Flexible labor and innovation performance: Evidence from longitudinal firm-level data

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Abstract: Firms with high shares of workers on fixed-term contracts have significantly higher sales of *imitative* new products but perform significantly worse on sales of *innovative* new products ("first on the market"). High functional flexibility in "insider-outsider" labor markets enhances a firm's new product sales, as do training efforts and highly educated personnel. We find weak evidence that larger and older firms have higher new product sales than do younger and smaller firms. Our findings should be food for thought to economists making unqualified pleas for the deregulation of labor markets.

Keywords: Innovation performance, new product sales, numerical flexibility, functional flexibility, OSA longitudinal dataset, SMEs

JEL Classifications: J5, M5, O15, O31

1. Introduction

In recent years, studies on the determinants of innovative behavior in Europe have been encouraged by the increasing availability of firm-level data through the European *Community Innovation Survey* (*CIS*). The emerging literature has focused on determinants of innovation such as market structure, firm size, knowledge spillovers, R&D collaboration, conditions for the appropriation of innovation benefits, and others. This paper will address a factor that has not been covered in *CIS* studies: What is the influence of the increased flexibility of labor on innovation?

Over the last twenty years, many labor market economists have strongly recommended that high unemployment should be reduced by making European labor markets more flexible. An example is the OECD's Jobs Study (1994). Subsequent to the Jobs Study, a literature has developed that tries to substantiate that more flexible labor markets would not only be favorable for employment, but may also allow for higher economic growth and higher productivity growth (e.g. Nicoletti and Scarpetta, 2003). Nonetheless, flexible labor contracts as determinants of innovation or productivity growth are still under-researched. There are only few firm-level studies, including Laursen and Foss (2003), Michie and Sheehan (2003), Kleinknecht *et al*. (2006), Arvanitis (2005), and Lucidi and Kleinknecht (2009). This is regrettable, as labor relations and human resources have been suggested to have a significant impact on innovation through their influence on knowledge processes (Amabile et al., 1996; Guest, 1997; Trott, 1998).

This study makes an empirical contribution to our sparse knowledge about the impact of flexible labor on innovation using firm-level data from several subsequent surveys with broad industry coverage in the Netherlands. Our database covers a "direct" measure of innovation: sales performance of new or improved products, introduced during the past 2 years. We take advantage of the fact that there is a wide spectrum of typical labor contract patterns in the Netherlands (and in our database). A number of Dutch firms still have fairly rigid "Rhineland" labor relations, while others have highly flexible "Anglo-Saxon" practices in hiring. "Rhineland" firms typically offer their personnel good wages, fair protection against dismissal, and longer-term commitments. "Anglo-Saxon" firms employ significant labor on fixed-term contracts, hired from employment agencies or freelance workers, which allows them to adapt to changing demand conditions by easily hiring or firing people.[1]

We trust that the wide spectrum of "Rhineland" versus "Anglo-Saxon" labor contracts in the Netherlands allows for a meaningful study of the possible impact of flexible labor on innovation performance. This paper is organized as follows: Section 2 provides a brief sketch of the theoretical background and discusses our hypotheses. Section 3 describes our data and the empirical model. Section 4 reports the regression results. Section 5 rounds up with conclusions.

2. Patterns of flexible labor and innovation

Labor market flexibility can be subdivided into three types of flexibility: (1) numerical flexibility, (2) functional flexibility and (3) wage flexibility (e.g. Beatson, 1995). This paper is confined to analyzing numerical and functional flexibility. Numerical (or "external") flexibility allows for easy hiring or firing of personnel, resulting in significant reductions of a firm's wage bill.[2] High numerical (or “external”) flexibility is at the core of the “Anglo-Saxon” model of labor relations.

Functional flexibility is the ability of firms to reallocate labor in their internal labor markets, relying on training that allows personnel to carry out a wider range of tasks (e.g. Beatson, 1995). Functional flexibility reflects the multiple competencies of workers, such as multi-skilling, multi-tasking, cooperation and the involvement of workers in decision making (Arvanitis, 2005). Functional (or “internal”) flexibility is characteristic of the “Rhineland” model of labor relations, providing opportunities for long-term careers in the same firm. Such long-term commitments may be interpreted as an investment in the trust, loyalty and commitment of individuals.

Many mainstream economists tend to be in favor of more flexible, “Anglo-Saxon” labor markets. In a traditional microeconomics view, markets can never be flexible enough. There are a number of detailed arguments in favor of more numerical flexibility. First, long tenured employees may become conservative, being attached to outdated products and processes, and reluctant to adapt to significant changes due to “lock-in” effects (Ichniowski and Shaw, 1995). Second, labor market rigidity may reduce the reallocation process of labor from old and declining to newly emerging industries, and the difficulty of firing personnel might frustrate labor-saving process innovations (Bassanini and Ernst, 2002; Scarpetta and Tessel 2004; see also Nickell and Layard, 1999). Third, with strong protection against dismissal, labor may become too powerful, increasing the chance that monopoly profits from innovation will be (partly) absorbed through higher wage claims. Monopoly profits from innovation are a reward for taking innovative risks; such risk-taking would be discouraged if labor could claim part of the premium. Powerful labor, negotiating wage contracts at the firm level, could therefore "hold up" investments in innovation (Malcomson, 1997). Finally, one might add that higher flexibility would also allow for easier replacement of less productive personnel by more productive people and the threat of firing might prevent shirking. Easier hiring and firing could also help keep wages low, as is evidenced by estimates of wage equations.[3] Moreover, as has recently been emphasized by Arvanitis (2005), firms can more effectively fulfill their demands for specialized services by making use of temporary work.

