation and boundary spanning. For this reason, it is less necessary for high-status academics to be high self-monitors in order to collaborate with industry. On the other hand, an excellent reputation can act as a substitute for those personal characteristics useful for collaborations that low self-monitoring individuals lack. As prestigious academics are very visible even outside academia, it is easier to engage with external actors even for low self-monitors. Thus

Hypothesis 2: The positive relationship between the position of a researcher on the self-monitoring scale and his/her individual engagement with industry will be less pronounced for high status scientists

Understanding individuals' motives to engage in a certain task is important because they are correlated to task performance (Cockburn et al., 1999, Prendergast, 1999). Motives can be defined as individuals' preferences for the benefits that can be derived from engaging in a certain activity (Sauermann and Cohen, 2010). The psychology literature categorizes motivational factors as intrinsic and extrinsic motives (Amabile, 1996, Ryan and Deci, 2000). Individuals are intrinsically motivated if they seek benefits that originate within themselves and the task they are performing; they are extrinsically motivated if they value the benefits that are provided by an external entity, such as the market or a superior. Extrinsic benefits do not derive directly from engaging in an activity, they are indirect outcomes and include monetary or other tangible rewards, such as prestige.

This categorization of motives has been extensively employed in analyses of scientists' motivations (Giuri et al., 2007, Katz, 2004, Stephan and Levin, 1992). Intrinsic motivation has long been associated with scientific work (Hall and Mansfield, 1975); however, we cannot ignore that in the scientific reward structure financial remuneration is central. The motivation to be successful in winner-takes-all contests in science can stem from two different (but not mutually exclusive) forces: scientists may want to solve a particular problem because of the intrinsic utility they derive from solving puzzles, alternatively they may be seeking recognition and the associated financial rewards. Academics' income streams can be greatly enhanced by technology transfer and commercialization activities (Stephan and Everhart, 1998). Therefore, if academic researchers put high value on extrinsic benefits in their job, they will be more likely to seek them through engagement in collaboration with private companies. Moreover, researchers working in academia may be motivated by reasons which are not directly related to research. Academics who progress through the university's administrative hierarchy may be seeking status and prestige: the dean of a university enjoys high visibility and a recognition that are independent of scientific merit.

As already highlighted, high self-monitoring academics may engage with industry for a variety of reasons. For example, if they are socially ambitious and keen to gain prestige, they may try to associate with high-profile companies to improve their image both inside and outside academia. Since their actions are often directed towards impressing others, they may engage in behaviours considered appropriate in their environment, independent of their personal assessment of the value of such behaviours. Low self-monitoring academics, on the other hand, tend to be "true to themselves" and to behave in a fashion consistent with their core values and beliefs. If a low self-monitoring researcher is extrinsically motivated, it means that she/he will actively look for extrinsic benefits (such as financial remuneration and prestige) in order to remain faithful to his/her personality and behaviours. This means that highly extrinsically motivated individuals will seek collaboration with industry independent of any personal characteristics that might facilitate this relationship. At the same time, self-monitoring will differentiate individuals who are not extrinsically motivated. Low self-monitoring scientists who are not driven by extrinsic motives will tend not to engage with industry: they lack the personal characteristics that ease the relationship, and such engagement is not aligned with their own inner motivations. For high self-monitors, this misalignment between motives and academic engagement is less important: they will collaborate with industry in any case. Thus,

Hypothesis 3: The positive relationship between t*he researcher's position on the self-*monitoring scale and his or her individual engagement with industry will be less pronounced for scientists extrinsically motivated in their profession.

Finally, it is possible that the environment may influence the importance of self-monitoring in facilitating individuals' engagement with industry. The literature shows that the presence of formal support mechanisms facilitates academic collaboration with firms and engagement in knowledge transfer activities (Landry et al., 2006, Lockett and Wright, 2005, Siegel et al., 2003). Working with industry, and commercializing research are activities that require different skills from the traditional academic repertoire (Owen-Smith, 2003). Making contact with potential industrial partners, managing relationships in fruitful ways and recognizing the economic or technological value of scientific findings are non-trivial activities that can benefit from organizational support. On the other hand, in environments that are not organized to provide support for collaboration activities, or which do not provide encouragement for academics to engage with industry, researchers have to rely on their personal skills and efforts to make contact with possible collaboration partners (Owen-Smith and Powell, 2001, Van Dierdonck, Debackere and Engelen, 1990).

Psychological climate theory claims that individuals tend to respond primarily to cognitive representations of the environments rather than to the actual environment (James et al., 1990, James and Sells, 1981). This means that academics' engagement with industry may be influenced by their perception of the level of supportiveness of the environment they operate in, rather than the level of resources actually available to facilitate collaboration. Given the centrality of departments in academic life, the support researchers perceive from their department of affiliation is crucial for determining their choices of behaviours. It has been shown that being embedded in an academic department with a culture that is supportive of entrepreneurial activities can counteract the disincentives created by a less than strongly supportive university environment (Kenney and Goe, 2004).

High self-monitoring academics possess some specific characteristics that ease their contact with external organization and interactions with different actors. It is less important for them to feel supported by their department. On the other hand, if departments are very supportive of academic engagement, and opportunities for collaboration are abundant, even those individuals who do not possess the characteristics that normally would allow them to be successful in finding suitable partners and to establish collaboration projects can be overtaken by a "tidal wave" of engagement, thus

Hypothesis 4: The positive relationship between the position of a researcher on the self-monitoring scale and his/her individual engagement with industry will be less pronounced for scientists who perceive their departments to be supportive of engagement with industry.

DATA AND METHODOLOGY

Data

To explore my hypotheses, I draw on a unique dataset covering a population of 6,200 academic researchers in the UK. I compiled the dataset from multiple sources.

First, I obtained information on this population from the records of principal investigators and co-investigators in projects funded by the UK Engineering and Physical Sciences Research Council (EPSRC) in the period 1992-2006. The EPSRC is the largest funder of research in the UK, especially in the fields of engineering, mathematics, chemistry, and physics. These data are comprehensive and cover all academics awarded EPSRC grants in the UK over a period of 15 years.

