Localized norms and academics' industry involvement: The moderating role of age on professional imprinting

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Abstract

This study explores the interaction between professional imprinting and age in the context of industry-science collaboration. Specifically, we examine the impact of localized and personal peer effects on academics' involvement with industry and how these effects are moderated by the career age of the scientist. We suggest that both localized and personal peer effects drive industry involvement but that the effects from such imprinting are more pronounced the more recent the vintage of the scientist's PhD degree is, suggesting that professional imprinting takes place in the early stages of a scientist's academic career. Based on a sample of 343 German academics in the field of biotechnology and publication data from the Science Citation Index Expanded (SCIE), we find that scientists with co-authors who have joint publications with industry personnel are more likely to be involved with industry (personal peer effect). Moreover, we find that the scientist's involvement increases with the share of publications in the scientist's department co-authored with industry personnel (localized peer effect). Only the latter effect turns out to be moderated by scientist's age. While personal peer effects are independent of the scientist's age, localized peer effects emerge for younger researchers.

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1 Introduction

Close interaction between science and industry has become a widespread phenomenon over the last decades, particularly since firms have been increasingly eager to open up their innovation processes in an effort to integrate external knowledge (Chesbrough, 2003). In this respect, universities and public research organizations have been regarded as particularly important collaboration partners because of the novelty and sophistication of the knowledge they can convey (Link et al., 2007). Scientific knowledge does however not spill over automatically to industry for further development and commercialization. Eventually, knowledge and technology transfer relies on the engagement of the individual academic scientist in industry-science activities (Bercovitz and Feldman, 2007). Researchers, for example, need to disclose new knowledge or collaborate with industry. Thus, the transfer is dependent on the individual's decision to actively participate in industry-science activities.

Our research is intended to contribute to the growing body of literature that investigates the factors driving academics to engage with industry (e.g., Meyer-Krahmer and Schmoch, 1998; Link et al., 2007). While existing research has largely focused on individual characteristics, faculty quality or the institutional environment as explanatory factors, this study aims at shedding new light on the effect that the scientist's peers will have through professional imprinting on her decision to get involved with industry (Bercovitz and Feldman, 2008). More specifically, we examine the impact of localized and personal peer effects on academics' involvement with industry and how these effects are moderated by the career age of the scientist. We suggest that a scientist's involvement with industry will increase with the share of publications in the scientist's department co-authored with industry personnel (localized peer effect). Moreover, we expect scientists with co-authors who co-author with industry personnel to be more likely being involved with industry (personal peer effect). However, both effects will be stronger the more recent the vintage of the scientist's PhD, suggesting that professional imprinting takes place in the early stages of a scientist's academic career.

The empirical investigation rests upon on a sample of 343 academic researchers working in the biotechnology field in Germany who were surveyed in 2010. In fact, one of the industries that is particularly knowledge-driven and close to scientific research is the biotechnology industry. Technologic impulses for new products, methods and services frequently occur in scientific institutions or in collaboration between firms and such institutions (e.g., Audretsch and Stephan, 1996; Zucker et al., 2002). Involving scientists from academia is thus more important for firms in biotechnology compared to other sectors (Higgins et al., 2008). In Germany, more than 200 public research institutions, including universities, technical colleges, non-academic research institutions, and sites for state departmental research, carry out research in the field of biotechnology. Public science disposes of an annual budget of about 2.8 billion Euro for biotechnological research. Around 27,000 people were involved in these research activities (BIOCOM, 2010).

The results indicate that professional imprinting plays a major role in shaping scientists' propensity to engage with industry. Both the localized and the personal peer effect turn out to be relevant which confirms and extends prior literature (Bercovitz and Feldman, 2008). However, we also find evidence for the imprinting effect being dependent on the scientist's career age. The more recent the vintage of the scientist's PhD degree, the less likely becomes industry involvement. But imprinting is particularly effective in the early years of the scientist's career. We find that this only pertains to the localized peer effect though, i.e. the scientist's department co-publications, while the personal peer effect is unaffected by the career age.

Our contribution to existing literature is threefold. First, we extend existing studies in the field by disentangling the professional imprinting effect further. We differentiate between effects that stem from localized (department) and personal (co-authors) peers. Second, a possible moderating effect of a researcher's age is neglected in the literature although it might be important for the researcher's "proneness" to imprinting. Third, we do not limit the researcher's commercial activity to a specific type such as the filing of an invention. Instead we consider a broader set of industry-science interactions by using an industry involvement index that comprises five different channels of industry-science interaction.

The remainder of the paper is organized as follows. The next section summarizes the current literature on academic involvement with industry and derives hypotheses. The data, variables and estimation methods are discussed in section 3. The results and concluding remarks appear in sections 4 and 5, respectively.

