

d'Andria, Diego; Uebelmesser, Silke

Conference Paper

The relationship between R&D intensity and profit-sharing schemes: evidence from Germany and the United Kingdom

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Firm Investment and Innovation: Empirical Studies, No. C24-V2

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: d'Andria, Diego; Uebelmesser, Silke (2016) : The relationship between R&D intensity and profit-sharing schemes: evidence from Germany and the United Kingdom, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Firm Investment and Innovation: Empirical Studies, No. C24-V2, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/145622>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

The relationship between R&D intensity and profit-sharing schemes: evidence from Germany and the United Kingdom

February 26, 2016

Abstract

We study the determinants of the use of profit sharing schemes (PSS) by exploiting two datasets for Germany and the United Kingdom. Our results replicate studies for the U.S. which report a positive correlation between R&D activity and PSS use. For Germany, Granger-causality tests support a causal interpretation. Similarly to U.S.-based studies, we also find that a firm's turnover is strongly associated with PSS use whereas this does not hold for the age of a firm and its organizational characteristics.

JEL Classifications: L2, J33, O31.

Keywords: innovation; R&D; profit sharing schemes; Germany; United Kingdom.

1 Introduction

At least since the 1980s, a number of studies – mostly for the U.S. – have documented an increase in the use of so called “profit sharing schemes”, or PSS¹. This type of compensation links part of employees’ pay to measures of the company’s success. In an attempt to understand which characteristics make firms and industrial sectors more likely to use PSS, some regularities have been observed. The focus here is to study one of these regularities, the link between the use of PSS and research and development (R&D) activities, in a European context.

PSS encompass a wide family of compensation types. Examples of PSS include stock grants, stock options, direct participation in profits, and bonus pay. It was established that U.S. firms and industries that are more active in R&D or that are involved in high-technology production tend to be more likely to offer PSS to their employees, in comparison to U.S. firms and industries not engaged in these activities. Also, and again only for the U.S., it was found that PSS are used to compensate key employees such as managers in specific functions, researchers and technical personnel (see the overview in the next section). Building upon these empirical findings, a number of theoretical works (Manso 2011, Hellmann and Thiele 2011) gives insight about why and how PSS can provide private companies with a means to foster their workforce’s commitment to innovation.

While the positive correlation between PSS use and R&D intensity has been replicated with samples from different years and locations, to our knowledge all the published studies rely on U.S. data (plus a single work using a sample of Brazilian companies, see Barros and Lazzarini 2012). With regard to European countries, we know that the use of PSS has increased in Germany and in the U.K. during the 1990s (Conyon and Schwalbach 2000). We also know about some determinants of PSS use that are linked to the organization of labor or to the presence of intangibles (Kroumova and Sesil 2006, Boeri et al. 2013). But we do not have any evidence whether the same correlation – let alone a causal relation – observed for U.S. companies between PSS use and R&D intensity also exists. This constitutes a major limitation for the portability of insights, which build upon said findings, to European policy-making as the positive correlation found in the U.S. could be just due to country-specific characteristics.

¹Here and throughout this work we use the following definition of PSS, taken from the European Company Survey 2009: “*Profit sharing schemes are specific elements of pay the amount of which depends on the company’s success.*”

The aim of the paper is to analyze whether European firms and industries that are more innovative or that have more R&D activities are also more likely to adopt PSS. Our focus is not on the effectiveness of PSS to increase innovation, but on the question whether PSS use differs between innovative and non-innovative firms (maybe as an optimal compensation strategy, maybe for other reasons). We run a series of regressions that exploit two datasets. The first one is the German IAB panel dataset which provides data for several thousand German firms over several years. This constitutes the main focus of our study. The second dataset is a survey conducted on a small sample of U.K.-based high-technology companies. While the latter dataset is much smaller, it is nevertheless of interest because of its innovation focus. We see the U.K. analysis mainly as a robustness check for our results for Germany. In addition, they allow us to test for some organizational characteristics of the firm that are not available in the IAB dataset.

To our knowledge, our study is the first to demonstrate a positive correlation between R&D intensity and PSS use in European firms, and also to provide an explicit discussion and testing of possible dynamic effects. It can be seen as a first step toward building a comprehensive study on the determinants of PSS use in European innovative firms.

The structure of the paper is as follows. Section 2 summarizes the existing literature. Section 3 exploits a Europe-wide survey to provide some information about PSS use and to inquire about self-reported motives for employing this type of compensation. Section 4 presents our econometric analyses for German and U.K. firms and compares them with the results from U.S. studies. Section 5 summarizes the main findings and concludes.

2 Previous literature

Table 1 summarizes results from the literature on the determinants of PSS use. At a first glance, it is evident that studies based on Europe are much fewer than U.S.-based studies. In addition, to the best of our knowledge no study inquires about the relation between PSS use and innovation or R&D intensity in Europe.²

²The only study that to our knowledge attempts to replicate the findings for the U.S. with E.U. data (specifically German data) is Aerts et al. (2015). The authors report a positive correlation between measures of product and process innovation, and the use or the introduction of PSS. The focus of this paper however is different from ours, as it is about the effectiveness of PSS as a means to foster innovation, and not about the

Table 1: Previous findings on the determinants of PSS use (*italic* entries are for works based on Brazilian firms)

Variable	Relation with PSS use	Found in (U.S. and Brazil):	Found in (Europe):
R&D intensity	+	Milkovich et al. (1991), Core & Guay (2001), Murphy (2003), Francis et al. (2011)	-
High-tech firm	+	Balkin & Gomez-Mejia (1984), Balkin et al. (2000), Ittner et al. (2003)	-
Innovation-led revenues	+	<i>Barros & Lazzarini (2012)</i>	-
Size of firm	+	Balkin et al. (2000), Core & Guay (2001), Ittner et al. (2003), Hochberg & Lindsey (2007), <i>Barros & Lazzarini (2012)</i>	Bellmann & Möller (2006), Boeri et al. (2013)
	-	Balkin & Gomez-Mejia (1984), Smith & Watts (1992), Gaver & Gaver (1993), Yermack (1995), Zenger & Lazzarini (2004), Baranchuk et al. (2014)	-
Age of the firm	-	<i>Barros & Lazzarini (2012)</i>	Bellmann & Möller (2006)
	0	Zenger & Lazzarini (2004)	-
Human capital	+	Core & Guay (2001), Ittner et al. (2003), Kroumova and Sesil (2006), Boeri et al. (2013)	Boeri et al. (2013)

U.S. based studies find a positive correlation between measures of R&D intensity or technological intensity and PSS use, both at firm level and at industry level. In these studies (Milkovich et al. 1991, Balkin, Markman, et al. 2000, Core and Guay 2001, Murphy 2003, Francis et al. 2011) R&D activities are proxied by expenditures for R&D or measures of innovation output (number of patent applications or grants, citation-weighted patent counts, self-reported innovations done in recent past). Technological intensity is proxied by the share of revenues generated by product or process innovation (Balkin and Gomez-Mejia 1984, Balkin, Markman, et al. 2000), or at the industry level by comparing the share of compensation as PSS offered by firms belonging to traditional or “new economy” sectors (Ittner et al. 2003).

With regard to firm size, both theory and U.S. evidence are mixed. On the one hand, bigger firms should face larger monitoring costs so that pay-for-performance compensation would be less effective, and also be better equipped to employ complex compensation schemes like stock options. Therefore we would predict a positive correlation between size (measured as sales or turnover) and PSS use. But larger firms also face problems as with many employees, the incentive to free-ride on co-workers’ effort is larger. This would predict a negative relation between size (measured as the size of the

determinants of PSS use.

workforce) and PSS use.

There might be a possible role of the age of a company in explaining PSS use. The argument is that older firms might be less able to change their organization and practices which stratified and consolidated over time, and this would include the inability to adopt newer compensation practices like PSS. Hence the prediction of a negative correlation between the company's age and PSS use. The evidence from U.S. studies so far is however mixed.

Both for the U.S. (for example in Kroumova and Sesil 2006) and for Europe (Boeri et al. 2013) it is shown that firms employing a larger share of highly educated people (or a larger share of employees whose job tasks would require a tertiary-level equivalent education) are more likely to offer PSS. A rationale for this correlation is that a higher share of highly educated employees would proxy for a larger presence of intangibles (related for example to intellectual properties). With more intangibles the costs associated with monitoring is larger as it becomes more difficult for the principal to assess the quantity and quality of job effort exerted by workers.