Second, I administered an internet-based survey to all the academics identified as grant holders in the EPSRC records and who, at the time of my fieldwork, were still listed on their university website as being active academics. The questionnaire covers various aspects of researchers' engagement with industry, such as engagement types and frequencies, and attitudes towards engagement, as well as individual motives and traits. The survey was built on and extends previous surveys of academics, including surveys conducted by D'Este and Patel (2007) in the UK, and the Research Value Mapping Program in the US (Bozeman and Gaughan, 2007, Link et al., 2007). A pilot study was conducted with 30 academics at Imperial College London. I administered the full questionnaire between April and September 2009. I sent a letter signed by the EPSRC's Chief Executive Officer and followed it a few days later with a personalized link to access the survey. Non-respondents were sent (up to two emails) and also received telephone reminders. This yielded a total of 2,194 completed questionnaires (34% response rate).

Third, to capture details of respondents' scientific productivity over their career, I collected extended bibliographic information on individuals from the ISI Web of Science, including number of journal articles, number of citations, journal names and associated disciplines.

Fourth, I matched my sample with the population of academics included in the Research Assessment Exercise (RAE) conducted in 2008 (HEFCE et al., 2008). The RAE was a government-mandated programme to assess the quality of research of all universities and colleges in the UK; its results were used to determine the allocation of research funding to universities other than that received through competitive bidding for grants. RAE submissions contain information on individuals' 'units of assessment' (usually their departments), including their size and the amount and nature of funding received from 2001 to 2008.

Finally, I matched the universities included in the sample with data derived from the government's Higher Education-Business and Community Interaction Survey (HE-BCI) conducted in 2008 and covering the years 2005-2007 (HEFCE, 2008). This annual survey collects financial and output data at the university level, on a range of activities from commercialization of new knowledge, the delivery of professional training, consultancy and services, to community-oriented activities.

I performed several checks on the sample used in the analysis to ensure its representativeness of the population being studied. To ensure reliability of the response pool, I tested for sources of bias in the sample. I performed a Wilcoxon-Mann-Whitney test to check for differences in the typology of university of affiliation of respondents compared to the rest of the sample, and found no significant differences. Since the survey targeted only grant holders, there is a risk of sample selection bias because non-grant holders may behave differently in terms of engagement with industry. Since I do not have information on researchers that did not receive grants in the period 1992 to 2006, as a proxy for non grant holders. I used the group of academics included in the survey who had not been awarded an EPSRC grant in the previous five years (2000 to 2006). I compared their levels of industry engagement with those of academics who had been awarded grants in that period, and found no statistically significant difference.

Dependent variable

My dependent variable captures academics' industry engagement behaviour across different activities. The questionnaire asks how many times the researcher engaged in different kinds of activities in the two years preceding the survey: (1) contract research projects, (2) joint research projects, (3) consultancies, (4) creation of commercial ventures. For the first three items respondents had to indicate frequency: "0 times", "1-2 times", "3-5 times", "6-9 times", "more than 10 times". In order to obtain a continuous variable for the analysis I assigned a numerical value to each frequency category. I decided to take the mid values: for example, for the category "3-5 times" I assumed the value 4 (D'Este and Patel, 2007). I then computed the sum of the number of times academics were involved in each activity. In enquiring about commercial ventures, the questionnaire asked for the exact number of start-ups created. I summed the values to obtain the total number of engagement instances, and a variable measuring individual engagement.

In order to check that results are not dependent on this particular construction of the dependent variable, I run the main model using different specifications of the dependent variable. The results are discussed in the "Robustness checks" section.

Independent variables

The main independent variable is the individual's score on the self-monitoring scale. Self-monitoring was measured using the 18-item scale developed by Snyder and Gangestad (1986). The scale includes items such as "In different situations and with different people, I often act like very different persons", and "I can only argue for ideas which I already believe" (reverse coded). Individuals were asked to rank the items as true or false relative to themselves. Items were scored zero if individuals answered true on reverse coded items and 1 otherwise (and vice versa); they then were summed (α=0.73). High scores indicate respondents are higher up the self-monitoring scale.

To analyse the contingencies of the relationship between self-monitoring and engagement with industry, I interacted the main independent variable with two individual-level variables and one environmental-level variable.

High-status academics are defined as researchers who are fellows of the Royal Society or the Royal Academy of Engineering. The Royal Society is the oldest scientific academy in the World – it was founded in 1660 – and awards fellowships each year to 44 of the best scientists in recognition of their achievements. There are currently 1,400 Fellows, 60 of whom are Nobel laureates. The Royal Academy of Engineering includes the UK's most eminent engineers. Each year up to 60 Fellows are elected on the basis of nominations by the existing Fellows. Fellowship in these societies brings high visibility and prestige outside academia, in part because Fellows are allowed to append their membership of the Society to their titles. I chose affiliation to the Royal Society or The Royal Academy of Engineering because, although correlated to scientific productivity, it represents a distinct and visible shock that greatly amplifies the status of the academic even outside academia (Azoulay, Stuart and Wang, 2011).

Extrinsic motives are measured by a question that asks researchers to rate the importance (on a 5-point Likert scale) of a set of benefits deriving from their profession as researchers, going from salary to intellectual challenge. The items are extracted from the Survey of Doctorate Recipients[1] conducted by the National Science Foundation in the US (Sauermann and Cohen, 2010). Factor analysis (principal component-factor, orthogonal varimax rotation) identified a factor comprising four items (salary, benefits, job security, opportunities for career advancement), which summarize extrinsic motives (α=0.73).

Finally, I measured the level of support for industrial engagement in the department from the responses to a question asking researchers to state their agreement, on a 5-point Likert scale, (from strongly disagree to strongly agree) to four statements: “My department is very effective is supporting collaboration with industry”, “My department is an obstacle in the collaboration with industry” (reverse coded), “My department reward me for working with industry”, and “My department actively encourages me to work with industry”. Items were assigned a value of 1 if the researcher scored them 4 or 5 (1, 2 or 3 in the case of the reverse coded item). To obtain the variable departmental support, scores were summed (α=0.78). I use a subjective measure of departmental supportiveness in order to capture individual perceptions of the assistance received in collaborating with industry since this is a powerful predictor of researchers’ willingness to engage in technology transfer activities (Owen-Smith and Powell, 2001). I specified the same model using as a proxy for availability of opportunities in the department for engagement with industry, the amount of industry funding per employee received by the department in the year preceding the survey. The results are discussed in the “Robustness checks” section.

Control variables

I include in the model several controls at the individual, department and university levels, to take account of individual and environmental effects observed previously to have an effect on the behaviour of academics towards activities with industry.