As counterarguments against high numerical flexibility, we propose the following: high numerical flexibility may weaken a firm's historical memory and continuity of learning. A high external labor turnover rate may reduce employees' loyalty and commitment, resulting in easier leakage of knowledge to competitors; such externalities would discourage investment in R&D. The argument that high numerical flexibility will make it difficult for firms to store innovative knowledge is particularly relevant for firms that have a "routinized" Schumpeter II innovation regime (Kleinknecht *et al*., 2006). In a Schumpeter II regime, the path-dependent historical accumulation of knowledge is critical to superior product and process performance. Much of the accumulated knowledge is "tacit." Different from documented and codified knowledge, "tacit" knowledge is ill-documented and idiosyncratic, as it is based on personal experience (Polanyi, 1966). Accumulation of such knowledge is favored by a longer tenure in the same firm.

Shorter job durations may also discourage investments in firm-sponsored training. In highly flexible labor markets, employees may be interested in acquiring general knowledge that increases their employability elsewhere, but they may be reluctant to acquire firm-specific knowledge (e.g., studying safety instructions) if they anticipate a short stay in the firm. Moreover, Naastepad and Storm (2006) have shown that (growing) flexibility in labor relations in OECD countries leads to a significant growth in management bureaucracies to control disloyal behavior. While adherents of flexible labor markets emphasize that difficult firing of redundant personnel would frustrate labor-saving innovations, it can also been argued that personnel who are easy to fire have strong incentives to hide information about how their work can be done more efficiently. This can be damaging to productivity growth as far as the management is dependent on their personnel's "tacit" knowledge to efficiently implement process innovations (see also Lorenz, 1999). Finally, easy firing may change power relations in a firm. Personnel on the shop floor are less likely to criticize powerful (top) managers, and poor critical feedback from the shop floor may favor problematic management practices.

Given the opposing theoretical arguments pertaining to numerical flexibility, it is interesting to look at empirical findings. Two recent studies using UK firm-level data show a *negative* correlation between numerical flexibility and innovation (Michie and Sheehan, 1999, 2001). Similar results are reported by Chadwick and Cappelli (2002) from US data. Arvanitis (2005) reports mixed results. In one of his specifications, he finds that temporary work has a positive impact on innovation, which he ascribes to the need to hire specialists on a temporary basis for the R&D process. When using part-time work as another indicator of flexible labor, he finds a significantly negative impact on innovation. His general conclusion is that "… firms with high productivity are those which apply new forms of workplace organization but do not engage many part-time and temporary workers" (Arvanitis, 2005: 1010). Given that the results by Arvanitis are not clear-cut, we shall also test whether there is a non-linear relationship, using quadratic terms of numerically flexible labor.

While the impact on innovation of numerical flexibility is doubtful, Arvanitis does find a positive impact on productivity and innovation for several of his indicators of functional flexibility. Similar results have been found by others (Michie and Sheehan, 1999, 2001; Chadwick and Cappelli, 2002; Kleinknecht *et al*., 2006). High functional flexibility in internal labor markets reflects a firm's ability to organize flexibly without destroying loyalty and commitment by firing. This is likely to reduce positive externalities through the exit of trained people or through disloyal behavior (e.g., the leaking of trade secrets to competitors). Furthermore, high functional flexibility can reduce communication barriers between different departments. Better sharing and transfer of knowledge across departments can favor innovation.

3. Data, variables and methodology

We use longitudinal firm-level data collected by the *Organization for Strategic Labor Market Research* (*OSA*) in the Netherlands. Since 1988, OSA has built an enterprise panel in all sectors of manufacturing, services, agriculture and in non-commercial services, including the government sector. In fact, OSA samples *all* organizations in the Netherlands that employ personnel, with a minimum of five people, stratified by industries and firm size classes. The database provides information about the labor force (e.g., inflow, outflow, type of contract, internal mobility), as well as about R&D and new products sales. Since 1989, the survey has been conducted every two years. Organizations taking part in a previous survey are also included in the next survey. New organizations are added to each wave in order to compensate for sample fall-out (see Appendix A). Data collection is performed using a combination of questionnaire-based face-to-face interviews and a questionnaire to be filled in by a manager and returned by mail.

We construct a longitudinal dataset that includes dependent variables in year *t* and lagged independent variables in year *t*-2, the latter coming from the previous survey. Our final dataset is confined to the period 1992-2000, as information from earlier surveys is not fully comparable. Furthermore, we estimate our models on the total sample as well as on a sub-sample of 929 commercial SMEs with less than 250 employees. Restriction to SMEs has the advantage of having a more homogeneous sample. We confine our sample to four business sectors, i.e., manufacturing (SBI 15- SBI 37), construction (SBI 45), trade (SBI 50-52) and (other) services (SBI 55, SBI 60-67, SBI 70-74, and SBI 77). We exclude government and other non-commercial organizations.

Our database allows the use of a "direct" indicator of product innovation; i.e., sales of new (or significantly improved) products and/or services. It is similar to the "innovation output" indicator in the CIS database. There are two deviations of the OSA questionnaire from the CIS concept as described in the OECD Oslo Manual (2005). First, the CIS asks for new or improved products introduced during the past *three* years, while OSA covers the past *two* years. Second the CIS distinguishes products that are "new to the firm" from those that are "new to the market," whereas OSA only asks for the former. We interpret products "new to the firm" as "imitative" innovations, and products "new to the market" as "true" innovations. As in the CIS, innovation performance in our OSA database is measured by asking respondents to subdivide their present product range into three types of product:

(1) Products that remained *largely unchanged* during the past two years;

(2) Products that were *incrementally improved* during the past two years; and

(3) Products that were *radically changed* or introduced as *entirely new* products during the past two years.