2 Academic involvement with industry

2.1 Literature Review

It has almost become conventional wisdom that knowledge produced in the public sector constitutes an important ingredient of economic growth and technological progress (Jaffe, 1989; Adams, 1990). Close links to academic research have further been shown to be beneficial for the innovation performance of firms (Cockburn and Henderson, 1998; Belderbos et al., 2004) that have opened up their innovation processes in an effort to integrate external knowledge (Chesbrough, 2003). Universities and public research organizations are particularly important collaboration partners because of the novelty and sophistication of the knowledge they create (Link et al., 2007). Interacting with public science is attractive from the firm's point of view because in-house knowledge production through R&D implies high cost, given the complex and dynamic processes that knowledge creation requires.

Universities offer in this respect access to complementary resources and allow to explore new technological opportunities (Dasgupta and David, 1994). Moreover, firms can hire public scientists to facilitate the transfer of tacit knowledge and to sustain their absorptive capacity for subsequent knowledge and technology transfer activities (Cohen and Levinthal, 1989; Song et al., 2003). In fact, several studies confirm the benefits of interacting with public science for firm performance. Industry-science interaction improves a firm's ability to innovate (Arvanitis et al., 2008) and increases the firm's share of sales with innovative products (Belderbos et al., 2004).

Academics' involvement with industry has been shown to take place through a variety of channels which can be characterized as either formal or informal. Formal involvement is typically based on a patent to be sold or licensed out (Bozeman, 2000; Thursby and Thursby, 2002), collaboration in R&D (Laursen et al., 2010) or industrial consulting (Jensen et al., 2010), while informal channels of interaction might involve joint publication of research results with industry personnel or informal contacts (Link et al., 2007; Grimpe and Fier, 2010). A large body of prior literature has investigated why individual scientists are involved with industry. One of the conceptual lenses adopted in this literature is the *scientific and technical human capital approach*, which recognizes scientific and technical human capital as "individual endowments", tacit and craft knowledge as well as social contacts and networks (e.g., Bozeman and Corley, 2004; Ponomariov and Boardman, 2010). Scientists accumulate scientific and technical human capital with their career age, scientific productivity, hierarchical position and previous successful collaboration with industry (Belkhodja and Landry, 2007). Moreover, scientists who are well connected, i.e. who occupy a central position in professional networks, build up higher scientific and technical human capital as "social capital begets human capital" (Ponomariov and Boardman, 2010: 616). Higher scientific and technical human capital is positively related with higher industry involvement because scientists with a high endowment are assumed to possess a higher ability to carry out research projects together with industry.

Another conceptual lens has focused on the *organizational context*, i.e. the characteristics of organizations that influence a scientist's involvement with industry (e.g., Meyer-Krahmer and Schmoch, 1998; Siegel et al., 2003; Siegel et al., 2004). Several studies have shown that industry involvement depends on the mission and institutional context of public scientists, with differences being particularly pronounced between university-affiliated scientists and those at mission-oriented public research institutes. Schmoch et al. (2000) and Heinze and Kuhlmann (2008) find for Germany that scientists at universities and Max Planck institutes, who are by and large more oriented towards basic research, collaborate less actively with industry than scientists at Fraunhofer institutes who typically conduct application oriented research and are dependent on industry funding. Ponomariov (2008) finds a negative correlation between the scientific quality of university units and their industry involvement. Furthermore, the presence of industry close to the university's location increases industry involvement. In this context, Siegel et al. (2004) argue that scientists require an appropriately designed reward and incentive system in order to be more actively involved with industry. The higher the royalty payments to the scientist, the higher the scientist's propensity to collaborate with industry (Link and Scott, 2005). Moreover, there is considerable evidence that scientists in different scientific fields exhibit different industry involvement (Meyer-Krahmer and Schmoch, 1998; Heinze and Kuhlmann, 2008).

A third approach has focused on the *localized social context* which refers to the physical space proximity to other scientists and professional relationships. Individuals observe people's behavior of their environment and tend to imitate or adopt the observed practice like, for example, the industry involvement of colleagues (DiMaggio and Powell, 1983; Bercovitz and Feldman, 2008). This influential effect has been referred to as professional imprinting. Kenney and Goe (2004) find a positive correlation between the encouragement and support of entrepreneurial activities by the institution (social embeddedness) and the corporate involvement by faculty while comparing the engineering and computer science department of two US universities (Berkeley and Stanford). Bercovitz and Feldman (2008) find for two medical schools in the US that the individual's decision to actively engage in technology transfer by disclosing an invention is influenced by the disclosing behavior of their local peers. Professional imprinting takes also place during the training phase. Scientists who are exposed to technology transfer activities during their graduate training have a higher probability to be involved in these activities later in their careers (Bercovitz and Feldman, 2008). Co-authors are also part of a scientist's social environment since co-authorship ties go along with regular interaction (Stuart and Ding, 2006). Stuart and Ding (2006) show that scientists with co-authors who had become academic entrepreneurs are more likely to become commercially active scientists.