The first group of control variables relates to the researcher’s individual characteristics. I include a set of characteristics for researchers such as gender, academic age (defined as current age minus their age at PhD award), and their academic rank (coded as a dummy which identifies the group of professors). Link et al. (2007) find a positive effect of

[1] http://www.nsf.gov/statistics/srvydoctoratework

being male and having tenure, on collaboration activities with industry, while, according to Bercovitz and Feldman (2008), the longer the length of time since completing their PhD degree, the less likely researchers will be to embrace commercialization behaviours. I control also for number of years of work experience in the private sector (industry experience) because researchers who have worked as employees in industry might be expected to have a better understanding of the private sector's modus operandi. I include the number of publications in the five years preceding the survey on which the academic appears as an author (publications) and the total amount of research funds received from the EPSRC in the period 2000-2006 standardized by average level of funding in the researchers discipline (grants). To control for training effects, I include a dummy variable identifying a holder of a British doctoral degree (British PhD). The researcher's scientific discipline is taken into account by introducing a dummy variable (basic discipline) identifying basic disciplines (mathematics, chemistry, physics). The researchers' scientific fields tend to define the extent of their engagement in collaborative activities with industry: more applied fields of science, such as engineering, make collaboration more likely (Lin and Bozeman, 2006). It has been observed also that for researchers working within the so-called Pasteur's Quadrant (Rosenberg and Nelson, 1994), practical problems provide a powerful stimulus for the development of new ideas (Stokes, 1997). I also include a variable for intrinsic motives, obtained through factor analysis of the items related to the benefits deriving from their profession as researchers (as in the case for extrinsic motives). Adherence to the traditional academic norms of openness may influence scientists' attitudes to collaboration: agreement with the values of academic capitalism (as opposed to Mertonian values) strong predictors of involvement with industry (Renault, 2006).

A second group of variables is related to department and university characteristics. I include in the regressions department research quality (measured as the percentage of staff rated 4* and 3* in RAE 2008) and total income received from industry per FTE (full time employee) in 2005-2007 (department industry funds). I take account of the profile of the universities in the sample by introducing measures of their quality based on the overall RAE 2008 score (university research quality) and I control for institutional involvement in commercialization and collaboration activities including the income received by the university from industry, per employee, in the period 2005-2007 (university industry funds). Institutional support has become more relevant for fostering collaboration between universities and industry and facilitating the technology transfer process. From the late 1980s, when researchers considered that personal networking efforts with industry were more effective than institutionalized transfer mechanisms (Arvanitis et al., 2008, Landry, Amara and Rherrad, 2006, Lee, 1996), we observe a shared belief that collaboration and entrepreneurial activities are enhanced by the presence of formal support infrastructures and institutional incentive mechanisms (Van Dierdonck, Debackere and Engelen, 1990), with those at department or research group level having a stronger effect (Baldini, 2007, Chrisman et al., 1995, Landry, Amara and Rherrad, 2006, Owen-Smith and Powell, 2001, Renault, 2006, Sellenthin, 2009, Yang et al., 2006).

Estimation

In order to investigate the impact of self-monitoring on individual industrial engagement, I use an ordinary least squares (OLS) model. This kind of model assumes a normal distribution of the dependent variable: I therefore employ the natural logarithm of individual engagement. To address the possible problem of heteroschedasticity, I use robust standard errors. Finally, OLS models assume that standard errors are independently and identically distributed: if errors are clustered, OLS estimates are unbiased, but standard errors may be incorrect, leading to incorrect inferences. Since the respondents in my sample come from different disciplines, I can expect some group correlation that is unobservable; therefore I cluster errors by scientific discipline. As a robustness check, I clustered errors also by department and university; the results were consistent with the main specification. All continuous variables (with the exception of the dependent variable) are standardized to facilitate comparison.

RESULTS

Tables 1 and 2 present the descriptive statistics and correlations for the variables employed. Correlations are generally low to moderate; therefore multicollinearity is not a problem in the estimations.

Table 3 presents the results of the econometric analysis. Model (1) provides a baseline model (controls and moderators) with the natural logarithm of the number of collaboration activities with industry as the dependent variable. Gender presents a significant coefficient in the regression. Women seem to collaborate less with industry (Ding et al., 2006, Murray and Graham, 2007, Thursby and Thursby, 2005); ceteris paribus, women engage with industry 13% less than men. Academic age has a negative and statistically significant effect: as observed by Bercovitz and Feldman (2008) the earlier the researcher completed his training, the less likely s/he will be to engage in collaboration activities with industry. Being a professor has a positive and strong effect on the level of engagement with industry (Link, Siegel and Bozeman, 2007). Ceteris paribus, professors engage 26% more than non-professors. As expected, work experience in the private sector is also positive and significant (Audretsch, 1998). The number of publications in the five years preceding the survey has a positive and significant effect on engagement with industry, while the amount of funding received from the EPSRC is not statistically significant. Academics trained in the UK are significantly more likely to engage with industry than those who received their training in another country. Interestingly, being affiliated to a basic discipline does not have a significant effect on engagement; the literature highlights how different fields of science present different technological opportunities and, therefore, different patterns of university-industry interaction (Link, Siegel and Bozeman, 2007). Being intrinsically motivated as an academic is not significant in determining engagement with industry. Scientific quality at both department and university level is not significant, while the amounts of department and university funds coming from industry are positively correlated with individual engagement. Faculty members from departments or universities involved in high levels of commercial activities are more likely to engage in collaboration with industry because they benefit from more opportunities.

For the variables later employed as moderators, I find that high-status academics seem to collaborate more with industry: this is a function of the esteem they enjoy outside the academic world, which makes them more visible to possible industrial partners and, therefore, more likely to receive offers to collaborate. High-status academics collaborate with industry 12% more than their less visible colleagues. Extrinsic motives are positively and significantly correlated with industry engagement: academics who are motivated by tangible rewards and benefits provided by an external entity are more likely to engage in collaboration activities that increase their utility in tangible terms (Stephan and Everhart, 1998). Finally, academics who perceive that their department is supportive of industry engagement activities are more likely to collaborate with industry partners: as observed in previous studies, support mechanisms at the level of the organization facilitate collaboration between academics and firms, not only by giving practical support but also by creating a favourable institutional culture (Owen-Smith and Powell, 2001).

Model (2) builds on the previous baseline specification by adding the variable capturing the individuals' score on the self-monitoring scale. The influence of self-monitoring is positive and significant, suggesting that high self-monitoring individuals engage more intensively in collaboration with industry, as predicted by H1. In particular, a standard deviation increase in the self-monitoring score increases individual engagement with industry by 5.2%, ceteris paribus. The effect is not as strong as other individual determinants, but it is relevant. All the control variables maintain the same effect as in the baseline model.