Subsequently, respondents are asked to report the share of these three types of product in their last year's total sales. As our dependent variable, we use the logs of new product sales per employee introduced during the past two years; when using logs, this variable conforms better to a normal distribution. Constructing this variable, we add categories (2) and (3), i.e., incremental and radical innovations. One should note that the new product sales under (2) and (3) need to be novel in that they include new technological knowledge; at least, they should be based on novel (and creative) combinations of existing technological knowledge, the latter being most relevant in the service industries. As mentioned earlier, the data do not allow us to distinguish "imitative" innovations ("new to the *firm*") from "true" innovations ("new to the *market*"). Only the 2001 survey provides information on novelty. It comes as no surprise that only a smaller portion of the innovating firms have products that are "new to the market"' (see Table 3-1). In other words, our indicator of new product sales is dominated by "imitative" innovations. We evaluate the slight evidence on "new to the market" innovations in a separate estimate.

Table 3-1 Degree of novelty of new products in OSA survey (only survey 2001)

Firms declaring that their new products were:	# of All firms (%)	# of SMEs (%)
'new to the market'	268 (15.7)	188 (14.6)
'partially new to the market'	903 (52.8)	655 (50.9)
'hardly new to the market'	540 (31.5)	445 (34.5)
Totals	1,711 (100)	1,288 (100)

Our most important ***independent variables*** are numerical flexibility and functional flexibility. We use two indicators of numerical flexibility: Annual external labor turnover (i.e., percentages of people that joined or left the firm during the last year) and percentages of people on fixed-term contracts (hired directly by the firm). The correlation tables in the appendix show that the two indicators are weakly correlated; fortunately, our robustness checks with the multivariate analyses below indicate that this is not disturbing. Annual external labor turnover is measured by the maximum value of either the share of newly hired people or the share of people that left the firm in the past year. We also made robustness checks, using, e.g., the *sum* of people that left or joined the firm. This changed our results very little. We expect both indicators of numerical flexibility to have positive impacts on innovation performance until an optimum point, thereafter turning negative. We try to capture such non-linear effects by the inclusion of quadratic terms. Our indicator of functional (or “internal”) flexibility is measured by the percentage of employees that changed their function and/or department within the firm during the past year. We expect functional flexibility to have a positive impact on innovation performance.

Control variables

We use the following control variables, which are described in more detail in Appendix B:

(1) Quality of human capital. This is measured by the percentage of employees with university or higher professional education degrees and by the percentage of employees who participated in training. Previous studies indicate that highly educated people can adapt more quickly to a changing environment, thus contributing to better business performance (Holzer, 1987; Becker and Huselid, 1992; Galende and Suarez, 1999). Furthermore, formal and informal training can enhance an employee's development and is likely to contribute positively to organizational outcomes and innovation (Russell *et al*., 1985; Bartel, 1994; Knoke and Kalleberg, 1994; Laursen and Foss, 2003). We thus expect both of these variables to have positive impacts on innovation performance.

(2) R&D intensity as a proxy of inputs to the innovative process.

(3) The logarithm of firm size. The relationship between firm size and a firm's innovation performance is inconclusive. On the one hand, small firms have little bureaucracy, short communication lines and dedicated management by their owners. On the other hand, strong dependence on the owner as a key figure can also have disadvantages. Moreover, small firms often suffer from a lack of (financial) resources and access to technological knowledge (see Tidd *et al*., 2006). A major disadvantage of small firms is that they have little capability to reduce risks by means of a diversified portfolio of innovative projects.

(4) The logarithm of firm age. The impact of firm age on innovation is again a two-sided story. Young firms can be expected to have highly dedicated and flexible

management and they can be more ambitious in innovation, as there is no internal resistance by vested interests in older product lines. Their innovation performance may, however, suffer from lack of experience with innovation (van de Panne *et al*., 2003). As far as innovative activities take advantage of accumulated technological knowledge and management experience from the past, firms with a long innovation history might use their R&D more efficiently.

(5) Export intensity. The causal relationship between export and innovation is bi-directional. First, innovation stimulates exports performance (Posner, 1961; Vernon, 1966). Then, endogenous growth and new trade theories emphasize that export stimulates investment in R&D as operations on export markets give better access to international knowledge spillovers through flows of ideas and/or goods (Grossman and Helpman, 1991; Aghion and Howitt, 1998). Hughes (1988) reports empirical evidence on the simultaneous relationship between export and R&D at sector level; evidence of a simultaneous relationship at the firm level has been reported by Kleinknecht and Oostendorp (2002). Using export shares in total sales lagged by two years, we try to mitigate the endogeneity problem.

(5) Industry average of new product sales. A firm's score on new product sales crucially depends on the typical length of the product life cycle in its sector of principal activity. Obviously, a sector like ICT with short product life cycles will have higher sales of new products than sectors with long life cycles, such as aircraft construction. The dependent variable can therefore <u>not</u> be compared across industries unless we correct for life cycle differences. As life cycle data are not easily collected in enterprise surveys, we use, as a substitute, the log of average new product sales in a firm's sector of principal

activity. Inclusion of this variable comes down to explaining the deviation of a firm's new product sales from the average of its industry. Besides correcting for typical differences in product life cycles between industries, this variable can also capture other unobserved specifics of industries, such as differences in technological opportunity or in the appropriability of innovation benefits. Not surprisingly, inclusion of this variable made industry dummies insignificant. In our robustness checks, it turned out that a tentative exchange of this variable against industry dummies had little effect on the coefficients of the other variables.