In addition to the determinants mentioned in Table 1, organizational practices could also affect PSS use. In particular, team work can bring two distinct effects: more team work could mean larger monitoring costs and stronger incentives to free-ride on co-workers effort. This would imply that having a workplace where team work is important should be associated with lower PSS use. But in the specific case of innovative production it might be that knowledge spillovers among co-workers more than offset incentives to free-ride. We should in this case expect a positive correlation (as experimentally found in Ederer 2013). Moreover, variable pay could induce more competition among co-workers. Because a highly competitive workplace can hamper productivity (Kohn 1993), it could be that intrinsically competitive work environments would benefit less from PSS use as a means to foster productivity.

These reported results will guide the choice of the explanatory variables in our analysis.

3 European evidence on PSS use

Based on data from the European Company Survey 2009 (ECS 2009), this section provides some information about the use of PSS in 30 European countries and more specifically in Germany and the U.K.. While no explicit

question is included with regard to innovation and R&D activities, the ECS 2009 dataset nevertheless allows shedding light on the distribution of PSS across industries and countries and on firms' self-reported motivation for PSS use. This allows us to get a first idea about whether the U.S. and Europe share some similarities.

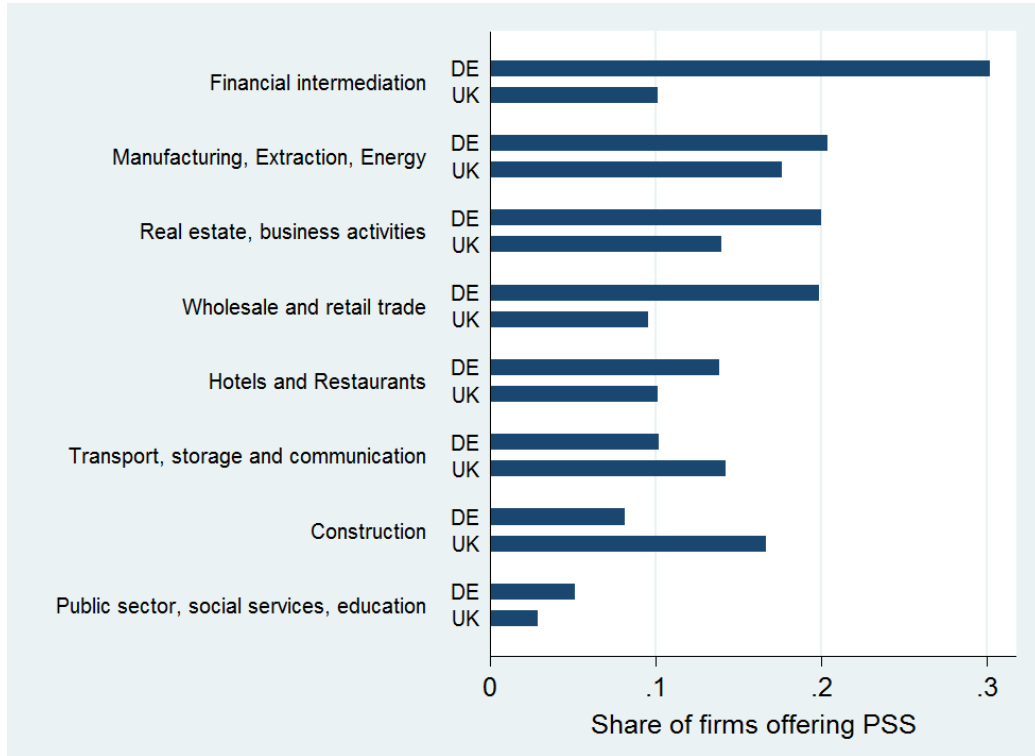
3.1 PSS use across countries and industries

A large heterogeneity in PSS use is observed across countries (Tremblay and Chenevert 2005). According to the ECS 2009 dataset France is leading the ranks with about 40% of respondents offering PSS to employees, while Germany and the U.K. are, respectively, slightly above (15%) and below (12%) the average.

Figure 1 reports PSS use by industrial sectors for Germany and the U.K.. Again, there is significant heterogeneity. The high (but not surprising) share observed for the financial intermediation sector in Germany and also the wide-spread use of PSS in the real estate and trade sectors, suggest that PSS compensation is used to motivate employees in production or commercial functions. In the manufacturing sector, where a large part of R&D activities takes place, PSS are used by close to one-fifth of the firms from both countries. Some differences between Germany and the U.K. are observed as well, particularly in the financial intermediation, trade and construction sectors. Such differences may arise from institutional characteristics similarly to what we argued with regard to the comparison of the U.S. versus the E.U., or from heterogeneity in the composition of sub-industries (the ECS 2009 data files only provides 1-digit industry classification).

For U.S. firms, it is observed (Oyer and Schaefer 2005) that PSS are offered both to the general workforce (especially in companies listed in stock exchange markets; see Hall and Murphy 2003), and to specific categories of employees (this is particularly true for high-tech firms compensating R&D employees, technical staff and key managers; see Balkin and Gomez-Mejia 1984). In Europe, we see from the ECS 2009 data that both types of PSS are offered as well. It seems, however, more common to offer PSS to all employees, followed by targeted PSS, while the use of both broad-based and targeted PSS at the same time is relatively rare.

Figure 1: Share of firms offering PSS, by industrial sector (ordered according to the PSS shares in German industries)



Source: ECS 2009

3.2 Self-reported motivations for offering PSS

Empirical analysis of the determinants of PSS use is complicated by the fact that PSS can be offered to employees for very different reasons. First, PSS can be introduced as a means to provide better incentives to employees. This could be the case when some employees, who are able to innovate, face a tension between committing effort into job tasks that exploit knowledge acquired in the past, or in tasks that entail some exploration of new approaches.³

³This tension between exploration and exploitation in a principal-agent framework could motivate the use of PSS by principals as a means to drive agents in investing more effort into exploration tasks, and thus in making them commit to innovation (Manso 2011). In other instances, individual pay-for-performance is not applicable due to unobservable intermediate goals or unobservable effort, therefore PSS act as a second-best choice for optimal contract design. The use of PSS would then be predicted to be more frequent in firms facing larger monitoring costs (Kroumova and Sesil 2006), like innovative firms.

Second, PSS can also be used as a means to select and attract highly skilled workers. As shown in Andersson et al. (2009) for the U.S. software industry, the expectation of large upswings in a company’s value could attract “star” employees who are able to produce valuable projects. Because such large jumps in a company’s value are expected to be more likely in innovative firms, this view could explain, at least partially, why R&D-intensive firms use PSS more.

Third, financial constraints can also explain the use of PSS as a way to alleviate short-term liquidity shortage. It might be that R&D-intensive firms, being less transparent and predictable in their expected profitability, face specific financial constraints. While this thesis is suggestive, empirical evidence so far has been mixed (Core and Guay 2001, Ittner et al. 2003). Also small firms should be observed to use PSS more than large firms as they usually face larger barriers in accessing credit regardless of pursuing R&D activities, but the opposite correlation has been found in many studies.⁴

For German and U.K. firms, the most relevant self-reported motives (ECS 2009 survey) include (Figure 2): to increase motivation, to increase productivity, to provide incentives to employees to participate in improvements of products or processes and to attract and retain qualified workers. Cost-reduction motives related to the cost of the workforce do not seem to play a major role. This is in line with the idea that financial constraints are likely to be a minor (if any) driver for the use of PSS.