In Model (3), I test H2 by introducing status as a moderator. As predicted the effect of the interaction term on self-monitoring is negative and significant, confirming the hypothesis. Figure 1a shows the predicted relationship between self-monitoring and academic engagement for high-status versus non-high-status scientists. High-status scientists are highly visible vis-à-vis audiences other than academia and they possess the resources necessary to seek engagement opportunities: the effect of self-monitoring on their engagement activities is therefore almost irrelevant. Low self-monitoring academics who are affiliated to prestigious scientific bodies have easier access to a large pool of opportunities for collaboration, which facilitates their engagement activities with industry, compared to their low self-monitoring colleagues who do not enjoy the same status. Figure 1b illustrates the significance of the moderation effect along the range of possible values of the independent variable. In analysing a moderation effect, we are comparing difference in the values of the dependent variable for a certain group (i.e. high-status academics) with the values of the dependent variable for another group (i.e. non high-status academics). In order to understand if the difference is significant along the whole range of values that can be assumed by the independent variable, we need to take account of the effect of the independent variable on the dependent variable, which is conditional on the values that the moderator takes. This has implications for the variance of the marginal effect of self-monitoring of academic engagement (Brambor et al., 2006). The confidence interval of the difference between the effect of self-monitoring on engagement for the high-status group versus the non-high-status group was computed following Zelner's (2009) methodology and code for STATA. In this particular case, the difference between the two groups is significant only for low values on the self-monitoring scale (up to 6): this means that after that value the slopes for the two groups are not statistically different.

Model (4) includes extrinsic motives as a moderator. The interaction term with self-monitoring is significant and has negative sign, confirming H3. Figure 2a shows the predicted relationship between self-monitoring and academic engagement for highly extrinsically motivated scientists versus low extrinsically motivated researchers. Extrinsically motivated scientists value the benefits derived from by external entities, and real rewards. Collaboration with industry can provide researchers with tangible rewards in terms of increased funds for their lab and for themselves. Low self-monitoring individuals tend to behave in a way that is always consistent with their core values and beliefs; therefore, if a low self-monitoring researcher is extrinsically motivated, it means that s/he will actively seek out extrinsic benefits, for example, by engaging with industry. The statistical significance of the difference between the two groups is shown in Figure 2b.

Model (5) tests H4 by including departmental support as a moderator. The hypothesis is confirmed as the sign of the interaction term for self-monitoring is negative and significant. Figure 3a shows the predicted relationship between self-monitoring and academic engagement, for scientists in supportive environments versus scientists working in not supportive departments. When the department is perceived as munificent in the provision of resources and support to foster engagement with industry, then the opportunities for collaboration are more easily accessible to everyone and individual differences in the ability to work across organizations and to manage collaboration activities become less relevant. The statistical significance of the difference between the two groups is shown in Figure 3b.

Finally, Model (6) tests the full moderated model. Results remain consistent and the explanatory power improves compared to the model including only the main direct effect (Model 2), with R^2 increasing significantly from 0.194 to 0.205 (F test=2.77, p-value=0.048).

ROBUSTNESS CHECKS

I performed several robustness checks to confirm the reliability of my results. I performed the same econometric analysis using different versions of the dependent variable. Different engagement activities require different levels of effort from academics and some activities are more frequent than others. In this case, research contracts and consultancies are more frequent than the creation of a new commercial venture. For this reason, I construct a dependent variable that takes account of the infrequency and difficulty of certain items. This variable is a modified version of the index developed by Bozeman and Gaughan (2007) and is constructed as follows. First, for every type of industry engagement, I established whether a researcher had collaborated or not (occurrence), then I computed the frequency for each type of engagement for the whole population. I constructed the index by multiplying the actual number of interactions declared by each academic for each channel and the frequency of their non-occurrence in the population and summed the scores. The results using this weighted dependent variable remained consistent with the main specification. To ensure the results were not dependent on the choice to use the mid value for the categories of different channels of engagement, I constructed the same variable using the lower value in the categories. Results are consistent with the main specification.

Finally, as the moderating variable to test H4 measures academics' perceptions of departmental support, I tested the hypothesis using a more factual measure of departmental munificence. I interact self-monitoring with the amount of funds the department received from industry in the year preceding the survey (per employee). I assume that a department that is heavily funded by industry will encourage its members to collaborate with private companies. The sign of the moderation is consistent with the main specification but is no longer statistically significant. I decided to keep the subjective measure of support in the main model because, in my view, it is a more accurate measure of individuals' perceptions of the opportunities available to them. In the case of department funds from industry I use the average value; however, I have no information that allows me to assess whether funds are homogeneously distributed in the department (signalling that, in effect, there is explicit support for engagement activities) or whether they are concentrated in the hands of few researchers. In the latter scenario, these funds may be measuring the ability to attract resources of only a few individuals, independent of the environment in which they operate, but not the actual opportunities to which all other academics are exposed.

DISCUSSION

My analysis suggests that self-monitoring may be a relevant factor in explaining academics' engagement with industry. High self-monitoring individuals are socially ambitious, adaptable and good at boundary spanning: therefore, they tend to collaborate more with industry than their low self-monitoring colleagues across various channels of interaction. Also, the influence of self-monitoring on researchers' collaboration activities is moderated by individual and environmental characteristics. For high-status researchers who have achieved high visibility outside academia, the influence of their self-monitoring score is less pronounced. The same applies to academics who are extrinsically motivated in their job and who value tangible benefits. Individuals who operate in an environment which is very supportive of industrial engagement need to rely less on their self-monitoring profiles because opportunities are readily available to everyone.

My study makes several contributions. First, I add to the work on university-industry relations and commercialization of university technologies. Scholars have pointed to the need to pay greater attention to the microfoundations of university-industry collaboration (Rothaermel et al., 2007). While several studies investigate the psychology of scientists, at the individual level the literature on university-industry collaboration focuses mainly on demographic characteristics and productivity. Some scholars point out that individuals in organizations may outperform their peers because of differences in personality (Mehra, Kilduff and Brass, 2001). While my findings confirm the role played by some key demographic characteristics, in particular academic rank, industry experience, gender and academic age, by analysing the effect of self-monitoring on academics' engagement with industry, I provide novel insights on the individual determinants of engagement activity, and especially the effect of researchers' personality. Self-monitoring theory provides compelling evidence suggesting that self-monitoring is a relatively stable trait across a life time; it is possible, therefore, to advance some causality claims about the relationship between self-monitoring and academic engagement.