2.2 Hypothesis development

Technology transfer has been shown to rely eventually on the engagement of the individual academic in industry-science activities (Bercovitz and Feldman, 2007; Link et al., 2007). Thus, the transfer is dependent on the individual's decision to be actively involved with industry. In this section we develop hypotheses regarding an individual's attribute, the researcher's academic age, and the social context of the researcher.

Age effect.

Industry involvement is likely to vary with the career age of a scientist, i.e. the time period since the scientist received her PhD. Based on the human capital argument more experienced researchers are likely to possess a higher ability to carry out research projects with industry. More established researchers typically have a larger network of researchers they know, not only in academia but also in industry compared to researchers at an early stage in their career. Social capital, in this respect, begets human capital. Since they have been active in this field for a longer time period more occasions have arisen for them to interact with industry researchers. Moreover, they probably even know researchers who switched from science to industry. Time in this regard is necessary to build up relationships. In fact, Haeussler and Colyvas (2011) find for life scientists in the UK and Germany a positive effect of a scientist's age on commercial activities, including consulting, patenting, and the founding of a firm.

There are however also indications that industry involvement might contradict traditional academic norms and that particularly younger researchers adopt new organizational initiatives. Bercovitz and Feldman (2008), for example, show that the probability of disclosing an invention decreases with the career age for faculty in medical schools in the US. This finding is confirmed by a study of the wine industry (Giuliani et al., 2010). Other research finds no effect at all. Ponomariov and Boardman (2010) cannot detect a significant association between career age and the number of publications with industrial collaborators for researchers affiliated with a university research center. Overall, the effect of a researcher's career age is thus not unambiguous. However, since industry involvement is not a new phenomenon, which is particular true for the life sciences, we expect that a researcher's industry involvement increases with career age. This leads to the first hypothesis:

<u>Hypothesis 1.</u> The scientist's involvement with industry will decrease the more recent the vintage of the scientist's PhD degree.

Professional imprinting effects.

An individual's behavior is shaped by the social environment. Organization theory suggests that based on mimetic isomorphic processes in organizations one entity adopts another entity's practice by imitating it in the belief that the new practice is beneficial because the other entity succeed with it (DiMaggio and Powell, 1983; Giuliani et al., 2010). Transferring this logic to our context implies that individuals observe the behavior of their close environment with regard to industry involvement and imitate the observed practice. In a similar way, social learning theory argues that individuals follow the behavior of relevant peers if they face uncertainty about norms (Bandura, 1986; Bercovitz and Feldman, 2008). Colleagues' behavior provides information of accepted and supported practice (Bercovitz and Feldman, 2007). If involvement with industry is common in one's environment, these activities are likely to be the norm. Thus, the individual decision to engage in commercial activity is most likely not only determined by individual attributes but also influenced by the individual's social environment. Only a few studies have analyzed whether scientists' commercial activity is influenced by their local work environment. Bercovitz and Feldman (2008) find a peer effect for faculty of medical schools on the decision to disclose an invention. Hence, we expect that a scientist's involvement with industry will be influenced by the behavior of the colleagues in the department (*localized peer effect*). We suggest:

Hypothesis 2. The scientist's involvement with industry will increase with the share of publications in the scientist's department co-authored with industry personnel.

Besides departmental colleagues, a scientist's co-authors might be a reference point regarding the norms of behavior. The rationale regarding the local peers can basically be transferred to co-authors. Individuals typically learn from those they frequently interact with (Bercovitz and Feldman, 2008) and co-authorship ties are characterized by frequent interaction. Moreover, researchers choose whom to collaborate with in contrast to colleagues they usually got to work with as long as they do not bear the responsibility for hiring. They might select scientists as co-authors who they respect and trust. Accordingly, the scientist's industry involvement is likely to be influenced by the behavior of the scientist's co-authors (*personal peer effect*). We therefore expect the following relationship:

Hypothesis 3. Scientists with co-authors who have co-authors from industry will be more likely to be involved with industry.

The moderating role of age.

If researchers face uncertainty they follow the behavior of peers as social learning theory suggests (Bandura, 1986; Bercovitz and Feldman, 2008). Since researchers are particularly in the early stages of their career uncertain about the norms, the influence by the social environment might be pronounced for younger researchers. Moreover, younger researchers are probably more open regarding their research agenda and practice. They still have to find and establish "their" place in the research community, and they learn by observing the research practice of others. If industry involvement is practiced by others they might follow and internalize this practice as well and act according to the observed research practice. Therefore, it is reasonable to assume that researchers at the beginning of a career are more susceptible than more established researchers. In addition, young researchers are also more dependent on the department so that in turn they are more eager to conform to the local environment. Established researchers can also observe the behavior of other researchers but are not as influenced by this compared to younger researchers. Influencing older researchers is probably more challenging and they might also not respond to incentives to the same extent as young researchers. Adoption of specific practices is more likely in the training and qualification phase of younger researchers. Bercovitz and Feldman (2007) find that researchers who were exposed to pro-commercialization activities during their training phase (measured by the number of patent applications at the individual's graduate institution during the time of their training) are more likely to adopt this practice in their own career. Thus, we argue that in particular researchers in an early stage of their career will adopt the practice they are exposed to. The influence of the professional environment consequently varies with the vintage of a researcher's degree. The localized peer effect will be stronger the more recent the vintage of the scientist's PhD, suggesting that professional imprinting takes place in the early stages of a scientist's academic career. Hence,

Hypothesis 4. The effect of a scientist's department share of publications co-authored with industry personnel on the scientist's involvement with industry will increase the more recent the vintage of the scientist's PhD degree.