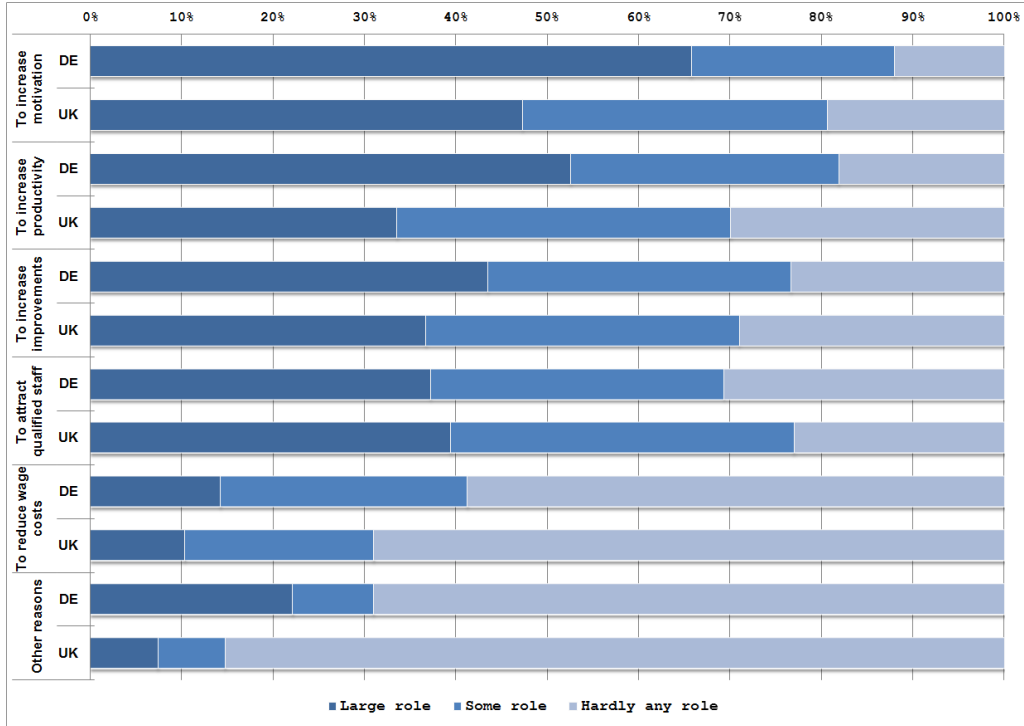
For a sample of U.S. “New Economy” firms, similar motives were reported in Ittner et al. (2003). Attraction and retention motives, and motivation and productivity reasons ranked top. In Oyer and Schaefer (2005) sorting and retention of workers appear to be much more important than motivation-related motives. The latter result is less in line with the findings presented in Figure 2 where motivation motives clearly rank higher in comparison to attraction motives.

Of special interest for the present study is the importance of the motive to “*increase active employee participation in the improvement of work processes or products*”. This motive (“To increase improvements” in Figure 2) is directly related to the pay-for-innovation theory. It is a very specific motivation reflecting a desire of the management to provide an environment where

But as innovation may also entail some degree of creative work, a crowding out of intrinsic motivation could happen due to pay-for-innovation compensations (“you cannot bribe creativity”, as argued in Kohn 1993).

⁴Other explanations for PSS use, like tax avoidance or rent-seeking motives, do not specifically apply to R&D activities. Therefore we will not discuss them here.

Figure 2: Main motives for offering PSS, by German and U.K. firms (ordered according to the role for Germany)



Source: ECS 2009

proactive initiative related to product or process innovation is rewarded. This supports the idea inspiring this study that the management of R&D firms may be willing to offer PSS targeted at employees in specific (technical) functions within the firm, in order to enhance their commitment to innovation.

4 An econometric study for Germany and the U.K.

In order to answer our main research question about the relationship between R&D activity and PSS use, we run Logit models where the dependent variable is binary and takes value 1 if profit sharing schemes are offered in the establishment or company, and 0 otherwise. The main explanatory variable, R&D activity, is proxied in the German dataset by the existence of an R&D

unit within an establishment or company, and by product innovation in recent years. For the U.K. sample, R&D expenditures, self-assessed measures of product or process innovation and the number of patent applications or grants are used.

In addition, we will try to replicate results previously obtained with U.S. data. Therefore, as discussed in Section 2 we include controls for firm size (both in terms of turnover and workforce), firm age and a set of industry dummies. For the German dataset we also consider the share of exports over total sales, and a West-Germany dummy. For the U.K. dataset, we include some organization-related regressors. The two distinct survey-based datasets and the estimation methodology are detailed in the respective sections.

4.1 Regressions on German data

In this section, we describe the dataset and our regression strategy for Germany. We then present the main results and some extensions. We first focus on a static setting and then introduce dynamic effects by means of Granger causality estimation.

4.1.1 Data and methodology

We employ the German IAB Establishment Panel dataset, which is a yearly firm level survey focusing on characteristics of production and organization. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently via remote data access. We use waves 2001, 2007, 2009, and 2011 (a description of the IAB surveys is found in Fischer et al. 2009, Drechsler 2011, Ellguth et al. 2014), as these are the only years for which questions about both PSS use and R&D activities are included.

To exploit our panel structure we employ Panel Logit with random effects as our main specification. One of the reasons for a random effects model is that many of our observed firms either never offer PSS (78% of the observations), or never have an R&D department in the four years surveyed (85% of the observations). In comparison to a fixed effects model, a random effects model avoids the loss of time-invariant observations. A related and even more important reason is that we are interested in both “within” and “between” effects. (Time-invariant) structural differences in the organization

of firms are likely related to PSS use. For example, the organization of the workforce within each firm could have an effect.⁵

The dependent variable is *PSS*, which is a binary variable equal to 1 if PSS is offered in the establishment. Our main independent variable is *RDdep*, again a binary variable taking value 1 if the respondent has an R&D department. We also include a binary variable *Product innovation* equal to 1 if at least one product innovation for which a new market had to be created was successfully developed and commercialized in the last year. We interpret *RDdep* as an input measure and *Product innovation* as an output measure of the innovation process.

We also include relevant control variables. First, we consider the size of the firms, as this was found to be an important determinant of PSS use in other studies also for German firms (Bellmann and Möller 2006). For this, we include the logarithm of the turnover (*Turnover (log)*), and a six-level discrete variable measuring the size of the employed workforce (*Workforce size*), which is used as a pseudo-continuous variable. This allows us to check simultaneously the effect of the firm's size in terms of value and number of employees, thus catching effects due to different degrees of labor intensity. Second, we introduce dummies for 10 industrial sectors which follow the NACE 1-digit classification (this is the same classification shown for the ECS 2009 dataset, after excluding the public sector, social works and education).⁶ In some specifications, we use a different grouping of industries captured by two dummies representing whether a firm is a manufacturing or a service company.⁷ The *High-tech* dummy expresses whether a firm belongs to a sector which is traditionally innovation led, that is chemical and pharmaceutical, manufacture of electrical, precision and optical equipment, machinery and equipment, information and communication and research and development. Third, we include the age of the firm (refer to Section 2), and fourth, the share of sales that are earned from exports as firms facing more global product competition could also face global competition in attracting and retaining specialized staff who is highly mobile. Finally, we include year dummies to catch year-specific effects. The summary of all variables is reported in Table A1 in Appendix A.

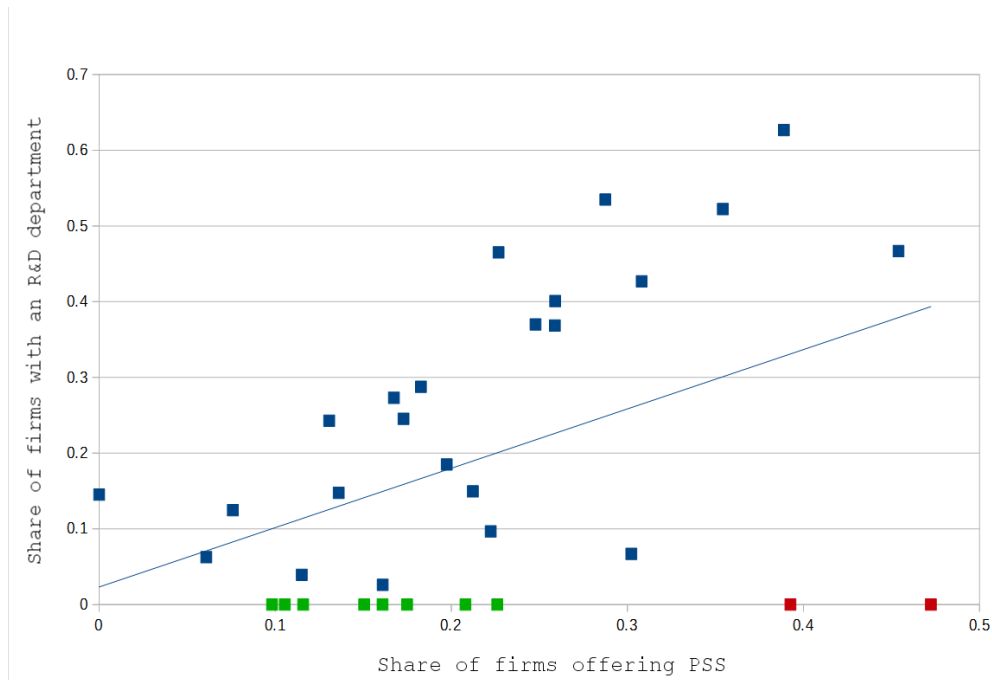
⁵In Section 4.1.2, we comment in more details on other specifications.

⁶We also run the same tests controlling for the full range of 41 industry dummies provided by the IAB dataset, instead of the 10 dummies presented in the following tables. Results are not affected by this change.

⁷One of the reasons for using manufacturing and services dummies is for comparability with the U.K. dataset (see Section 4.2).