My study also provides a broader view of academic engagement, encompassing several collaboration mechanisms in addition to academic entrepreneurship. A large part of the literature on university-industry interactions analyses the incidence and impact of filing patents and founding spin-offs by academic scientists (Agrawal and Henderson, 2002, Shane, 2002). Patents, licensing and new venture creation are clearly relevant means of technology transfer, but they are also less frequent than forms of interaction, such as joint research projects and consultancy agreements (Agrawal and Henderson, 2002, D'Este and Patel, 2007, Gulbrandsen and Smeby, 2005, Louis, Blumenthal, Gluck and Stoto, 1989). While entrepreneurship is an "extreme" commercialization behaviour, which requires a huge effort and a specific set of skills, academic engagement through joint research projects and consultancies is activity that requires different and more nuanced involvement with industry and may be within reach of a larger share of academics.

Finally, from a policy perspective, because collaboration with industry represents discretionary behaviour among academics, and the individual willingness to participate in knowledge transfer is what eventually determines its success, it is important to understand who in the university is more likely to engage with industry. Recognizing that individuals are different and that their personality differences affect the way they see opportunities and respond to incentives, is crucial for the design of effective mechanisms to foster technology transfer activities. A one-size-fits-all approach may not be an efficient way to promote collaboration with industry because the differences between individual researchers, both in terms of their characteristics and motivations, make them sensitive to different kinds of incentives and different levels of support. This does not mean that only individual characteristics matter for determining academic engagement with industry or that the only viable option is to pre-select individuals with the characteristics that will make them more likely to collaborate with private companies. For example (as in the case presented in this study) low self-monitors, who would naturally be less inclined to participate in technology transfer, can be supported in this activity through their organization, which needs to make the opportunities for collaboration more accessible to its members.

Limitations and future research

This study suffers from some limitations which suggest avenues for future research. First, although I have shown that high self-monitoring individuals are more at ease in boundary spanning roles required for activities involving industry, I cannot make any claims about differences in scientific productivity. Future research should explore whether differences in personality contribute to different trajectories in terms of scientific research. Second, my analysis provides insights into the relationship between self-monitoring and the number of instances of collaboration between researchers and industry. Some of the personal characteristics associated with self-monitoring may also contribute to the success of these collaborations. We can imagine that since high self-monitors are better at understanding the feedback they receive from certain situations, they will also be better at managing collaboration activities, making them smoother and consequently more successful. On the other hand, low self-monitors are generally more committed to the relationships they initiate: it is plausible then that after embarking on engagement with a specific partner, they will be especially dedicated to the project, which will lead ultimately to high levels of trust. Future research could try to unpack this relationship between self-monitoring and the quality of the interaction in order to deepen our understanding of the mechanisms that lead to repeated collaboration between certain academics and companies.

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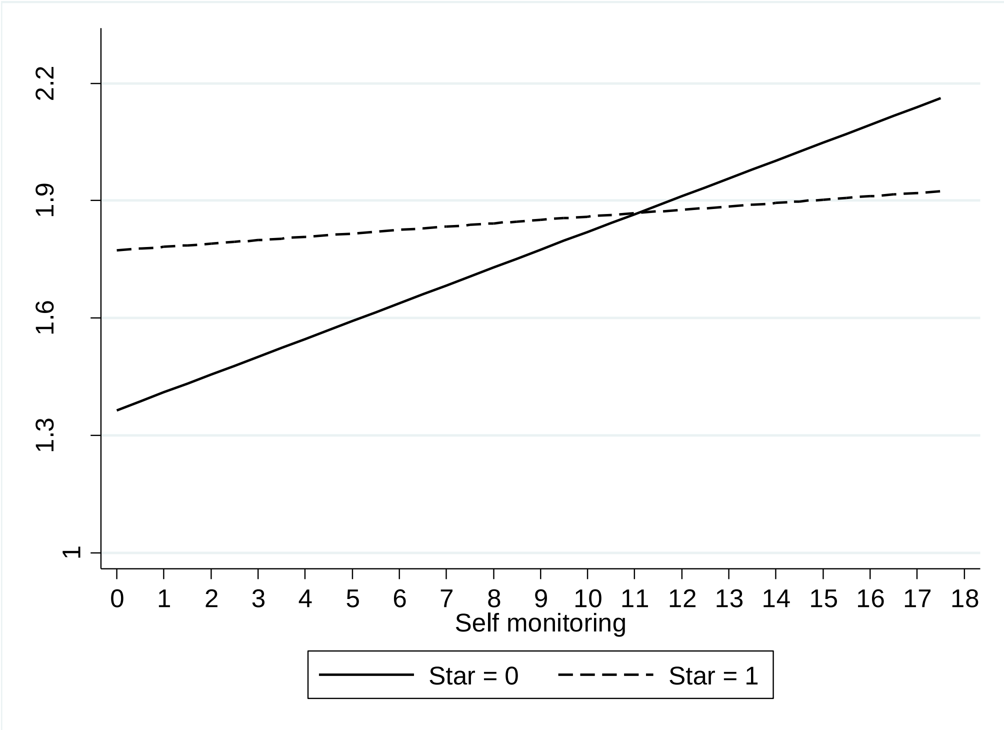
FIGURES AND TABLES

Figure 1a: Relationship between self-monitoring and academic engagement, high-status vs. non high-status



Notes: all continuous variables set at mean value, female=0, professor=1, UK PhD=1, Basic= 0

Figure 1b: Difference in academic engagement between high-status and non high-status, by self-monitoring (95% confidence interval)