Basically the same argument for a moderating effect of the researcher's age can be applied to the influence of personal peers on a researcher's industry involvement. This leads to the last hypothesis:

Hypothesis 5. The effect of co-authors who have co-authors from industry on the scientist's involvement with industry will increase the more recent the vintage of the scientist's PhD degree.

3 Data and Methods

3.1 Data

To analyze the relationship between age, professional imprinting and industry involvement we make use of a unique and novel dataset. In summer 2010, the Centre for European Economic Research (ZEW) undertook an online survey of academic researchers working in the field of biotechnology in Germany. The population targeted comprised researchers who worked at either a university or a public research institution and who had published at least one paper in a peer reviewed journal in the field of biotechnology. Researchers were identified using journal publications from the Science Citation Index Expanded (SCIE) in the field of biotechnology between 2004 and 2008. The comprehensive list of relevant journals was compiled based the subject categories assigned to each journal. Only authors working at an institution located in Germany are considered. If provided, email-addresses were taken from the publications. Otherwise email-addresses were collected manually from the internet which involved a complex search since only the authors and affiliations located in Germany were known for each publication but not the link between them. In total, we approached 3,359 researchers of whom 458 filled in the questionnaire. After dropping observations with missing values in the variables of interest the empirical investigation rests upon a sample of 343 researchers.

The publication data from the SCIE not only conveys information about the publication activities of the individual researcher between 2004 and 2008 but also about the departmental publication activities through the mentioned affiliations on a publication. After harmonizing the affiliations we constructed a measure for each institution with the number of publications originating in the specific institution. For universities this measure is on department level; for public research institutions it is on the institution level. The department's or institution's publication record is linked then to the researcher.

Furthermore, we identified the region where the scientist's institution is located to control for the regional environment. To allow for a reasonable size the region is defined as the district (NUTS-3) in which the scientist's institution resides plus the immediate neighboring districts. Regional information on the GDP per capita and the number of plants is collected and merged.

3.2 Variables

Dependent variable. In order to measure a scientist's involvement with industry, we follow Bozeman and Gaughan (2007) who construct an industry involvement index based on faculty responses whether they engaged in different types of industry interaction. In our survey, scientists were asked to indicate interaction with respect to five items: (a) direct collaboration with industry personnel in a joint research project, (b) performing a service (measuring, analyzing, consulting) or creating a technical artifact (bacteria, cell cultures) on behalf of a company, (c) licensing-out research results, (d) joint publication of research results with industry personnel, and (e) informal contacts with industry personnel. The time frame the scientists were asked to refer to were the last 12 months, i.e. from about mid 2009 to mid 2010. We then calculated the frequency (in %) of each item's occurrence in the sample and used the inverse as a weight for the corresponding item. Subsequently, we multiplied each type of interaction with its weight and summed the factors to create a weighted industrial involvement index. As a robustness check, we use the summed number of interaction types without considering their frequency of occurrence in the sample.

Focus variables. We use three main explanatory variables. The first refers to the scientist's career age, i.e. the number of years since the scientists received her PhD. This information is available from the survey. As the variable is skewed, we take the natural logarithm of it. The second variable focuses on the scientist's localized peers. To construct this measure, we identified all publications listed in the SCIE that affiliates with the scientist's department or institute published between 2004 and 2008. We then identified those publications that were co-authored with industry personnel and calculated the share of those publications in the total number of publications by department members. The third variable is intended to capture personal peer effects. We measure those by identifying all publications by the scientist's co-authors between 2004 and 2008. If any of the scientist's co-authors had published a paper together with industry personnel, we create a dummy variable that takes the value of one and zero otherwise. Since the dependent variable refers to 2009 and 2010, the explanatory variables based on publication information are lagged.