3.1. Econometric model

We assume that flexible labor patterns are related to a firm's new product sales as follows:

$$y_{i,t} = \alpha + \beta_1 NFL_{i,t-2} + \beta_2 FFL_{i,t-2} + \beta_3 Con_{i,t-2} + \beta_4 Years_t + \varepsilon_{i,t-2} \qquad \text{Equation (1)}$$

Here, y (for firm i and year t) denotes the log of "new product sales per employee." We include lagged values of the following independent variables: "NFL" includes variables of numerical flexibility measured by external labor turnover and percentages of people on temporary contract; "FFL" denotes functional flexibility, i.e., the percentages of employees changing function or department within firms; "Con" represents seven control variables; and "Years" represents year dummies. By using 2-year lagged values of independent variables, we reduce potential endogeneity problems.

We use four econometric models on pooled longitudinal data: an OLS model, a Tobit model, a Heckman model and a Heck-tobit model. We do not estimate panel data models because of high attrition. A balanced panel covering 5 waves of data would leave only very few firms. Rather than using one-way error component models or equally complex methods for unbalanced panels (for a survey see Baltagi and Song, 2004), we use straightforward regression techniques on pooled longitudinal data, correcting for repeated observations (clustering) with robust estimation methods.

First, we use a pooled OLS model (Model 1). This has the disadvantage of sample selection bias since it only includes firms that have positive innovation output. Firms with zero or missing innovation output are excluded (also because of the log transformation), with a possible sample selection bias as a result. In order to correct for selection bias, we have two options, and we use both. First, we use the Tobit model (Model 2). A Tobit model (e.g. Maddala, 1985) corrects for non-normality of the distribution of our dependent variable that is caused by the high probability mass at zero due to firms that have no new product sales. Including firms with no innovation reduces the sample selection bias.

The mathematical representation of a simple Tobit procedure is as follows:

$$y_i = \begin{cases} y_i^* & if\ y_i^* > 0 \\ 0 & if\ y_i^* \le 0 \end{cases} \qquad \text{Equation (2)}$$

Where y_i^* is a latent variable: $y_i^* = \beta x_i + u_i, u_i \sim (0, \sigma^2)$ Equation (3)

Second, we use a Heckman model (Model 3) to correct for item non-response bias. The Heckman model also includes firms that did not report their innovation output, again reducing sample selection bias. In the Heckman model, a selection equation is introduced with a binary variable *z* (for firm *i* and year *t*), which indicates whether the dependent variable (*y*) is observed or not. The underlying continuous variable is modeled as follows:

Heckman selection equation: $z_{i,t} = w_{i,t-2}\gamma + u_{i,t-2}$, Equation (4)

where *w* represents the independent variables listed in the linear equation (Equation 1) and an instrumental variable. We choose for the latter a variable that measures a firm's sensitivity to economic fluctuations. The latter does not correlate with the error terms in the linear equation, but does have a significant impact on the propensity to innovate in the selection equation. This instrumental variable thus ensures the identification of the Heckman model (Heckman, 1979; Greene, 2002).

Finally, we also use a Heck-tobit model (Model 4) to control for both aforementioned possible selection biases. We first formally test for sample selection bias using a Heckman two-step procedure and generate an inverse Mill's ratio (Heckman 1979; Berk, 1983). This ratio captures the probability of responding to the survey as a function of the variables listed in *w* of equation 4. We then include this ratio in the Tobit model to statistically control for item non-response bias.

4. Results from four regression models

Descriptive statistics are reported in Appendix C. Appendices D and E show the correlations between our independent variables in the total sample and the SME sample. No correlation exceeds 0.5. The variance inflation factors (VIFs) range from 1.03 to 1.21, from which we conclude that multicollinearity is unlikely to be a problem. Tables 4-1A and B present the results of four regression models in the total sample and in the SME sample.

We explain *the log of new product sales per employee* achieved by firms that have such sales. In other words, our interpretation is strictly confined to innovating firms. The four regression models produce fairly consistent results. It is reassuring that the coefficients proved robust to tentative inclusion or exclusion of various independent variables. An important result in the earlier rounds of our estimates (not documented here) comes from experiments with quadratic terms of our variables on numerical flexibility. Their inclusion had little influence on the other coefficients, and, against our expectations, these quadratic terms proved insignificant throughout. They are therefore omitted from our final version.

Both tables show that, as expected, R&D intensity is highly significantly positive in all four models. The positive effect of export intensity on innovation performance is also highly significant in all versions. It is no surprise that an individual firm's new product sales are heavily related to the average new product sales in its sector of principal activity. Including industry average new product sales implies that our model explains deviations of an individual firm's new product sales from its industry average. The two indicators of human capital (educational achievements and training) have positive impacts on a firm's innovation performance (significant at the 5% level in all four models). This reconfirms the importance of qualified human capital to the innovation process.

Pertaining to firm size and firm age, we conclude that the advantages and disadvantages of a firm being small or big and being young or old seem almost to cancel each other out. We find only weak evidence (at the 10% level) that older and larger firms might have higher new product sales when considering the total sample (see Table 4-1A).

When taking SMEs separately, however, the coefficients for size or age become insignificant (see Table 4-1B).

As expected, high rates of individual changes in function or department *within* the firm (“functional flexibility”) contribute positively to new product sales, being significant at 5% level in all four models in both samples. This underlines the importance of “insider-outsider” labor markets for keeping knowledge in the firm and investing in the loyalty and commitment of employees while allowing for flexibility.

Finally, all four models in both samples indicate that a high external labor turnover has no impact on innovation. In three out of four models, however, high shares of employees on temporary contract seem to have a positive impact on innovation performance (significant at the 5% level in the SME sample and at the 10% level in the total sample). This finding supports the argument by Ichniowski and Shaw (1995) discussed earlier, but is hard to reconcile with recent firm-level studies in the Netherlands (Kleinknecht *et al.*, 2006) and in Italy (Lucidi and Kleinknecht, 2009) that find a negative impact of numerically flexible labor on labor productivity growth. It is important to keep in mind that two studies using UK firm-level data also show a negative correlation between numerical flexibility and innovation (Michie and Sheehan, 1999, 2001), and that similar results are reported by Chadwick and Cappelli (2002) from US data. As mentioned above, Arvanitis (2005) reports mixed results on the topic.