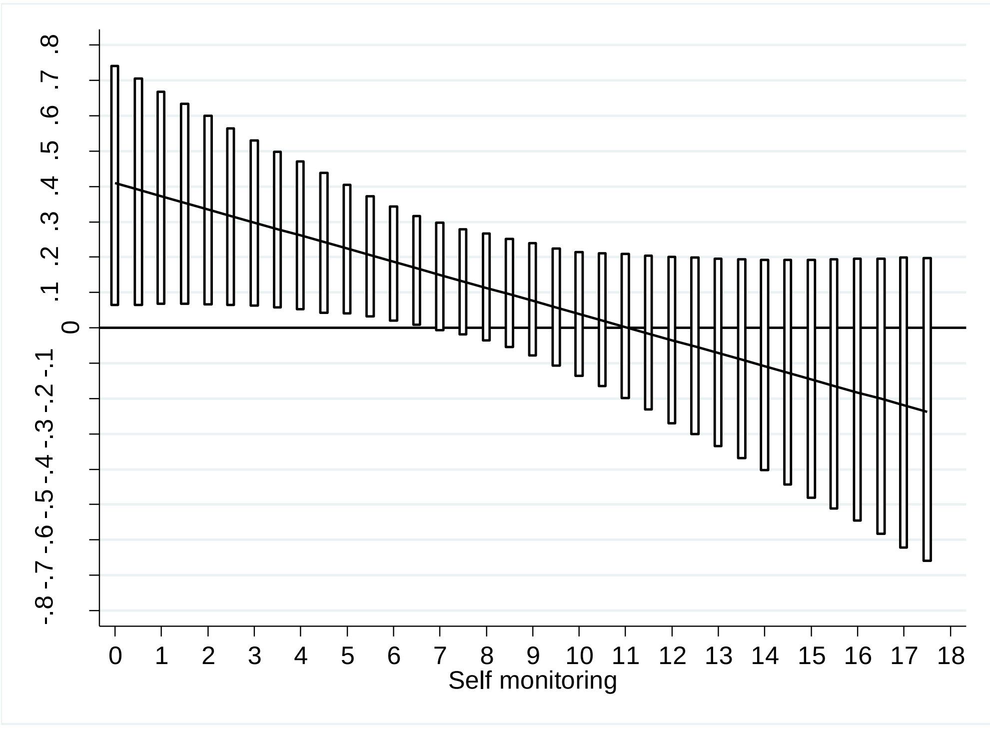
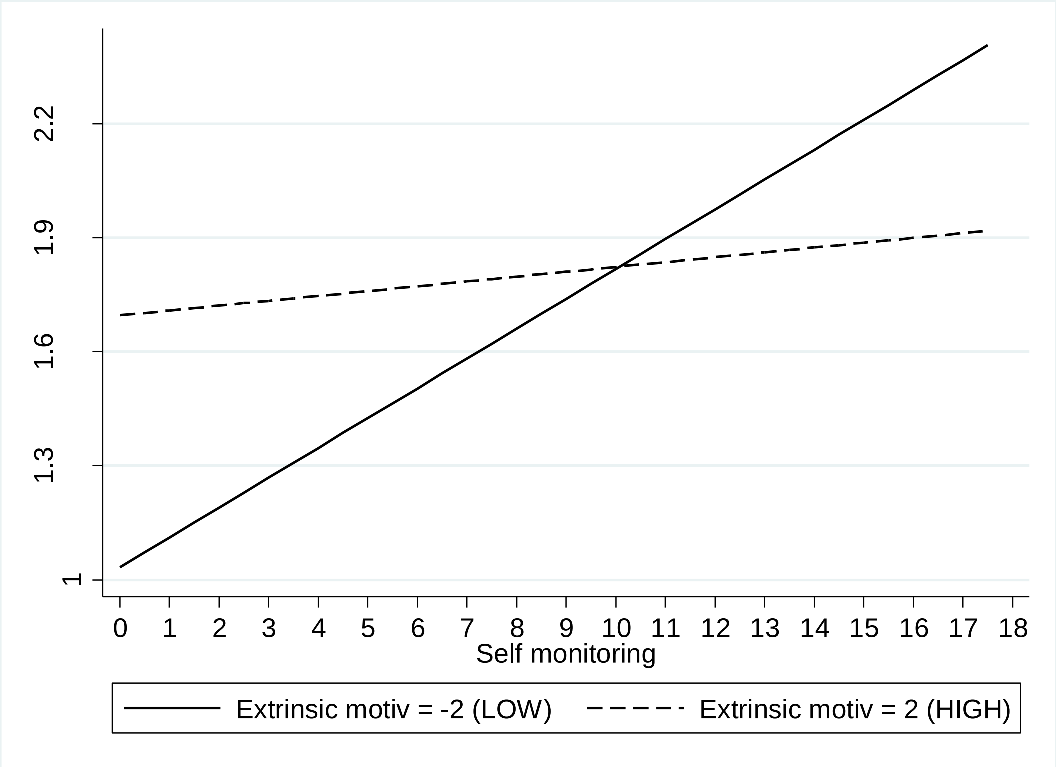


Figure 2a: Relationship between self-monitoring and academic engagement, high extrinsic motives vs. low extrinsic motives



Notes: all continuous variables set at mean value, female=0, professor=1, UK PhD=1, Basic= 0, star=0

Figure 2b: Difference in academic engagement between high extrinsic motives and low extrinsic motives, by self-monitoring (95% confidence interval)