Figure 3 shows a scatter plot of the share of firms with PSS (x-axis) and the share of firms with an R&D department (y-axis), where each point represents values for one of the 41 German industrial sectors in 2001. The sectors with at least some R&D activity display a rather clear positive correlation: Industries where a larger percentage of firms has some R&D activity tend to have a larger share of firms offering PSS to their employees.

Figure 3: Cross-industry comparison of PSS use and presence of an R&D department – scatter plot



Source: IAB 2001. The points lying on the x-axis (no R&D performed) include: financial intermediation and insurance (red points on the right-most part of the axis); agriculture, trade, realties, legal services, and other low-tech services (green points).

4.1.2 Results

Table 2 reports the results for the full sample. Results are expressed as coefficients which, as such, represent the natural logarithm of the odds ratio of the probability to offer PSS.

The coefficients for *RDdep* are always statistically significant at the 1% level, and they are always much larger⁸ than the coefficients for *Product innova-*

⁸We also calculated marginal effects for all our estimates. The relative magnitude of

Table 2: Panel data analysis: All sectors – random effects model

	(1)	(2)	(3)
	PSS	PSS	PSS
RDdep	1.84*** (.061)	1.09*** (.102)	1.09*** (.102)
Product innovation	.814*** (.060)	.556*** (.096)	.572*** (.097)
Turnover (log)		.720*** (.040)	.731*** (.040)
Workforce size		-.074 (.048)	-.091* (.048)
Age		-.003 (.007)	-.002 (.007)
Exports		.002 (.002)	.001 (.002)
Manufacturing dummy			-.176* (.107)
Service dummy			.903*** (.096)
High-tech dummy			-.125 (.095)
Industry dummies		<i>yes</i>	
Year dummies		<i>yes</i>	<i>yes</i>
West German region		<i>yes</i>	<i>yes</i>
_cons	-3.32*** (.049)	-13.2*** (.587)	-13.7*** (.552)
<i>N</i>	49,366	19,501	19,501

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

tion.⁹

Turnover is also found to be positively and significantly correlated to PSS use, while the workforce is negatively and less significantly associated (regressions

the marginal effects closely mirrors that of the coefficients. In particular, marginal effects of *RDdep* are about twice as large as the marginal effects obtained for *Product innovation* in random effects models, and about 50% larger in fixed effects models. See Table A9 in Appendix B.

⁹This result (a positive correlation between PSS use and R&D activity, statistically significant at least at the 0.05% level and with coefficients larger than the coefficients found for the variable *Product innovation*) is replicated in all of our alternative model specifications. Causality issues will be addressed in the next section.

Table 3: Panel data analysis: Manufacturing and service sectors – random effects model

	<i>Manufacturing sector</i>			<i>Service sector</i>		
	(1) PSS	(2) PSS	(3) PSS	(1) PSS	(2) PSS	(3) PSS
RDdep	.855*** (.092)	.833*** (.092)	1.04*** (.142)	1.41*** (.135)	1.35*** (.136)	.971*** (.179)
Product innovation	.367*** (.093)	.327*** (.094)	.290** (.147)	.894*** (.125)	.883*** (.126)	.774*** (.164)
Turnover (log)	.718*** (.052)	.716*** (.053)	.734*** (.080)	.580*** (.036)	.610*** (.037)	.822*** (.068)
Workforce size	-.137** (.067)	-.132* (.068)	-.165* (.099)	-.233*** (.047)	-.222*** (.047)	-.202*** (.072)
Age			.033** (.013)			.029** (.011)
Exports			.002 (.002)			.008** (.004)
High-tech dummy		.276*** (.085)	.183 (.128)		-.377*** (.112)	-.742*** (.159)
Year dummies		<i>yes</i>	<i>yes</i>		<i>yes</i>	<i>yes</i>
West German region			<i>yes</i>			<i>yes</i>
_cons	-13.4*** (.676)	-13.5*** (.679)	-13.9*** (1.04)	-10.5*** (.481)	-11.4*** (.514)	-13.5*** (.881)
<i>N</i>	12,394	12,394	5,805	13,860	13,257	7,095

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(2) and (3)). Note that when we omit the variable for turnover (not shown), coefficients for the workforce size become positive and significant: this hints at the fact that the positive relation found in some previous studies between workforce size and PSS use was likely catching the effect of turnover size. As to the age of the firm and the revenues from exports, the coefficients are rarely statistically significant and always very small. There seems to be important differences between sectors in the German dataset, similarly to the ECS 2009 dataset (refer to Figure 1).

To account for possible omitted variable bias, in Table A3 in Appendix A the results from conditional fixed effects models are reported, where fixed effects are at the firm level. Again the sign and relative magnitude of the coefficients are of interest. Although the magnitude of the coefficients changes significantly when switching to the less efficient fixed effects model (which is

not surprising given that the sample obtained by omitting observations with time-invariant variables is significantly smaller than the full dataset), the positive and significant relation between R&D and PSS remains. As before, *RDdep*'s coefficients are about 50% larger than *Product innovation*'s coefficients. Turnover is still an important explanatory variable. For robustness, we also run a number of alternative specifications including Probit models instead of Logit, regressions with pooled Logit or Probit models with robust errors and clustered errors at the level of firms, and also simple OLS regressions. The results were qualitatively unaffected (see Table A8 in Appendix B for some alternative specifications).

Table 4: Panel data analysis: High-technology sector – random effects model

	(1) PSS	(2) PSS	(3) PSS
RDdep	.715*** (.140)	.716*** (.140)	.596*** (.212)
Product innovation	.312** (.149)	.295** (.150)	.165 (.225)
Turnover (log)	.687*** (.069)	.694*** (.070)	.721*** (.107)
Workforce size	-.148* (.085)	-.141 (.086)	-.050 (.122)
Age			.007 (.017)
Exports			-.001 (.003)
Year dummies		<i>yes</i>	<i>yes</i>
West German region			<i>yes</i>
_cons	-12.4*** (.940)	-12.7*** (.967)	-13.3*** (1.49)
<i>N</i>	5,720	5,720	2,928

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The inter-sectoral differences mentioned before can be due to industries using PSS for different scopes. To deal with this form of heterogeneity (at least partially), we re-run the regressions separately for the manufacturing and the service sector and on a smaller subsample of high-tech firms. As can be seen in Tables 3 and 4, *RDdep* still has a strong effect on PSS use even in these three industry subsamples. The coefficients are always statistically significant at the 1% level, and they are always much larger than the coefficients reported

for the variable *Product innovation*.

4.1.3 Some extensions

The relation between R&D and PSS use has been demonstrated in the previous sections. However, it might still be that R&D activities capture the effect of some other variables which we did not include in our regressions. In the following, we focus on revenue variability over time and across workers.¹⁰

As to the degree of revenue variability over time, PSS could be used as a means to share the risks of entrepreneurial activity with workers. Because R&D-intensive firms could also be more prone to large swings in profits and revenues over time, our variable *RDdep* could proxy for these larger variances. We therefore built two additional controls in order to account for revenue volatility in the short and long term: one is the variance of turnover in the three years preceding the time of observation, and the other is a time-invariant measure of the variance of turnover which uses the full length of the IAB dataset from 1992 to 2012. We re-run our basic specifications as in Table 2, this time also including alternatively one of our measures of volatility. The volatility controls are never statistically significant, even after excluding *RDdep* or *Product innovation*. We conclude that revenue volatility over time and risk-sharing play no role in explaining PSS use.

Also, revenue variability across workers could play a role. In order to check for this, we exploit the Linked-Employer-Employee Data from the IAB (LIAB). This additional dataset provides individual-level data of employees linked to establishments included in the IAB data (for information about the LIAB dataset refer to: Alda 2005, Alda and Herrlinger 2005, Jacobebbinghaus, Seth, et al. 2010, Heining et al. 2013). The LIAB contains information about the average gross daily wage earned by individuals. Because income data comes from social security records, the annual value is truncated from above at a threshold and therefore does not provide a perfect picture of the underlying distribution of wages. Still, we believe it conveys a first idea.