Table 4-1A: Explaining logs of new product sales per employee [a] (Summary of regressions from total sample)

Dependent variable **Log (new product sales per employee)**	**Model 1** **OLS**	**Model 2** **Tobit**	**Model 3** **Heckman (linear part)**	**Model 4** **Heck-tobit**
Labor flexibility:	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)
External labor turnover (max.)	0.004 (0.76)	0.007 (0.95)	0.005 (0.91)	0.014 (1.16)
% of temporary work	0.039 (1.92)†	0.061 (2.03)*	0.037 (1.83)†	0.047 (1.29)
Functional flexibility	0.063 (2.75)**	0.091 (2.68)**	0.064 (2.83)**	0.099 (2.74)**
Control variables:				
Qualified personnel	0.026 (2.93)**	0.040 (2.97)**	0.025 (2.88)**	0.035 (2.29)*
Training efforts	0.017 (2.24)*	0.026 (2.10)*	0.017 (2.26)*	0.026 (2.10)*
Export intensity	0.020 (3.04)**	0.030 (3.05)**	0.020 (3.11)**	0.033 (3.02)**
Firm age	0.012 (1.80)†	0.019 (1.88)†	0.012 (1.86)†	0.021 (2.01)*
R&D intensity in new product/service	0.074 (5.71)**	0.119 (5.96)**	0.074 (5.71)**	0.118 (5.90)**
Firm size	0.001 (1.71)†	0.001 (1.86)†	0.001 (1.54)	0.001 (0.56)
Industry average new product sales	0.962 (3.09)**	1.411 (2.85)**	0.904 (2.86)**	0.948 (1.16)
Year1997 [b]	-7.423 (-3.40)**	-11.042 (-3.17)**	-6.993 (-3.14)**	-7.603 (-1.28)
Year1999	-7.080 (-3.25)**	-10.499 (-3.03)**	-6.773 (-3.09)**	-8.044 (-1.65)†
Year2001	-8.747 (-3.93)**	-13.393 (-3.76)**	-8.583 (-3.87)**	-12.094 (-3.02)**
Constant term	0.693 (0.53)	-4.295 (-1.99)*	0.465 (0.35)	-6.085 (-1.89)†
Instrumental variable				
Nonselection hazard				4.729 (0.73)
Economic fluctuations [c]			-0.096 (-2.48)*	-0.094 (-2.53)*
Number of observations	1032	1032	2329	1031
Censored observations		395	1298	395
Uncensored observations		637	1031	636
Statistics summary	R^2 = 0.1354	Log likelihood = -2561.5084 Pseudo R^2 = 0.0272	Wald chi2(13): 183.00 Prob>chi2: 0.0000 Wald test of independent equations (rho=0): chi2(1)=0.90 Prob>chi2 = 0.3438	Log likelihood = -2562..3007 Pseudo R^2 = 0.0257

[a] $\dagger$: at 0.1 significance level; *: at 0.05 significance level; **: at 0.01 significance level; two-tailed test
[b] The reference group of year dummies is 1995
[c] The coefficient of 'sensitivity to economic fluctuations' is in the selection equation of the Heckman model, not in the linear equation

Table 4-1B: Explaining logs of new product sales per employee [a] (Summary of regression from SME sample)

Dependent variable **Log (new product sales per employee)**	**Model 1** **OLS**	**Model 2** **Tobit**	**Model 3** **Heckman (linear part)**	**Model 4** **Heck-tobit**
Labor flexibility:	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)	Coefficient (t-value)
External labor turnover (max.)	0.007 (1.14)	0.012 (1.31)	0.008 (1.35)	0.023 (1.59)
% of temporary work	0.045 (2.19)*	0.070 (2.30)*	0.042 (2.06)*	0.046 (1.15)
Functional flexibility	0.062 (2.33)*	0.091 (2.22)*	0.062 (2.35)*	0.091 (2.21)*
Control variables:				
Qualified personnel	0.026 (2.79)**	0.042 (2.86)**	0.026 (2.76)**	0.037 (2.38)*
Training	0.019 (2.34)*	0.029 (2.22)*	0.020 (2.44)*	0.034 (2.43)*
Export intensity	0.018 (2.38)*	0.027 (2.39)*	0.019 (2.52)*	0.036 (2.49)*
Firm age	0.011 (1.52)	0.018 (1.60)	0.011 (1.59)	0.022 (1.83)†
R&D intensity in new product/service	0.074 (5.38)**	0.122 (5.69)**	0.074 (5.37)**	0.122 (5.66)**
Firm size	0.003 (0.95)	0.005 (0.99)	0.003 (0.84)	0.002 (0.28)
Industry average new product sales	1.002 (2.99)**	1.574 (2.86)**	0.942 (2.80)**	1.058 (1.39)
Year1997 [b]	-8.062 (-3.43)**	-12.767 (-3.31)**	-7.608 (-3.23)**	-8.904 (-1.61)
Year1999	-7.522 (-3.21)**	-11.880 (-3.10)**	-7.248 (-3.10)**	-9.562 (-2.12)*
Year2001	-9.415 (-3.93)**	-15.314 (-3.87)**	-9.350 (-3.93)**	-14.789 (-3.71)**
Constant term	0.479 (0.34)	-5.283 (-2.18)*	0.050 (0.03)	-8.900 (-2.08)*
Instrumental variable				
Nonselection hazard				7.386 (1.00)
Economic fluctuations [c]			-0.097 (-2.34)*	-0.093 (-2.35)*
Number of observations	928	928	2044	927
Censored observations		372	1117	372
Uncensored observations		556	927	555
Statistics summary	R^2 = 0.1348	Log likelihood = -2266.7467 Pseudo R^2 = 0.0279	Wald chi2(14): 172.41 Prob>chi2: 0.0000 Wald test of independent equations (rho=0): chi2(1)=2.13 Prob>chi2 = 0.1440	Log likelihood = -2263.0926 Pseudo R^2 = 0.0281