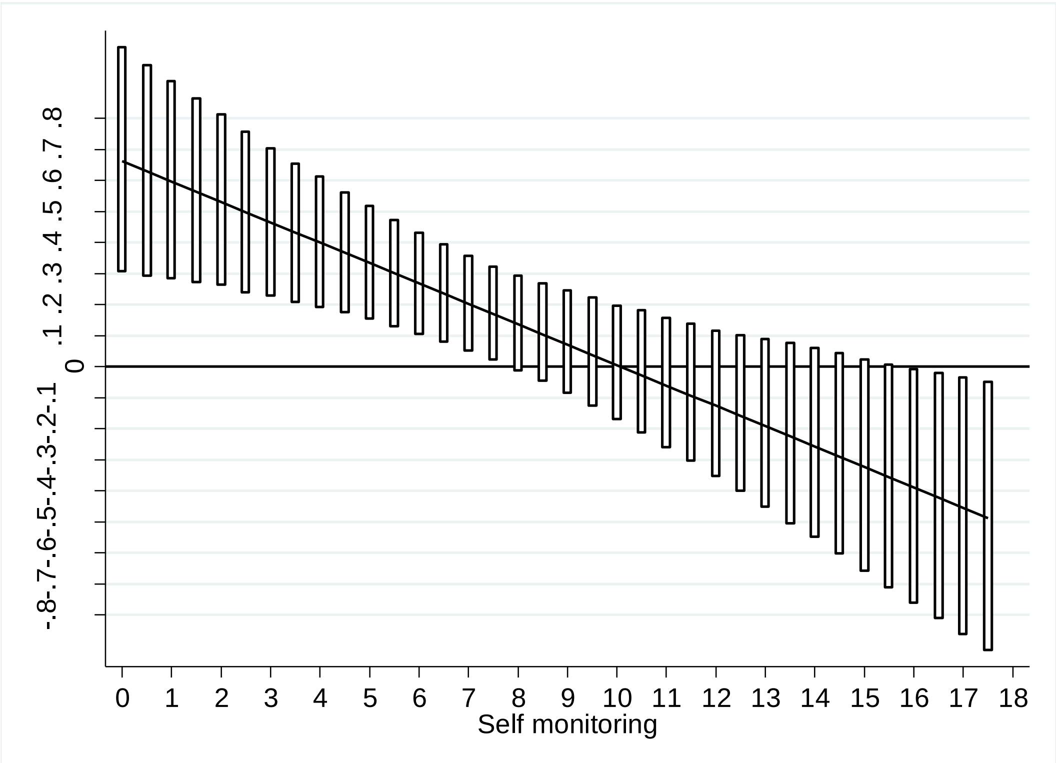
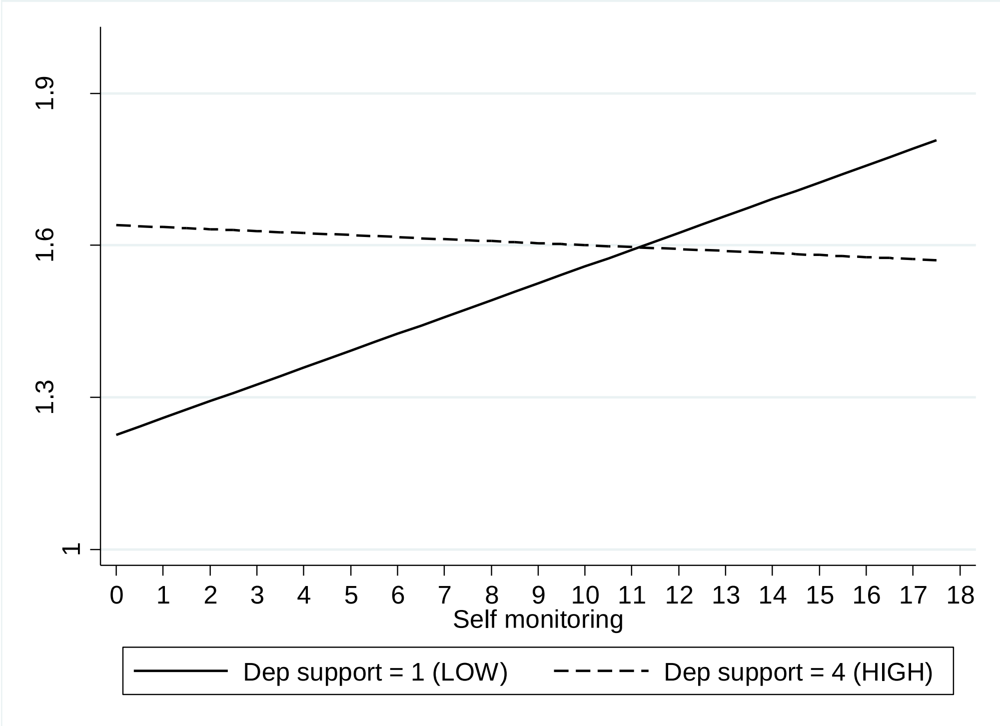


Figure 3a: Relationship between self-monitoring and academic engagement, high department support vs. low department support



Notes: all continuous variables set at mean value, female=0, professor=1, UK PhD=1, Basic= 0, star=0

Figure 3b: Difference in academic engagement between high department support and. low department support, by self-monitoring (95% confidence interval)

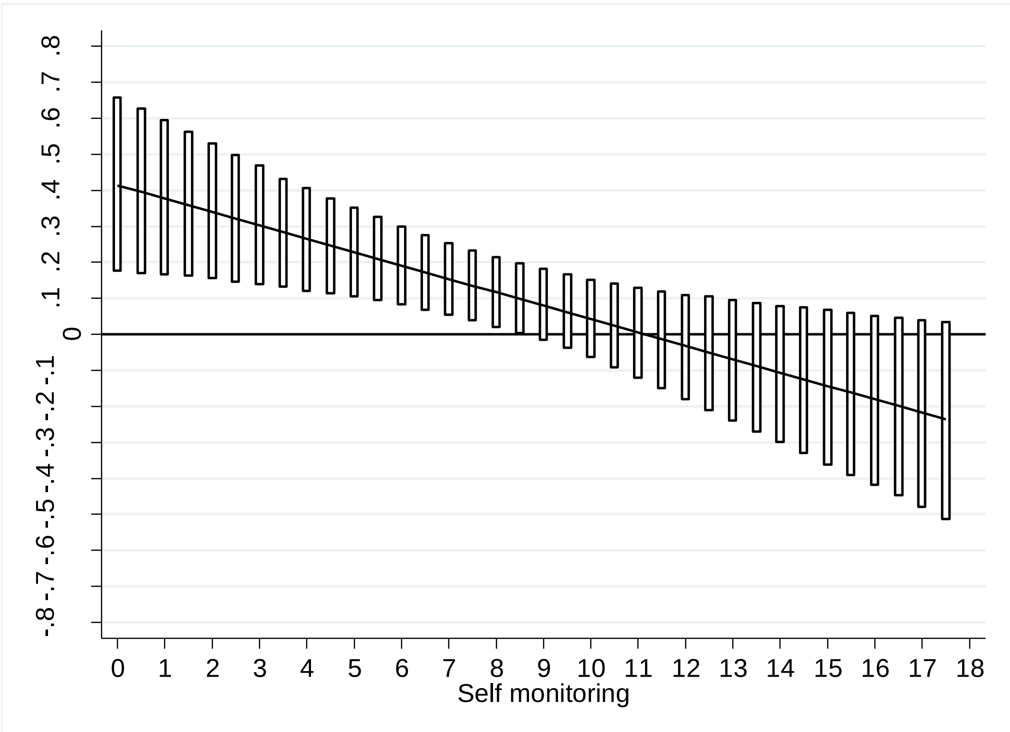


Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Individual engagement	1081	1.31	0.82	0	3.43
Female	1081	0.11	0.32	0	1
Academic age	1081	20.50	9.71	2	55
Professor	1081	0.51	0.50	0	1
Industry experience	1081	2.85	5.20	0	40
Publications	1081	24.29	25.80	0	393
Grants	1081	880976	2004434	1016.4	3.10E+07
UK PhD	1081	0.84	0.37	0	1
Basic discipline	1081	0.37	0.48	0	1
Intrinsic motive	1081	0.02	0.99	-4.72	1.84
Department quality	1081	62.53	15.62	10	95
Dept. industry income	1081	11107.74	12311.12	-175.96	64556.93
University quality	1081	2.67	0.21	1.75	3.15
Univ. industry income	1081	27.66	18.46	1.84	95.59
High-status	1081	0.07	0.25	0	1
Extrinsic motive	1081	0	1	-3.84	2.60
Department support	1081	2.32	1.16	0	4
Self-monitoring	1081	7.88	3.57	0	18