We used the (logarithm of) variance and the (logarithm of) standard deviation of wages of said daily wage data, as done in other studies (see as examples: Leonard 1990, Pfeffer and Langton 1993, Hibbs Jr and Locking 2000), to build a measure of intra-firm wage inequality. Due to data availability, the number of observations decreases to 3,000 in each of the years 2001, 2007 and 2009 (the year 2011 is not available in the LIAB dataset). In

¹⁰All results discussed in this section can be obtained upon request.

a first step, we ran again our basic specifications on this smaller dataset. The results are very similar in terms of statistical significance and magnitude. In a second step, we added wage dispersion as an additional control variable to our main specifications. Given the small correlation of wage dispersion and *RDdep* (0.07) and of wage dispersion and PSS use (0.16) we did not expect large changes of our main results. The regression results confirm this: the coefficients for *RDdep* always remain large and statistically significant at the 1% level, ranging from a minimum of 0.638 when using the logarithm of wage dispersion, to 1.540 when using the standard deviation of wages. Even at their minimum value, coefficients for *RDdep* are always visibly larger than for product innovation and wage dispersion.

We conclude that, regardless of variability in revenues, R&D firms are still more likely to offer PSS than non-R&D firms.

4.1.4 Causality

The results displayed so far indicate a strong positive correlation between *PSS* and *RDdep*. Our interpretation based on previous theoretical studies is that firms which perform R&D activities are more likely to offer PSS to key employees to drive them into innovating more (this is the pay-for-innovation theory as in Manso 2011), or to attract highly skilled staff (as in “supermanagers” models like Acharya et al. 2013 and Baranchuk, Kieschnick, et al. 2014). This explanation implies that the positive relation between PSS use and R&D (where we interpret R&D as an input to the innovation process and not as its output) exists within each period and is not due to inter-temporal effects.

However, from the results so far, the causality link between *PSS* and *RDdep* is not clear. If causality goes indeed from R&D to PSS, as we postulate, this could still happen across different periods of time. First, it might be that firms which made important innovations in the past (with or without having a formal R&D department) become able to signal their capacity to innovate, and as a consequence start to use PSS to attract highly skilled staff. This would imply a positive correlation between lagged values of *Product innovation* (or *RDdep*) and *PSS*.

Second, firms might start at some point in time to commit to an informal production of innovation, without an R&D department. Later as the innovative activities grow in size or importance a formal R&D department is established to further sustain such activities. The latter scenario would imply a positive

correlation between innovation produced in the past, and *RDdep*. In this case the positive correlation between *RDdep* and *PSS* would still hold within each period but the real driver would be found in innovation produced in the past.

Based on logical grounds we exclude that starting to offer PSS can drive firms to also start R&D activities in the same period, as this causality direction is both unrealistic and unsupported by the literature. However if PSS were used in the past for reasons unrelated to innovative activity and as a by-product it contributed to promoting innovation, then we would expect – as a third possible inter-temporal link – to see in the data that past PSS use is correlated to present *RDdep*, and possibly to *Product innovation*.

To address all these forms of causality, we run Granger-causality tests. We want to control whether past behavior affects present outcomes. While we cannot make any claim about the effectiveness of PSS to foster innovation (not least because for this we should have data about the type and composition of PSS pay as discussed in Lerner and Wulf 2007, which we do not have), we can check whether hypotheses built by assuming inter-temporal causality can be rejected. Our prior is that inter-temporal causality is not to be found in the data.

Table 5 reports some of the results obtained by means of fixed effect model specifications.¹¹ We look at how *PSS*, *RDdep* and *Product innovation* are affected by lagged values of the two other variables, respectively. The lags are for one period, which means 2 years or (only for the time interval between the 2001 survey and the 2007 survey) 6 years.

To test our second and third possible causality links, if inter-temporal causality were true and was led by innovation made in the past, then we would observe a correlation between lagged values of *Product innovation*, and the variables *PSS* or *RDdep*, but we do not (refer to columns 1, 2 and 4 in Table 5). If inter-temporal causality were due to PSS used in the past, we would observe a correlation between lagged values of *PSS*, and the variables *Product innovation* or *RDdep*. Again, we do not find such correlations (see columns 3 and 4 in Table 5).

When we include both present and lagged values of *RDdep* (column 1 in Table 5) to see whether the first causality link is supported, the lagged value

¹¹To run Granger-causality tests the use of fixed effects models appears a more sensible choice, as we are interested only in *within* effects across time. Also, due to the dynamic nature of the regression which includes lagged values of the dependent variable, random effects models could be biased due to autocorrelation of the error term.

of *RDdep* is not significantly correlated. The non-lagged value of *RDdep* obtains similar coefficients as per our fixed effects estimations (compare Table A3 in Appendix A). Although we lose statistical significance, the standard error is much smaller than the coefficient.

Table 5: Granger-causality tests for the IAB sample – fixed effects model

	(1) PSS	(2) PSS	(3) Product innovation	(4) RDdep
RDdep	.438 (.296)			
RDdep (lag)	.174 (.241)	-.006 (.219)	.284 (.198)	-2.11*** (.215)
Product innovation (lag)	.042 (.178)	.044 (.175)	-1.87*** (.141)	-.112 (.218)
PSS (lag)	-2.11*** (.146)	-2.07*** (.144)	.009 (.164)	-.057 (.221)
Turnover (log)	.227 (.182)	.246 (.181)	-.093 (.220)	.243 (.309)
Workforce size	.107 (.219)	.107 (.218)	-.080 (.249)	.439 (.337)
Manufacturing dummy	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
Service dummy	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
High-tech dummy	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
Year dummies	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
West German region	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
<i>N</i>	2,077	2,112	1,903	967
<i>loglik</i>	-570	-584	-524	-260
<i>McFadden's R²</i>	.232	.226	.229	.246
<i>McFadden's Adj. R²</i>	.217	.212	.214	.214

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

These findings suggest that the causality direction we support better fits the observed behavior of firms with regard to PSS use. We conclude that having an R&D structure in place is associated with offering PSS in the same time period, and reject the alternative hypothesis of inter-temporal effects.

4.2 Regressions on U.K. data

4.2.1 Data and methodology

We now turn to the U.K. dataset of 236 firms (out of 400 contacted firms) which were selected based on their “high technology” industry sector (according to SIC code). A summary of the variables is presented in Table A4 in Appendix A. Firms were interviewed between December 2000 and January 2001 by the Centre for Business Research in Cambridge, U.K. (details about the methodology and sample selection are provided in Quince and Whittaker 2002). This dataset is much smaller than the IAB dataset, it is only for a single year, and only includes firms from the high-technology sectors. Its advantage, however, is that its focus is on innovation, and as a consequence it includes many questions not covered by the IAB surveys. We employ it as a comparison – and as a further robustness check – for our German analysis, exploiting the fact that the comparability of the IAB survey in 2001 with the U.K. dataset in terms of year-dependent effects should be relatively high.

Other differences arise in comparison to the German IAB dataset. First, interviewed firms are older in the U.K. sample (where on average firms were founded between 1980 and 1989) than in the IAB sample (where on average firms are 10 years old). Second, the U.K. dataset does not include information directly comparable to the *RDdep* variable from the IAB. Rather, we employ five alternative proxies for R&D intensity and activity: 1) *RDexpenditure* measures the amount of money spent on R&D activities in the past two years, excluding the observations where respondents reported a value of zero (this is done for better comparability with the analysis of Germany); 2) *RDexpenditure_zeros* is built as *RDexpenditure* but includes observations with reported values of zero; 3) *RDshare* measures R&D expenditures (including values of zeros) as a percentage of total turnover; 4) *SomeRD* is a reduction to a binary variable of the values reported in *RDexpenditure_zeros* and takes value 1 if *RDexpenditure_zeros* > 0, and zero otherwise; 5) finally, *RDintensive* is built from subjective judgments and is made equal to 1 if the respondent reports that R&D activities are deemed important or very important for the firm.

To capture innovation output, we introduce a variable similar to the previously employed regressor *Product innovation*: a binary variable (labeled *Patented innovations*) that is equal to 1 if the respondent applied for a patent for at least one innovation in the last two years.¹² As for the IAB sample,

¹²Differently from the IAB sample, though, here we cannot make any claim about causal-

we expect to find a positive correlation with PSS use, but with smaller coefficients than for R&D expenditures.

There are some issues which have to be addressed. In comparison to the IAB sample, this sample is both small and more homogeneous: the majority of firms report some R&D activity, and all belong to the high-technology sector. For these reasons we expect that the effects we are looking for are less visible and hence less statistically significant than in the IAB sample. Still, the richer set of innovation-related questions included in this survey like the exact amount of R&D expenditures and questions related to the organization of work make it of special interest. In particular, we are able to use the same kind of dependent variable as with the IAB and the ECS 2009 samples (*PSS*), and to compare the U.K. sample with the IAB sample not only on R&D intensity, but also on turnover, workforce size (both at establishment and at company group level), and the age of the firm. Sector heterogeneity is controlled for by adding 9 industry dummies.