[a] †: at 0.1 significance level; *: at 0.05 significance level; **: at 0.01 significance level; two-tailed test
[b] The reference group of year dummies is 1995
[c] The coefficient of 'sensitivity to economic fluctuations' is in the selection equation of the Heckman model, not in the linear equation

Interpreting our finding of a positive impact of temporary contracts on new product sales, two caveats should be kept in mind. The first qualification shown in Table 4-2, is that the screening of personnel is an important motive for employing people on a fixed-term basis. The motive of savings on the wage bill plays only a minor role (3.2%). More than 40% of the temporary contracts in the OSA database serve as a trial period, after which individuals may extend their employment with the firm. This indicates that firms are dependent on probationary periods to select the right personnel. In particular, recent university graduates typically begin their employment on a temporary basis. After a period of good performance, they can expect tenure. In this context, it is interesting to see a correlation between qualified personnel and temporary work (significant at the 5% level) in Appendices D and E.

Table 4-2: Descriptive statistics: Reasons of using fixed term contracts a

Reasons for fixed-term contracts:	Total sample:	SME sample:
1. Fluctuations	217 (28.07%)	154 (27.11%)
2. Cost purpose	25 (3.23%)	18 (3.17%)
3. Personal preference of people	7 (0.91%)	6 (1.06%)
4. Replacement because of illness / absence	61 (7.89%)	49 (8.63%)
5. (Extended) try-out period	330 (42.69%)	254 (44.72%)
6. Seasonal peaks	17 (2.20%)	14 (2.46%)
7. Temporarily off work	60 (7.76%)	40 (7.04%)
8. Others	56 (7.24%)	33 (5.81%)

[a] Source: OSA database; information available only in surveys 2001 and 1997

As a second qualification, recall that our dependent variable is heavily influenced by products that are new to the *firm*, i.e., by "*imitative"* rather than "*innovative"* ("new to the market") products. We cannot distinguish between "imitative" and "innovative" products, except in the survey administered in 2001, which includes a separate question about degrees of novelty. Table 3-1 showed that the majority of firms that introduce new products are market followers (or imitators) rather than market leaders: less than 16% of the firms have products that are fully "*new to the market*." Using these data, we estimated an ordered logit model in Table 4-3. The table shows three things: First, firms with high R&D intensities tend to have higher probabilities of introducing products that are "new to the *market*." Second, the same holds for firms in industries with high shares of new products sales. Third, high percentages of workers on temporary contracts have a <u>negative</u> impact on the probability that a firm's new products will be "new to the market." Similar results hold when we confine the sample to firms with less than 250 workers (not documented here). The finding in Table 4-3 is opposed to the positive coefficient of temporary contracts in our estimate in Table 4-1. It appears that the arguments in favor of rigid labor relations mainly hold for the market leaders that undertake substantial R&D efforts. For the larger stream of imitators, more flexible labor relations are more attractive.

Table 4-3: What factors determine whether a product will be new to the market rather than new to the firm? [a] (Summary of Ordered logistic regressions, total sample)

The dependent variable is: Novelty of innovative products (1 = new to firm; 2 = partially new to market; 3 = new to market (reference group: 'new to the firm')		
	Model 1:	Model 2:
Labor flexibility:	Coefficient (t-value)	Coefficient (t-value)
External labor turnover (max)	-0.010 (-0.12)	-
Percentage of workers on temporary contract	**-0.038 (-1.69)**†	**-0.042 (-2.01)** *
Functional (internal) flexibility	0.010 (0.57)	0.010 (0.56)
Control variables:		
Export intensity	-0.004 (-0.70)	-0.003 (-0.50)
Firm age	0.003 (0.43)	0.003 (0.46)
R&D intensity (product or service-related R&D)	**0.018 (1.66)** †	**0.018 (1.71)** †
Firm size	0.000 (0.02)	-0.000 (-0.04)
Industry average new product sales	**0.594 (1.84)** †	**0.604 (1.89)** †
Cut1	5.539	5.621
Cut2	8.173	8.260
Number of observations	150	155
Log likelihood	-144.33	-149.08
Pseudo R^2	0.031	0.032
Statistics summary	Wald chi2(8)= 10.80	Wald chi2(8)= 11.09

[a] The results are based on a cross-sectional OSA data; the dependent variable is taken from the 2001 survey (covering year 2000); the independent variables come from the 1999 survey, covering year 1998.
[b] † : at 0.1 significance level; *: at 0.05 significance level; **: at 0.01 significance level; two-tailed test

5. Discussion and conclusions

This paper makes an empirical contribution to the sparse knowledge about the impact of flexible labor on innovation, using new product sales as a direct measure of innovation and controlling for factors such as human capital, R&D intensity, export intensity, firm size and age, and industry average new product sales. As opposed to some previous studies, our data allow a 2-year lag between the dependent and independent variables, which we hope will relax the problems of endogeneity that are notorious in this type of analysis. Not surprisingly, R&D intensity, export intensity and levels of education and training all contribute positively to new product sales. As expected, an individual firm's new product sales are heavily related to average sales in its sector of principal activity.