Table 2: Correlation Matrix

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
[1] Individual engagement	1.00																	
[2] Female	-0.07	1.00																
[3] Academic age	0.07	-0.18	1.00															
[4] Professor	0.17	-0.12	0.53	1.00														
[5] Industry experience	0.21	-0.08	0.11	0.06	1.00													
[6] Publications	0.10	-0.03	0.17	0.27	-0.07	1.00												
[7] Grants	0.08	-0.05	0.16	0.21	0.04	0.18	1.00											
[8] UK PhD	0.16	0.01	0.11	0.07	0.09	0.04	0.10	1.00										
[9] Basic discipline	-0.19	0.01	0.03	0.05	-0.11	0.10	0.08	-0.09	1.00									
[10] Intrinsic motive	0.03	0.11	-0.07	0.01	-0.07	0.08	-0.01	0.00	0.08	1.00								
[11] Department quality	0.04	0.00	0.02	0.01	0.00	0.08	0.09	0.05	-0.18	0.00	1.00							
[12] Dep. industry income	0.27	0.01	0.05	-0.03	0.11	0.04	0.02	0.10	-0.36	-0.02	0.24	1.00						
[13] University quality	-0.08	0.02	0.01	-0.01	-0.08	0.14	0.09	-0.01	0.13	0.04	0.63	0.09	1.00					
[14] Univ. industry income	0.16	-0.02	0.02	0.04	0.09	-0.04	0.06	0.02	-0.12	-0.08	0.03	0.27	-0.06	1.00				
[15] High-status	0.11	-0.05	0.31	0.24	0.06	0.20	0.18	0.09	-0.07	-0.03	0.16	0.12	0.14	0.07	1.00			
[16] Extrinsic motive	0.06	0.00	-0.07	-0.03	-0.05	0.03	0.02	-0.02	-0.01	-0.02	-0.06	0.04	-0.07	0.03	-0.07	1.00		
[17] Department support	0.13	-0.03	-0.02	0.04	0.01	-0.01	0.05	0.06	-0.11	0.03	0.05	0.17	-0.08	0.03	0.09	0.05	1.00	
[18] Self-monitoring	0.09	-0.03	-0.11	0.02	0.00	0.03	0.06	0.10	0.01	0.02	0.06	-0.01	0.07	0.03	0.00	0.08	0.06	1.00

Table 3: Regression results, standardized variables

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.1318*	-0.1237*	-0.1200*	-0.1272*	-0.1320**	-0.1312**
	(0.046)	(0.046)	(0.045)	(0.045)	(0.043)	(0.041)
Academic age	-0.0687*	-0.0592*	-0.0584*	-0.0610*	-0.0596*	-0.0607*
	(0.024)	(0.025)	(0.025)	(0.024)	(0.026)	(0.025)
Professor	0.2608***	0.2512***	0.2485***	0.2535***	0.2549***	0.2543***
	(0.035)	(0.036)	(0.035)	(0.037)	(0.037)	(0.037)
Industry experience	0.1367**	0.1360**	0.1369**	0.1376**	0.1324**	0.1352**
	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)	(0.035)
Publications	0.0624**	0.0619**	0.0603**	0.0613**	0.0606**	0.0587**
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Grants	0.0134	0.0112	0.0152	0.0123	0.0138	0.0181
	(0.049)	(0.049)	(0.050)	(0.049)	(0.051)	(0.051)
UK PhD	0.2461*	0.2302*	0.2290*	0.2299*	0.2248*	0.2241*
	(0.100)	(0.099)	(0.099)	(0.100)	(0.100)	(0.100)
Basic discipline	-0.1402	-0.1420	-0.1401	-0.1400	-0.1397	-0.1362
	(0.123)	(0.122)	(0.122)	(0.124)	(0.122)	(0.124)
Intrinsic motive	0.0475	0.0471	0.0476	0.0460	0.0506	0.0496+
	(0.028)	(0.028)	(0.027)	(0.027)	(0.029)	(0.027)
Department quality	0.0135	0.0123	0.0124	0.0132	0.0160	0.0165
	(0.032)	(0.033)	(0.033)	(0.034)	(0.033)	(0.034)
Dept. industry income	0.1531**	0.1546**	0.1542**	0.1563**	0.1558**	0.1569**
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
University quality	-0.0719	-0.0752+	-0.0752+	-0.0766+	-0.0745+	-0.0759+
	(0.041)	(0.041)	(0.041)	(0.042)	(0.040)	(0.042)
Univ. industry income	0.0622*	0.0605*	0.0603*	0.0626*	0.0645*	0.0660*
	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
High-status	0.1225+	0.1222	0.1190	0.1267+	0.1209	0.1227+
	(0.091)	(0.093)	(0.089)	(0.093)	(0.094)	(0.091)
Extrinsic motive	0.0409+	0.0373+	0.0381+	0.0365+	0.0360	0.0360+
	(0.026)	(0.026)	(0.027)	(0.026)	(0.027)	(0.026)
Department support	0.0469+	0.0446+	0.0455+	0.0422	0.0476+	0.0457+
	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)
Self-monitoring		0.0520*	0.0610**	0.0569**	0.0484*	0.0617**
		(0.021)	(0.020)	(0.021)	(0.020)	(0.021)
High status*Self-monitoring			-0.1478*			-0.1309*
			(0.062)			(0.061)
Extrinsic mtv.*Self-monitoring				-0.0592**		-0.0593**
				(0.020)		(0.020)
Dept. support*Self-monitoring					-0.0585**	-0.0514*
					(0.020)	(0.020)
Constant	1.0317***	1.0503***	1.0516***	1.0534***	1.0562***	1.0598***
	(0.128)	(0.129)	(0.129)	(0.131)	(0.132)	(0.133)
Observations	1,081	1,081	1,081	1,081	1,081	1,081
R-squared	0.190	0.194	0.196	0.199	0.199	0.205

Notes: Ordinary Least Squares, robust standard errors clustered by discipline. One-tailed tests for main variables, two-tailed tests for controls. $^{+}p<0.10$, $*p<0.05$, $**p<0.01$, $***p<0.001$