Additionally we study organizational characteristics of firms. We would expect, based on previous studies and based on what we saw in the ECS 2009 data sample, that a highly educated workforce is associated with higher chances of firms offering PSS. We also study the effects of team work. More team work could either be associated with a more likely use of profit sharing (due to unobservability of individual effort and positive knowledge spillovers among coworkers, as pointed out experimentally in Ederer 2013), or with a less likely use (due to free-riding behavior of coworkers). Data from the ECS 2009 suggest that the positive effect of team work should be generally dominant in European firms, and we inquire whether this result also holds specifically for innovative firms by including a variable equal to 1 if team work is reported to be important in the firm (*Team work*). Furthermore, we add a variable equal to 1 if the firm's work place is a very competitive one (*Competitive workplace*). We expect to observe negative coefficients for *Competitive workplace*, as argued in previous psychology studies (for example in Kohn 1993, Cordery 1997, Bandura 2001).

4.2.2 Results

Results for the full sample are reported in Table 6. The first four columns are for a model including the age of the firm (*Age*), the share of employees with a tertiary-level education (*Highly educated*), whether team work is important

ity when comparing coefficients for our four proxies for R&D intensity, and for *Patented innovations*. This is because we do not have a panel structure to exploit.

in the firm (*Team work*), and whether the firm's work place is competitive (*Competitive workplace*).

Of the four proxies used for R&D intensity, all obtain positive coefficients. *RDexpenditure*, *RDexpenditure_zeros* and *RDshare* provide more robust findings, as we either get significance at least at the 10% level, or in the case of specification (2) the standard deviation for *RDshare* is smaller than the coefficient. Coefficients for *SomeRD* are still positive, but without any acceptable statistical significance. As also with the IAB sample, turnover remains a strong and always very significant positive predictor of PSS use, while the employed workforce in the establishment is not significantly associated with PSS use.

The variable *Age* always obtains negative, but not-significant coefficients. The variables *Team work* and *Competitive workplace* always have the expected sign, but again no acceptable statistical significance.

In columns 5 to 8 a different model is tested which includes a measure of innovative output (*Patented innovations*) and a binary variable (*RDintensive*) equal to 1 if the respondent deems that R&D activities are important or very important for the firm. Our expectation is to find positive coefficients. We see that *Patented innovations* always produces positive coefficients, but they are never statistically significant, while *RDintensive* provides mixed and insignificant results.

As already done with the IAB sample, we replicate the same estimates for the manufacturing and services subsamples (Tables A6 and A7 in Appendix A). Results for the manufacturing sector are rather similar to the full sample. The service sector, being also of smaller sample size, reports mixed results for the variables of interest.

5 Conclusions

Our results obtained for Germany and the U.K. confirm previous studies done for the U.S.. In both the German and the U.K. data, a positive and significant relationship is found between R&D activity and the likelihood to offer PSS to the workforce.

In the German data the finding is very robust. Having an R&D department, or having done some product innovation in the recent past, is always significantly and positively associated with offering PSS. The coefficients for R&D

Table 6: Results from U.K. 2000/2001: All sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>
RDexpenditure (log)	.360* (.202)				.390** (.176)			
RDexpenditure_zeros (log)		.172 (.118)				.239* (.135)		
RDshare			.037*** (.011)				.016 (.011)	
SomeRD				.236 (.437)				.223 (.515)
Patented innovations					.389 (.452)	.562 (.451)	.519 (.423)	.624 (.438)
RDintensive					-.808 (.572)	-.693 (.567)	-.179 (.399)	.093 (.463)
Turnover (log)	2.86*** (1.07)	3.03*** (.901)	3.55*** (.948)	2.97*** (.792)	2.59*** (1.04)	2.66*** (.857)	2.96*** (.899)	2.77*** (.832)
Workforce size (log)	-.567 (.599)	-.826 (.520)	-.857* (.479)	-.795 (.498)	-1.078** (.513)	-.995** (.460)	-.836* (.428)	-.891** (.414)
Workforce size group (log)	.363 (1.03)	1.20 (.984)	1.36 (.913)	1.45 (.967)	1.30 (1.00)	1.49 (.910)	1.36 (.865)	1.43* (.841)
Age	-.305 (.266)	-.023 (.021)	-.031 (.023)	-.378 (.238)				
Highly educated (percentage)	-.746 (.984)	.109 (.881)	-.015 (.901)	.047 (.911)				
Team work	.915 (1.30)	.320 (.952)	.239 (.966)	.621 (.715)				
Competitive workplace	-.560 (.523)	-.417 (.420)	-.341 (.432)	-.288 (.408)				
Industry dummies	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>	<i>yes</i>
_cons	.215 (1.62)	1.66 (1.98)	2.21 (2.07)	1.08 (1.26)	-.209 (.874)	-.097 (.714)	-.169 (.689)	-.066 (.700)
<i>N</i>	126	173	173	184	122	168	168	178
<i>McFadden's R²</i>	.24	.25	.27	.24	.15	.17	.16	.16
<i>McFadden's Adj. R²</i>	.04	.10	.12	.10	.07	.11	.10	.10

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

activity are always much larger than for product innovation. This is suggestive of a causal direction that goes from R&D activity to PSS. Granger-causality tests support this view. We consequently claim that firms with some R&D activity currently in place are more likely to offer PSS.

As for the other determinants, the size of a firm measured as turnover is always strongly associated with PSS use. Also, after controlling for turnover, the size of the workforce is negatively associated with PSS use, or not significantly associated at all. These results are at odds with some previous U.S. studies which found a negative correlation, for example Baranchuk, Kieschnick, et al. (2014) where size is measured as sales. Our results also question results like in Ittner et al. (2003) where a positive correlation is found for the size of the workforce, again without controlling for turnover or sales. Our results suggest that both size effects can be at play: a dominant effect due to the company size in terms of value (turnover) with larger firms benefiting more from PSS use; and a secondary effect due to workforce size, which implies that having more employees (or belonging to a more labor-intensive industry) raises monitoring costs and profit dilution of PSS, and therefore makes it less likely that PSS will be used, given other characteristics of firms.

Similarly to Zenger and Lazzarini (2004) we find that the age of a company is not a meaningful explanatory variable for PSS use: it is seldom statistically significant. When we looked for effects due to different organization of labor, we obtain some suggestive results. In the U.K. sample a positive correlation is found with team work, but without being statistically significant. Also as expected, for the U.K. sample a highly competitive work environment is negatively associated with PSS use.

These findings suggest some avenues for future research. First, empirical research should inquire the relative importance of different motives for PSS use in innovative firms, in order to better understand what is really driving the positive correlation between R&D and PSS use. Due to data limitations we could not disentangle whether pay-for-innovation or attraction and retention motives are dominant. Second, as U.S. and European surveys point to the fact that pay-for-innovation and attraction motives are important self-reported determinants of PSS use, future theoretical analysis should incorporate both motives in models dealing with PSS offered by knowledge-intensive firms, in a way similar to what was done, for example, in Baranchuk, MacDonald, et al. (2011) for the managerial job market. From a theoretical perspective and because innovation is a dynamic process which can involve strategic behavior by competing firms, it would be also interesting to inquire the welfare implications (in the direction of Bénabou and Tirole 2013) of a possible *race to the top* of PSS use in markets with compensation contracts set endogenously by firms and with fast labor turnover and technological competition, as was apparently the case during the New Economy boom in the U.S. in late 1990s.