We find weak evidence that larger and older firms have higher new product sales than their young and small counterparts. It seems as if the (dis)-advantages of a firm being small or big or being old or young almost cancel each other out. This is hard to reconcile with evidence reported earlier by Acs and Audretsch (1993) using new product announcement data. They found that, in many sectors, smaller firms made a disproportionately large contribution to innovative output. Investigating new product announcement data more thoroughly, however, evidence has been found indicating that the data are biased in favor of smaller firms (see van der Panne, 2004). The output indicator used in this paper does not seem to have such a bias (Kleinknecht *et al*., 2002). We conclude that the advantages typical of small and young firms, such as little bureaucracy and short communication lines, dedicated management by the owners or the ability to occupy market niches that are less interesting for big firms, seem to be compensated (or perhaps slightly over-compensated) by the advantages enjoyed by bigger and older firms, such as the ease of financing of innovations due to some monopoly power, the exploitation of strong marketing functions and brand names, accumulated knowledge and experience from (the management of) earlier innovations, or the diversification of risks through a large portfolio of innovation projects.

The positive impact of functional flexibility is significant in all four models of both samples and is consistent with previous results by Michie and Sheehan (1999, 2001); Chadwick and Cappelli (2002) and Arvanitis (2005). Our findings confirm the important role of functional flexibility in reducing barriers to knowledge sharing and building multiple competencies of employees in internal labor markets. Functional flexibility in "insider-outsider" labor markets allows for flexibility while being socially responsible towards a firm's personnel. The latter might be interpreted as an investment in trust, loyalty and commitment. Such investment is likely to economize on supervision and monitoring costs and reduces the leaking of a firm's knowledge to competitors.

Our model is remarkably robust to changes in specifications and in sample size. This also holds for inclusion of non-linear terms of numerical flexibility variables. Specifications with non-linear terms are not documented in this paper, as these terms all proved insignificant. Intuitively, one might have expected that there is some optimum level of numerical flexibility that would enhance innovation and that beyond the optimum point, flexibility becomes counter-productive. However, the data do not support this.

We find mixed results on numerical flexibility. While one of the proxies of numerical flexibility, external labor turnover, is insignificant in all four models, another proxy, temporary work, has a positive effect on innovation performance, or, being more precise, on "imitative" ("new to the firm") products. As could be seen from Table 3-1, most of our new product introducers are market followers rather than market leaders, i.e., they introduce products that are "new to the firm" rather than products "new to the market." Many of these firms are likely similar to what Pavitt (1984) named "supplier-dominated innovators," i.e., firms that innovate mainly by adopting (and creatively using) new equipment from suppliers. Such adoption may be favored by carefully screening the right personnel. As we saw from Table 4-2, an important motive behind using temporary contracts is personnel screening. Typically, young university graduates are hired under a probationary period and can expect tenure if they perform well. Such temporary contracts seem to be positively related to "imitative" innovations.

Further explorations suggest, however, that the probability of having products "new to the market" (rather than "new to the firm") is negatively influenced by high shares of temporary workers. Hence, the minority of R&D intensive market leaders tends to rely significantly less on flexible work, which is consistent with the findings of Arvanitis' (2005) study on data from Switzerland. It also underlines the arguments by Lucidi and Kleinknecht (2009) about the need for the continuous accumulation of (tacit) knowledge that is favored by longer commitments of workers to their firms. It appears that the much criticized "rigidity" of insider-outsider labor markets is favorable to R&D intensive market leaders, while the larger stream of imitators and market followers prefer using temporary contracts to try out new people with fresh ideas, which may favor technology adoption.

Finally, our results warn against the unconditional plea by mainstream economists for the deregulation of labor markets (see e.g. the OECD's Job Study, 1994). It seems that the "rigidity" of insider-outsider labor markets also has advantages, as it allows for "functional" flexibility. The often criticized protection of "insiders" can be interpreted as an investment in the loyalty and commitment of workers. Moreover, functional flexibility on internal labor markets has advantages for the continuity of (organizational) learning, and strengthens the historical memory of firms. Neoclassical economists should note that temporary contracts might have advantages for imitative firms, but definitely are not an option preferred by market leaders who seem to have a greater need for continuity in learning and in preventing knowledge from leaking to competitors.

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Appendix A: Overview of firms that participated in each wave (1991-2005)[a]

Year of first wave	1989	1991	1993	1995	1997	1999	2001	2003	2005
1989	*2041*[b]	1391	985	676	467	292	131	72	36
1991		*626*	404	297	194	120	38	26	17
1993			*653*	407	252	152	69	38	25
1995				*1316*	797	450	192	96	50
1997					*825*	438	172	96	52
1999						*1273*	551	282	120
2001							*2046*	986	446
2003								*3152*	1186
2005									*1199*
Total	2041	2017	2042	2696	2537	2725	3199	4748	3131

[a] Source: OSA Labour Demand Panel (Explanatory notes) 1991-2006

[b] *Italics*: Numbers of newly participating firms

Appendix B: Description of variables

Variable names:	Variables description:
Dependent variable:	
Log (new product sales per employee)	The logarithm of turnover from new products 'new to the firm and/or 'new to the market' introduced during the past two years divided by total employees. Note that 'imitative' innovations ('new to the firm' but already known in the market) are much more numerous than innovations 'new to the market'. In fact, we measure imitation rather than innovation.
Variables on flexible labor:	
External flexibility	Maximum of the share of newly hired employees and the share of employees that left the firm during the last year.
Temporary work	The percentage of employees having fixed-term contracts hired directly by the firm.
Functional flexibility	The percentage of employees that changed their function and/or department within the firm.
Control variables:	
Qualified personnel	The percentage of employees with university or higher professional education degrees.
Training	The percentage of employees that participated in training (both internal and external trainings).
Export	Export as the share of turnover.
R&D intensity	R&D expenditure on new products or services as a percentage share of turnover
Firm age	Difference between survey year and establishment year
Firm size	Number of employees in full-time equivalents
Industry average new product sales	Average of logs of new product sales per employee in a firm's sector of principal activity.
Instrumental variable	
Economic fluctuations	Categorical variable: Whether the firm is sensitive to fluctuations in the economy; 1=not sensitive, 2= a little bit sensitive, 3=very sensitive.