Control variables. We control for several factors that have been shown to be relevant in studies explaining scientists' involvement with industry (e.g., Link et al., 2007). In this respect, we control for the scientist's research productivity in terms of papers published in SCIE journals from 2004 and 2008. Scientists were also asked to indicate whether they had previously applied for patent.[1] Department research productivity is controlled for by taking the sum of publications by department affiliates from 2004 to 2008. Another indicator of faculty quality is whether a scientist is tenured or not. Scientific field effects within biotechnology are controlled for by including dummy variables for a research orientation towards life sciences, natural sciences, engineering, and other sciences. Moreover, we use a dummy variable to indicate whether the scientist's research is applied (in contrast to basic research), which is taken from the questionnaire to control for the technological opportunity of the research. The regressions will also control for whether the scientist is employed at a public research organization (in contrast to a university). Some scientists in the sample are affiliated with both a PRO and a university though. Besides controlling for the scientist's gender, we also include two measures that are intended to capture the "supply side" of industry-science interaction opportunities. In this regard, we include the GDP per capita in the region where the scientist's institution is located as well as the regional number of plants in natural logarithm. The idea behind these two control variables is that industry-science interaction tends to be localized (Laursen et al., 2010) and that more opportunities for interaction arise the higher regional level of economic development is. In this context, the region is defined as the district (NUTS-3) in which the scientist's institution resides plus the immediate neighboring districts. Correlations between the explanatory variables are fairly low (see Table 3 in the appendix). Moreover, the average variance inflation factor (VIF) equals 1.26. Thus, there is no indication for a multicollinearity problem in the data.

3.3 Methods

Our dependent variable is the industry involvement index which is the weighted sum of the different types of a researcher industry interaction. Thus the dependent variable is a continuous variable subject to left-censoring. The variable takes a value of zero which

[1] The questionnaire refers to the number of inventions for which patent protection was sought. There is thus no double-counting of applications made at different patent offices.

represents the lower limit if the researcher is not involved in any of the five types of industry interaction. The largest value of the dependent variable in the sample is 2.6. Consequently, the industry involvement is estimated applying a tobit model (for details on the model see, e.g., Wooldridge, 2007).

As a robustness check we use the number of industry involvement channels as dependent variable. The variable takes integer values from 0, in case of no industry involvement, to 5, if the researcher is involved in all five types of interaction. Since the variable has an upper limit, a count data model would not be an appropriate estimation method. Instead we use the ordered probit model to take into account the ordinal structure of the variable (Wooldridge, 2007).

4 Results

4.1 Descriptive results

Table 2 presents descriptive statistics for the variables used in the analysis for the full sample and a split sample, depending on a researcher’s above or below median industry involvement index. On average 7.8 percent of the publications within a department are co-authored by personnel from industry. Departments of scientists with below median industry exhibit lower shares than departments of scientists with above median industry involvement activities. However, based on a one-tailed t-test for this hypothesized variable the difference is only significant on the 10%-level. A positive relationship between scientists’ industry involvement and joint publications of their co-authors with industry personnel becomes evident based on the mean comparison between the two groups. Scientists with higher industry involvement activities have statistically more often co-authors who have published jointly with industry personnel than scientists with lower industry involvement activities. The descriptive results also indicate that a scientist’s industry involvement varies with academic age. We find that the mean of the academic age of scientists with more industry involvement is statistically larger than the mean for scientists with less industry involvement at any level greater than 0.8 percent. The descriptive results already indicate support for hypotheses 1, 2 and 3. A multivariate analysis is warranted.

Table 1: Sample averages, total and by industry involvement

	All observations (N=343)				Below median industry involvement index (N=171)		Above median industry involvement index (N=172)	
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variable								
Industry involvement index	0.929	0.717	0	2.616	0.316	0.275	1.538	0.454
No. of industry involvement channels	2.327	1.432	0	5	1.082	0.747	3.564	0.677
Focus variable								
Joint publications w/ industry by dept. (share)	0.078	0.071	0	0.571	0.073	0.060	0.084	0.080
Co-authors published w/ industry (d)	0.566	0.496	0	1	0.444	0.498	0.686	0.465
Years since PhD (ln)	2.197	1.132	0	3.932	2.050	1.142	2.344	1.106
Control variable								
No. of publications by dept.	63.921	62.814	0	266	65.795	64.791	62.058	60.917
No. of publications by individual	3.799	4.361	1	26	2.871	2.989	4.721	5.239
Patent application (d)	0.475	0.500	0	1	0.316	0.466	0.634	0.483
Applied research orientation (d)	0.697	0.460	0	1	0.544	0.500	0.849	0.359
Field: Biosciences (biology, medicine) (d)	0.735	0.442	0	1	0.789	0.409	0.680	0.468
Field: Natural Sciences (d)	0.128	0.335	0	1	0.099	0.300	0.157	0.365
Field: Engineering (d)	0.070	0.255	0	1	0.035	0.185	0.105	0.307
Field: Other (d)	0.067	0.250	0	1	0.076	0.266	0.058	0.235
Tenured position (d)	0.554	0.498	0	1	0.503	0.501	0.605	0.490
Public research institution (d)	0.382	0.487	0	1	0.398	0.491	0.366	0.483
Female (d)	0.292	0.455	0	1	0.351	0.479	0.233	0.424
GDP per capita in region	31.355	8.958	19.638	54.763	32.070	9.118	30.645	8.766
No. of plants in region (ln)	9.816	0.964	7.231	11.234	9.840	1.031	9.791	0.895

Note: (d): dummy variable.