References

- Acharya, Viral V., Marco Pagano, and Paolo Volpin (2013). *Seeking Alpha: Excess Risk Taking and Competition for Managerial Talent*. Working Paper 18891. National Bureau of Economic Research.
- Aerts, Kris, Kornelius Kraft, and Julia Lang (2015). “Profit sharing and innovation”. *Industrial and Corporate Change*, dtv009.
- Alda, Holger (2005). “Datenbeschreibung der Version 1 des LIAB-Längsschnittmodells”. *FDZ-Datenreport* (02).
- Alda, Holger and Dagmar Herrlinger (2005). “LIAB-Datenhandbuch”. *FDZ-Datenreport* (07).
- Andersson, Fredrik et al. (2009). “Reaching for the Stars: Who Pays for Talent in Innovative Industries?” *The Economic Journal* 119(538), F308–F332.
- Balkin, David B. and Luis R. Gomez-Mejia (1984). “Determinants of R and D Compensation Strategies in the High Tech Industry”. *Personnel Psychology* 37(4), pp. 635–650.
- Balkin, David B., Gideon D. Markman, and Luis R. Gomez-Mejia (2000). “Is Ceo Pay In High-Technology Firms Related To Innovation?” *Academy of Management Journal* 43(6), pp. 1118–1129.
- Bandura, Albert (2001). “Social Cognitive Theory: An Agentic Perspective”. *Annual Review of Psychology* 52(1), pp. 1–26.
- Baranchuk, Nina, Robert Kieschnick, and Rabih Moussawi (2014). “Motivating innovation in newly public firms”. *Journal of Financial Economics* 111(3), pp. 578–588.
- Baranchuk, Nina, Glenn MacDonald, and Jun Yang (2011). “The Economics of Super Managers”. *Review of Financial Studies* 24(10), pp. 3321–3368.
- Barros, Henrique M. and Sergio G. Lazzarini (2012). “Do organizational incentives spur innovation?” *BAR - Brazilian Administration Review* 9(3), pp. 308–328.
- Bellmann, L. and I. Möller (2006). *Die Betriebe in Deutschland haben Nachholbedarf*. Institut für Arbeitsmarkt- und Berufsforschung (IAB) Discussion Papers.
- Bénabou, Roland and Jean Tirole (2013). *Bonus Culture: Competitive Pay, Screening, and Multitasking*. Working Paper 18936. National Bureau of Economic Research.
- Boeri, Tito, Claudio Lucifora, and Kevin J. Murphy (2013). *Executive Remuneration and Employee Performance-Related Pay: A Transatlantic Perspective*. Oxford University Press. 312 pp.

- Canyon, Martin J. and Joachim Schwalbach (2000). “Executive compensation: evidence from the UK and Germany”. *Long Range Planning* 33(4), pp. 504–526.
- Cordery, John (1997). “Reinventing Work Design Theory and Practice”. *Australian Psychologist* 32(3), pp. 185–189.
- Core, John E. and Wayne R. Guay (2001). “Stock option plans for non-executive employees”. *Journal of Financial Economics* 61(2), pp. 253–287.
- Drechsler, Jörg (2011). *Methodenreport: Synthetische Scientific-Use-Files der Welle 2007 des IAB-Betriebspanels*. FDZ-Methodenreport, 01/2011, Nürnberg.
- Ederer, Florian P. (2013). *Incentives for Parallel Innovation*. SSRN Scholarly Paper ID 2309664. Rochester, NY: Social Science Research Network.
- Ellguth, Peter, Susanne Kohaut, and Iris Möller (2014). “The IAB Establishment Panel - methodological essentials and data quality”. *Journal for Labour Market Research* 47(1-2), pp. 27–41.
- Fischer, Gabriele et al. (2009). “The IAB Establishment Panel – things users should know”. *Schmollers Jahrbuch. Zeitschrift für Wirtschafts- und Sozialwissenschaften* 129(1), pp. 133–148.
- Francis, Bill B, Iftexhar Hasan, and Zenu Sharma (2011). “Incentives and innovation: Evidence from CEO compensation contracts”. *Bank of Finland Research Discussion Paper* (17).
- Hall, Brian J. and Kevin J. Murphy (2003). “The Trouble with Stock Options”. *Journal of Economic Perspectives* 17(3), pp. 49–70.
- Heining, Jörg, Theresa Scholz, Stefan Seth, et al. (2013). “Linked employer–employee data from the IAB: LIAB cross-sectional model 2, 1993–2010 (LIAB QM2 9310)”. *FDZ-Datenreport* (02).
- Hellmann, Thomas and Veikko Thiele (2011). “Incentives and Innovation: A Multitasking Approach”. *American Economic Journal: Microeconomics* 3(1), pp. 78–128.
- Hibbs Jr, Douglas A and Håkan Locking (2000). “Wage dispersion and productive efficiency: Evidence for Sweden”. *Journal of Labor Economics* 18(4), pp. 755–782.
- Ittner, Christopher D., Richard A. Lambert, and David F. Larcker (2003). “The structure and performance consequences of equity grants to employees of new economy firms”. *Journal of Accounting and Economics* 34(1), pp. 89–127.
- Jacobebbinghaus, Peter, Stefan Seth, et al. (2010). “Linked Employer-Employee Data from the IAB: LIAB cross-sectional model 2 1993-2008 (LIAB QM2 9308)”. *FDZ Datenreport* (05).
- Kohn, Alfie (1993). “Why incentive plans cannot work”. *Harvard business review* 71(5), pp. 54–60.

- Kroumova, Maya K. and James C. Sesil (2006). "Intellectual Capital, Monitoring, and Risk: What Predicts the Adoption of Employee Stock Options?" *Industrial Relations: A Journal of Economy and Society* 45(4), pp. 734–752.
- Leonard, Jonathan S (1990). "Executive pay and firm performance". *Industrial & Labor Relations Review* 43(3), 13S–29S.
- Lerner, Josh and Julie Wulf (2007). "Innovation and Incentives: Evidence from Corporate R&D". *The Review of Economics and Statistics* 89(4), pp. 634–644.
- Manso, Gustavo (2011). "Motivating Innovation". *The Journal of Finance* 66(5), pp. 1823–1860.
- Milkovich, George T., Barry Gerhart, and John Hannon (1991). "The effects of research and development intensity on managerial compensation in large organizations". *The Journal of High Technology Management Research* 2(1), pp. 133–150.
- Murphy, Kevin J. (2003). "Stock-based pay in new economy firms". *Journal of Accounting and Economics* 34(1), pp. 129–147.
- Oyer, Paul and Scott Schaefer (2005). "Why do some firms give stock options to all employees?: An empirical examination of alternative theories". *Journal of Financial Economics* 76(1), pp. 99–133.
- Pfeffer, Jeffrey and Nancy Langton (1993). "The effect of wage dispersion on satisfaction, productivity, and working collaboratively: Evidence from college and university faculty". *Administrative Science Quarterly*, pp. 382–407.
- Quince, Thelma and Hugh Whittaker (2002). *Entrepreneurs and their Businesses*. Centre for Business Research, University of Cambridge, Cambridge (UK).
- Tremblay, Michel and Denis Chenevert (2005). "The effectiveness of compensation strategies in international technology intensive firms". *International Journal of Technology Management* 31(3), pp. 222–239.
- Zenger, Todd R. and Sergio G. Lazzarini (2004). "Compensating for innovation: Do small firms offer high-powered incentives that lure talent and motivate effort?" *Managerial and Decision Economics* 25(6), pp. 329–345.

APPENDIX A

German dataset

Table A1: IAB dataset – summary of variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
PSS	51,297	.1780026	.3825187	0	1
RDdep	50,395	.1377518	.3446427	0	1
Product innovation	51,635	.1041735	.3054885	0	1
Turnover	41,982	6.19e+07	.248e+09	900	4.60e+11
Workforce size	52,096	2.462166	1.566184	1	6
Age	25,957	10.0527	5.704322	0	21
Exports	48,413	7.052135	18.67396	0	100
Manufacturing dummy	51,068	.2957821	.456398	0	1
Service dummy	52,096	.3741938	.4839187	0	1
High-tech dummy	51,068	.1429075	.3499819	0	1
West German region dummy	52,096	.6240018	.4843842	0	1

Table A2: IAB dataset – description of variables used

Variable	Description	Values
PSS	Whether the establishment offers profit sharing schemes to employees	binary
RDdep	Whether the establishment has a formal R&D department	binary
Product innovation	Whether products for which a new market was created have been started in the last 2 years	binary
Turnover	Total turnover in thousand Eur	continuous
Age	No. of years since foundation	discrete
Exports	Share of sales to foreign countries	continuous 0 to 100
Industry dummies	10 industry classes, based on 1-digit NACE codes	industry classes (used as dummies)
Manufacturing dummy	Dummy representing whether a firm belongs to the manufacturing sector	binary
Service dummy	Dummy representing whether a firm belongs to the service sector	binary
High-tech dummy	Dummy representing whether a firm belongs to the high-technology sector	binary
Workforce size	6 size classes, based on the size of the employed workforce	ordered discrete 1 to 6
West German region	Dummy representing whether a firm is located in a region of the former West Germany	binary

Table A3: Panel data analysis: All sectors – conditional fixed effects model

	(1)	(2)	(3)
	PSS	PSS	PSS
RDdep	.384*** (.108)	.437** (.179)	.403** (.177)
Product innovation	.220*** (.080)	.239* (.143)	.241* (.142)
Turnover (log)		.496*** (.135)	.510*** (.135)
Workforce size		-.033 (.140)	-.044 (.139)
Age		.026 (.030)	.031 (.030)
Exports		.002 (.005)	.002 (.005)
Manufacturing dummy			-.842*** (.296)
Service dummies			-.699** (.318)
High-tech dummy			.267* (.153)
Industry dummies		<i>yes</i>	
Year dummies		<i>yes</i>	<i>yes</i>
West German region		<i>yes</i>	<i>yes</i>
<i>N</i>	7,101	2,512	2,512
<i>McFadden's R²</i>	.004	.033	.032
<i>McFadden's Adj. R²</i>	.003	.012	.017