Appendix C: Descriptive statistics (Total sample vs. *SME sample*)

Variable name	Mean	Median	Std. Dev.	Min	Max
Dependent variable					
Log (new product sales per employee)	5.88	7.86	5.32	0	25.52
	(*6.71*)	(*10.00*)	(*5.62*)	(*0*)	(*19.80*)
Variables on flexible labor					
External labor turnover	14.18	10.71	19.79	0	1111
	(*14.96*)	(*10.73*)	(*20.10*)	(*0*)	(*500*)
Personnel on temporary contract	4.37	0	9.76	0	100
	(*3.94*)	(*0*)	(*8.29*)	(*0*)	(*100*)
Functional flexibility	2.88	0	6.54	0	117
	(*2.72*)	(*0*)	(*5.83*)	(*0*)	(*75*)
Control variables					
Qualified personnel	23.22	10.53	28.57	0	100
	(*13.90*)	(*7.12*)	(*19.20*)	(*0*)	(*100*)
Training	35.51	26.91	27.88	0.3	100
	(*31.35*)	(*24.15*)	(*24.35*)	(*0*)	(*100*)
Export	8.25	0	22.09	0	100
	(*14.36*)	(*0*)	(*27.22*)	(*0*)	(*100*)
R&D intensity	8.31	0	13.17	0	30
	(*9.67*)	(*0*)	(*13.69*)	(*0*)	(*30*)
Firm age	27.04	17	27.77	0	99
	(*26.55*)	(*18*)	(*26.09*)	(*0*)	(*103*)
Firm size	205.05	51	540.36	5	23500
	(*63.21*)	(*39*)	(*60.37*)	(*5*)	(*250*)
Industry average new product sales	9.59	10.49	2.64	1.74	13
	(*9.41*)	(*10.84*)	(*2.99*)	(*1.74*)	(*13*)
Instrumental variable					
Economic fluctuation	1.94	2	0.78	1	3
	(*0.24*)	(*2*)	(*0.72*)	(*1*)	(*3*)

Appendix D: Correlations between variables (total sample)

	Variable name	1	2	3	4	5	6	7	8	9	10	11	VIFs
1	Log (new product sales per employee)												
2	External labor turnover	0.01											1.19
3	Temporary work	0.01	0.15*										1.17
4	Functional flexibility	0.11*	0.11*	0.05*									1.13
5	Qualified personnel	0.13*	-0.03*	0.13*	0.03*								1.16
6	Training	0.10*	0.01	0.03*	0.07*	0.19*							1.07
7	Export	0.14*	-0.02	-0.02*	0.05*	-0.12*	-0.09*						1.12
8	R&D intensity	0.17*	0.03*	0.02*	0.08*	0.03*	-0.06*	0.23*					1.20
9	Firm age	-0.07*	-0.07*	-0.01	-0.02	-0.06*	-0.06*	0.06*	0.04*				1.02
10	Firm size	0.10*	-0.01	-0.01	0.19*	0.02	-0.06*	0.02*	0.06*	0.04*			1.07
11	Industry average new product sales	-0.02	0.08*	-0.02*	0.05*	-0.06*	0.14*	0.04*	0.05*	-0.02*	0.00		1.03
12	Economic fluctuation	0.02	0.03*	-0.03*	0.00	-0.22*	-0.07*	0.14*	0.10*	0.03*	-0.04*	0.02*	

* p<0.05, two-tailed tests

Appendix E: Correlations between variables (SME sample)

	Variable name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**VIFs**
1	Log (new product sales per employee)												
2	External labor turnover	0.06											1.21
3	Temporary work	0.12*	0.27*										1.20
4	Functional flexibility	0.14*	0.23*	0.11*									1.10
5	Qualified personnel	0.15*	0.10*	0.15*	0.12*								1.13
6	Training	0.11*	0.01	0.03	0.08*	0.16*							1.06
7	Export	0.16*	-0.03	0.01	0.08*	0.01	-0.07*						1.19
8	R&D intensity	0.24*	0.02	0.07*	0.09*	0.16*	-0.01	0.25*					1.18
9	Firm age	0.05	-0.10*	-0.00	-0.02	-0.04	0.06*	0.00	-0.01				1.06
10	Firm size	0.13*	-0.07*	0.09*	0.11*	0.05*	-0.01	0.26*	0.20*	0.16*			1.19
11	Industry average new product sales	-0.06	0.06*	0.05*	0.06*	0.09*	0.13*	0.01	0.01	-0.00	-0.10*		1.03
12	Economic fluctuation	0.04	0.01	-0.02	0.02	-0.12*	0.00	-0.01	0.02	0.01	0.05*	-0.06*	

* p<0.05, two-tailed tests

[1] Hall and Soskice (2001) suggested that rigid “Rhineland” arrangements are more conducive to incremental innovation, while flexible “Anglo-Saxon” contracts are better for radical innovation. This suggestion did, however, meet some criticism recently (see Akkermans *et al*., 2009).

[2] For evidence from the OSA database on the wage-reducing effects of flexible work, both at the firm and the individual levels see Kleinknecht *et al*. (2006).

[3] Kleinknecht *et al.* (2006) give evidence from individual-level as well as firm-level wage equations that flexible personnel earn lower hourly wages, and that firms with high shares of flexible personnel pay lower wages. Similar evidence from individual-level wage equations has been reported by Booth *et al*., 2002, McGinnity and Mertens 2004; Sànchez and Toharia 2000, or Ségal and Sullivan, 1995.