4.2 Main results

Table 2 shows our main model results. Model 1 and model 2 report findings from the tobit regressions, in which the industry involvement index is used as the dependent variable. In the baseline model 1 we find that both co-author publications with industry and the career age exhibit a positive effect on industry involvement. The effect of the share of publications with industry in the scientist's department is however not significant. Model 1 thus finds support for hypotheses 1 and 3. Looking at the results in model 2 which incorporate the interaction effects, we find the two results from model 1 confirmed. Additionally, we find a significant positive effect of the share of publications with industry in the scientist's department which lends support to hypothesis 2. Regarding the interaction with scientist age we find a negative and significant interaction for the share of joint publications with industry in the scientist's department but no significant effect of the interaction for co-authors' publication with industry. This result supports hypothesis 4 but rejects hypothesis 5. Models 3 and 4 use the number of different interaction channels with industry as dependent variable and are consequently estimated by ordered probit regressions. All results turn out to be consistent to models 1 and 2.

Our results indicate that professional imprinting plays a major role in shaping scientists' propensity to engage with industry. Both the localized and the personal peer effect turn out to be relevant which confirms and extends prior literature (Bercovitz and Feldman, 2008). However, we also find evidence for the imprinting effect being dependent on the scientist's career age. The more recent the vintage of the scientist's PhD degree, the less likely becomes industry involvement. But imprinting is particularly effective in the early years of the scientist's career. We find that this only pertains to the localized peer effect though, i.e. the scientist's department co-publications, while the personal peer effect is unaffected by the career age. This suggests that personal peer effects are less sensitive towards the scientist's professional "lifecycle" and that the scientist's department acts as a major reference point for the scientist's activities in her or his early years of the career.

Regarding the control variables, we find consistent effects across all models. It appears that the number of publications in the department has a slightly negative effect on industry involvement. This result confirms prior literature in that the general research orientation of a department, as evidenced by a high publication output, decreases industry involvement (e.g., Ponomariov, 2008). Moreover, and as expected, we find that scientists with patent applications and those whose research is application oriented exhibit higher industry involvement. Prior literature has suggested that industrial firms are particularly interested in collaborating with those scientists who have demonstrated their ability and interest in application and commercialization of research results (e.g., Link et al., 2007), which is what we can confirm. Moreover, we find that engineering scientists are significantly more engaged with industry while there are no other significant discipline effects, except for a marginally significant and positive effect of natural sciences. This result again confirm prior findings (e.g., Grimpe and Fier, 2010). Interestingly, all other control variables seem to be irrelevant for explaining a scientist's involvement with industry. In this respect, we find no effect of whether the scientist is tenured, working at a public research organization (as opposed to at a university) and for the scientist's gender. Moreover, our regional control variables which are intended to capture the local "pool" of collaboration opportunities turn out to be insignificant, although prior literature had shown that collaboration patterns tend to be localized (e.g., Czarnitzki and Hottenrott, 2009).

Table 2: Estimation results

	Model 1	Model 2	Model 3	Model 4
	Industry involvement index	Industry involvement index	No. of industry involvement channels	No. of industry involvement channels
Joint publications w/ industry by dept. (share)	0.330	2.676**	0.595	4.578**
	(0.539)	(1.244)	(0.862)	(1.998)
Co-authors published w/ industry (d)	0.322***	0.375**	0.549***	0.592**
	(0.083)	(0.168)	(0.131)	(0.266)
Years since PhD (ln)	0.104**	0.202***	0.186***	0.339***
	(0.043)	(0.068)	(0.067)	(0.108)
Int.: dept. joint publ. w/ ind. * years since PhD		-1.058**		-1.800**
		(0.510)		(0.818)
Int.: co-authors publ. w/ ind. * years since PhD		-0.020		-0.011
		(0.069)		(0.109)
No. of publications by dept.	-0.001*	-0.001*	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
No. of publications by individual	0.011	0.012	0.016	0.018
	(0.010)	(0.010)	(0.015)	(0.015)
Patent application (d)	0.266***	0.273***	0.375***	0.389***
	(0.084)	(0.084)	(0.133)	(0.133)
Applied research orientation (d)	0.502***	0.496***	0.796***	0.794***
	(0.086)	(0.086)	(0.138)	(0.139)
Field: Natural Sciences (d)	0.198*	0.179	0.289*	0.258
	(0.111)	(0.110)	(0.175)	(0.176)
Field: Engineering (d)	0.427***	0.434***	0.737***	0.753***
	(0.147)	(0.147)	(0.237)	(0.239)
Field: Other (d)	0.138	0.166	0.235	0.283
	(0.150)	(0.150)	(0.235)	(0.236)
Tenured position (d)	0.021	0.006	0.002	-0.021
	(0.092)	(0.092)	(0.144)	(0.145)
Public research institution (d)	0.055	0.063	0.093	0.106
	(0.079)	(0.079)	(0.125)	(0.125)
Female (d)	-0.078	-0.054	-0.141	-0.102
	(0.083)	(0.083)	(0.130)	(0.131)
GDP per capita in region	-0.006	-0.005	-0.008	-0.008
	(0.005)	(0.004)	(0.007)	(0.007)
No. of plants in region (ln)	0.025	0.018	0.041	0.030
	(0.043)	(0.043)	(0.068)	(0.068)
Constant	-0.137	-0.298		
	(0.401)	(0.411)		
Pseudo R2	0.16	0.17	0.11	0.12
N	343	343	343	343
LR/Wald chi2	130.037	134.767	133.672	138.813
P-value	0.000	0.000	0.000	0.000
Log likelihood	-340.332	-337.967	-514.374	-511.803