Standard errors in parentheses
 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The U.K. dataset

Table A4: U.K. 2000/2001 – summary of variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
PSS	214	.546729	.498978	0	1
RDexpenditure	150	500.366	1453.79	0	15,000
RDexpenditure_zeros	211	355.710	1245.51	0	15,000
RDshare	203	7.14226	15.8955	0	108.333
RDintensive	236	.508474	.500990	0	1
Patented innovations	219	.232876	.423632	0	1
SomeRD	229	.733624	.443031	0	1
Turnover	215	1.86046	.885537	1	5
Workforce size	232	61.4224	168.499	0	2,000
Workforce size group	232	2.75862	1.46308	0	6
Age	233	1.97854	.853220	1	3
Highly educated	212	.223220	.249565	0	1
Team work	220	.936363	.244660	0	1
Competitive workplace	219	.634703	.482616	0	1

Table A5: U.K. 2000/2001 – description of variables used

Variable	Description	Values
PSS	Whether the establishment offers profit sharing schemes to employees	binary
RDexpenditure	Expenditures for R&D, only including respondents doing some R&D activity	continuous (in thousands GBP)
RDexpenditure_zeros	As RDexpenditure but including firms doing no R&D activity	continuous (in thousands GBP)
RDshare	R&D expenditure as a share of turnover	continuous 0 to 1
RDintensive	Takes value 1 if firm engaged continuously in R&D activities	binary
Patented innovations	Takes value 1 if firm applied for a patent in the last two years	binary
SomeRD	Whether some R&D activity was done in previous two years	binary
Turnover	Turnover at the establishment level	ordered discrete 1 to 5
Workforce size	Number of employees in the establishment	discrete
Workforce size group	Number of employees in the company's group	discrete
Age	No. of years since foundation (3 classes)	ordered discrete 1 to 3
Highly educated	Share of employees with a degree, over number of employees in the establishment	continuous 0 to 100
Team work	Whether team work is important in the establishment	binary
Competitive workplace	Whether workplace is highly competitive codes	binary
Industry dummies	9 high-technology industrial categories	industry classes (used as dummies)

Table A6: Results from U.K. 2000/2001: Manufacturing sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>
RDexpenditure (log)	.270 (.225)				.481** (.235)			
RDexpenditure_zeros (log)		.226* (.134)				.363** (.178)		
RDshare			.057*** (.023)				.070** (.031)	
SomeRD				.862 (.534)				.550 (.679)
Patented innovations					.736 (.603)	.840 (.626)	.678 (.563)	1.08* (.622)
RDintensive					-.556 (.669)	-.534 (.687)	-.146 (.549)	.252 (.587)
Workforce size (log)	-.237 (.775)	-.551 (.661)	-.634 (.581)	-.528 (.552)	-.424 (.835)	-.730 (.707)	-.752 (.618)	-.633 (.612)
Workforce size group (log)	.241 (1.19)	.515 (1.12)	.798 (1.02)	.980 (1.03)	.514 (1.31)	.635 (1.24)	.853 (1.13)	.774 (1.12)
Turnover (log)	2.16* (1.28)	3.00** (1.24)	3.86*** (1.38)	2.64*** (.992)	2.49* (1.44)	3.54** (1.38)	4.81*** (1.69)	3.59*** (1.25)
Age	.000007 (.031)	-.007 (.027)	-.010 (.028)	-.012 (.025)				
Highly educated (percentage)	.246 (1.59)	.610 (1.56)	.065 (1.50)	1.23 (1.46)				
Team work	.573 (2.17)	.653 (2.01)	.575 (1.93)	.788 (1.79)				
Competitive workplace	-.538 (.554)	-.249 (.487)	-.094 (.503)	-.181 (.487)				
_cons	-1.70 (2.76)	-1.15 (2.61)	-.954 (2.56)	-1.19 (2.49)	-2.08 (1.62)	-1.28 (1.27)	-1.45 (1.11)	-1.26 (1.16)
<i>N</i>	83	105	105	112	81	104	104	110
<i>McFadden's R²</i>	.137	.192	.218	.178	.201	.254	.274	.238
<i>McFadden's Adj. R²</i>	0	.066	.092	.060	.068	.155	.176	.144

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Results from U.K. 2000/2001: Service sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>	<i>PSS</i>
RDexpenditure (log)	.160 (.199)				.699* (.420)			
RDexpenditure_zeros (log)		-.056 (.141)				.127 (.245)		
RDshare			-.001 (.014)				.006 (.013)	
SomeRD				-.345 (.610)				-.168 (.862)
Patented innovations					-1.43 (.893)	-.335 (.759)	-.369 (.771)	-.537 (.748)
RDintensive					-1.83 (1.57)	-.778 (1.15)	-.417 (.693)	.093 (.974)
Workforce size (log)	-1.41 (.884)	-1.39* (.661)	-1.39* (.813)	-1.47* (.776)	-2.05* (1.17)	-1.31* (.778)	-1.19* (.725)	-1.24* (.666)
Workforce size group (log)	1.74 (1.64)	3.34* (1.74)	3.34* (1.74)	3.00* (1.65)	2.13 (2.15)	2.71 (1.65)	2.59 (1.61)	2.53* (1.46)
Turnover (log)	3.56* (1.98)	2.50** (1.10)	2.40** (1.08)	2.87** (1.12)	3.16* (1.75)	1.94* (1.14)	1.99* (1.17)	2.05* (1.14)
Age	-.039 (.038)	-.050 (.034)	-.049 (.035)	-.054 (.033)				
Highly educated (percentage)	-.014 (1.30)	.715 (1.14)	.573 (1.12)	.547 (1.11)				
Team work	1.47 (1.58)	.723 (.968)	.693 (.959)	1.03 (.890)				
Competitive workplace	-.609 (.756)	-.850 (.601)	-.866 (.618)	-.678 (.602)				
_cons	1.36 (2.87)	2.65 (2.23)	2.54 (2.25)	3.00 (2.11)	1.12 (1.67)	.754 (1.02)	.692 (.999)	.908 (.974)
<i>N</i>	43	68	68	72	41	64	64	68
<i>McFadden's R²</i>	.221	.228	.226	.227	.172	.124	.156	.123
<i>McFadden's Adj. R²</i>	0	.037	.035	.046	0	0	0	0

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX B

Table A8: IAB data: some robustness checks using different model specifications

	(1) Pooled OLS	(2) Pooled Logit (robust errors)	(3) Pooled Logit (clustered errors)
RDdep	.128*** (.008)	.751*** (.061)	.751*** (.069)
Product innovation	.055*** (.008)	.362*** (.062)	.362*** (.066)
Turnover (log)	.052*** (.002)	.463*** (.022)	.463*** (.025)
Workforce size	.002 (.003)	-.071** (.029)	-.071** (.032)
Age	-.0003 (.0004)	-.0007 (.004)	-.0007 (.004)
Exports	.0002 (.0001)	.0006 (.001)	.0006 (.001)
Industry dummies	<i>yes</i>	<i>yes</i>	<i>yes</i>
Year dummies	<i>yes</i>	<i>yes</i>	<i>yes</i>
West German region	<i>yes</i>	<i>yes</i>	<i>yes</i>
_cons	-.608*** (.033)	-8.35*** (.587)	-8.35*** (.344)
<i>N</i>	49,366	19,501	19,501

Clustered errors are at the level of the establishments.

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: IAB data: Marginal effects of Panel data analysis: All sectors – random effects model

	(1)	(2)	(3)
	PSS	PSS	PSS
RDdep	.101*** (.004)	.068*** (.006)	.067*** (.006)
Product innovation	.034*** (.003)	.034*** (.006)	.035*** (.006)
Turnover (log)		.045*** (.002)	.045*** (.002)
Workforce size		-.004 (.003)	-.005* (.003)
Age		-.0002 (.0004)	-.0001 (.0004)
Exports		.0001 (.0001)	.0001 (.0001)
Manufacturing dummy			-.010* (.006)
Service dummy			.056*** (.006)
High-tech dummy			-.007 (.005)
Industry dummies		<i>yes</i>	
Year dummies		<i>yes</i>	<i>yes</i>
West German region		<i>yes</i>	<i>yes</i>
<i>N</i>	49,366	19,501	19,501

Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$