Note: Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%). (d): dummy variable. Reference field: biosciences (biology, medicine).

4.3 Robustness test

It could be argued that it needs some time to observe other colleagues' behavior. Therefore, as a robustness check we repeated the analyses for a sub-sample of scientists. To ensure that researchers get a chance to become imprinted by the department only researchers who worked at the corresponding department for a relevant period are considered. Thus, the sub-sample is restricted to researchers who were hired before 2005. As the results show (see models 5 and 6 in Table 4 in the appendix) the imprinting and age effects hold although the imprinting effects are not as pronounced. The same applies for the interaction effect. This is due to the lack of very young researchers in the sub-sample since it excludes per definition very young researchers who are within their first five years of their academic career.

Moreover, to check the robustness of the role of a scientist's career age we split the sample at the median career age (14 years) and re-estimated the regressions for the split sample (see models 7 and 8 in Table 4 in the appendix). For the younger scientists both professional imprinting effects are present while for the older researchers only the personal peer effect becomes apparent. Therefore, this check backs up the main results.

Moreover, a potential endogeneity/selection bias might arise if staff hiring relies on the applicant's former industry involvement so that resulting departmental effects are not driven by the department's influence but due to the department's hiring strategy. But the most important task of a researcher is publishing, followed – at a great distance – by teaching which applies primarily for universities, and to a smaller extent for public research institutions. Commercial activities play only a minor role. This is also confirmed by the assessments of the researchers in the sample. 91 percent of the researchers assess publishing as a very important task of researchers; an additional 8 percent rated it as an important task. In contrast technology transfer is rated by 9 percent (20 percent) of the respondents as a very important (important) task. Patenting activities reach similar values (9 percent very important; 16 percent important). Accordingly, hiring decisions are primarily based on the publication record of the applicant, not on their prior industry involvement (see also Bercovitz and Feldman, 2007).

5 Conclusion

Our research sheds new light on the factors driving academics to engage with industry. We suggest that professional imprinting has a major role to play, which we distinguish into localized and personal peer effects. Moreover, we explicitly account for the scientist's career age and how this affects professional imprinting. Based on a sample of biotechnology scientists in Germany, our results suggest that imprinting in fact depends on the scientist's career age, with younger scientists being more receptive to imprinting that stems from the local environment, i.e. the scientist's department. While imprinting through co-authors, i.e. personal peers, is important to explain industry involvement, the effect does not appear to be dependent on the scientist's career age. In this respect, we extend existing literature in the field by disentangling the professional imprinting effect into localized (department) and personal (co-authors) peer effects. Moreover, prior literature has all too often treated the scientist's age as a control variable and neglected its moderating impact on imprinting. Finally, previous studies have focused on single areas of scientists' involvement with industry. By employing an industry involvement index that integrates different channels of potential collaboration, we provide a more holistic picture of academics' engagement with industry.

Our research, however, needs to acknowledge several limitations. First, our measure for personal peer effects, i.e. an indicator for whether co-authors of the scientist have published together with industry personnel, could be related to the measure for localized peer effects in case the scientist's co-authors work at the same department, although we generally find a very low correlation between the two measures. Moreover, our survey data just represent a cross-section. Ideally, it would be desirable being able to follow scientists through their career in order to make a better informed analysis of how the career age affects professional imprinting.

Nevertheless, our research offers important insights for science, technology and innovation (STI) policy making. Given that the traditional mission of public science has shifted in recent years from educating students and conducting (basic) research towards becoming more "entrepreneurial" and engaging with industry (Etzkowitz et al., 2000), our research makes clear that it is not only the personal motivation of the scientist or the organizational infrastructure like the presence of a technology transfer office that matter for industry involvement, but it is also the scientist's immediate environment to which he or she makes reference in the decision to become engaged with industry. Efforts to promote industry involvement should therefore not ignore peer effects, which however can be difficult to influence. Policy measures should hence be targeted primarily at groups of researchers and not (only) individual scientists. Moreover, industry involvement has been shown to typically occur in later stages of the career. It thus seems pivotal to facilitate industry-science interaction particularly for scientists in their early stage of career. As imprinting has turned out to be more effective in those years, STI policy could target researcher groups with a high share of early-stage researchers.

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Appendix

Table 3: Correlation matrix (343 observations)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Joint publications w/ industry by dept.	1													
(2) Co-authors published w/ industry (d)	0.15	1												
(3) Years since PhD (ln)	0.04	0.04	1											
(4) No. of publications by dept.	0.10	0.21	0.06	1										
(5) No. of publications by individual	0.04	0.37	0.25	0.10	1									
(6) Patent application (d)	0.20	0.16	0.34	0.04	0.25	1								
(7) Applied research orientation (d)	0.14	0.15	0.03	0.08	0.09	0.31	1							
(8) Field: Natural Sciences (d)	0.02	0.05	0.02	-0.13	-0.03	0.02	-0.03	1						
(9) Field: Engineering (d)	-0.06	-0.06	-0.12	-0.10	0.03	0.04	0.11	-0.11	1					
(10) Field: Other (d)	-0.03	0.00	-0.09	-0.08	0.11	-0.05	0.13	-0.10	-0.07	1				
(11) Tenured position (d)	-0.03	0.10	0.58	0.01	0.25	0.21	0.01	0.05	-0.08	-0.04	1			
(12) Public research institution (d)	-0.04	-0.03	-0.04	0.21	0.04	-0.04	-0.07	0.00	-0.07	-0.09	0.03	1		
(13) Female (d)	-0.07	-0.10	-0.15	-0.02	-0.19	-0.20	-0.02	0.06	-0.03	0.03	-0.13	-0.03	1	
(14) GDP per capita in region	0.00	0.03	0.00	0.05	0.03	-0.01	-0.02	-0.02	0.06	0.03	0.03	-0.18	0.05	1
(15) No. of plants in region (ln)	-0.15	0.02	0.02	0.24	0.01	-0.03	-0.02	-0.02	0.05	0.00	0.02	0.05	0.02	0.39

Table 4: Robustness checks with various sub-samples

	Model 5	Model 6	Model 7	Model 8
	Only researchers who were hired before 2005		Below median career age	Above median career age
	Industry involvement index	Industry involvement index	Industry involvement index	Industry involvement index
Joint publications w/ industry by dept. (share)	0.189	3.912*	1.751**	-0.963
	(0.658)	(2.258)	(0.741)	(0.789)
Co-authors published w/ industry (d)	0.372***	0.531*	0.453***	0.241**
	(0.108)	(0.285)	(0.121)	(0.113)
Years since PhD (ln)	0.119**	0.289***	0.069	0.375**
	(0.057)	(0.100)	(0.061)	(0.168)
Int.: dept. joint publ. w/ ind. * years since PhD		-1.476*		
		(0.855)		
Int.: co-authors publ. w/ ind. * years since PhD		-0.069		
		(0.107)		
No. of publications by dept.	-0.002***	-0.002**	0.000	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
No. of publications by individual	0.014	0.016	-0.007	0.019*
	(0.010)	(0.010)	(0.021)	(0.010)
Patent application (d)	0.237**	0.254**	0.152	0.307***
	(0.101)	(0.100)	(0.127)	(0.108)
Applied research orientation (d)	0.482***	0.481***	0.343***	0.623***
	(0.108)	(0.107)	(0.123)	(0.115)
Field: Natural Sciences (d)	0.226	0.213	0.026	0.323**
	(0.145)	(0.145)	(0.163)	(0.145)
Field: Engineering (d)	0.598***	0.604***	0.350*	0.536***
	(0.188)	(0.187)	(0.204)	(0.206)
Field: Other (d)	0.096	0.081	0.182	0.293
	(0.210)	(0.209)	(0.203)	(0.217)
Tenured position (d)	0.015	0.003	-0.051	-0.163
	(0.111)	(0.111)	(0.133)	(0.142)
Public research institution (d)	0.060	0.074	0.077	0.002
	(0.098)	(0.099)	(0.120)	(0.100)
Female (d)	-0.099	-0.076	-0.044	-0.025
	(0.109)	(0.108)	(0.117)	(0.116)
GDP per capita in region	-0.008	-0.008	-0.010	-0.002
	(0.005)	(0.005)	(0.007)	(0.006)
No. of plants in region (ln)	0.052	0.032	-0.062	0.054
	(0.054)	(0.055)	(0.066)	(0.055)
Constant	-0.270	-0.531	0.803	-1.108
	(0.515)	(0.532)	(0.589)	(0.722)
Pseudo R2	0.18	0.18	0.13	0.22
N	218	218	166	177
LR/Wald chi2	92.29	96.87	49.87	92.43
P-value	0.000	0.000	0.000	0.000
Log likelihood	-216.519	-214.232	-162.108	-162.194

Note: Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%). (d): dummy variable.