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## LINKING INNOVATION TO PRODUCTIVITY GROWTH USING TWO WAVES OF CIS<sup>1</sup>

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### ***Abstract***

*Using two waves of the Community Innovation Survey for the Netherlands we integrate recent lines of research to estimate the contribution of innovation to manufacturing multi-factor productivity (MFP) growth. The model exploits the CIS data to control for the complementarity between internal and external knowledge bases and also investigates the importance of within-firm time interdependencies for inputs into innovation and innovation output. Our results show the benefits of including more information on the technological environment of firms. Furthermore, our model shows that we have a lower persistence of innovativeness measured from the output side than for R&D if we track the innovation performance of the same firms across time. It has also been found that the contribution of innovation to MFP increases if we use all available data. The latter result reflects the difficulty to account properly for the non-rivalry of innovation and the associated inter-firm “spillovers” of knowledge creation when using firm-level panel data only.*

KEY WORDS: Innovation, Research, Technological opportunities, Simultaneous-equations models, productivity.

JEL Classification: C24, C31, C34, L60, O31, O32

### **1. Introduction**

1. It is about ten years ago that the OECD took the initiative to set up guidelines for the formulation and the design of innovation surveys. Since the emergence of the Oslo Manual (OECD, 1992) a number of countries have launched at least two surveys, known as CIS (Community Innovation Surveys). Contrary to

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other countries, and prior to the third wave of the big and harmonised European CIS3 survey which is now underway, Statistics Netherlands has carried out an intervening survey (called CIS2,5) on the basis of a panel design. This paper presents the results of a first attempt to exploit two similar innovation surveys (CIS2 and CIS2,5) and the production surveys for the same reporting units to construct a panel for both innovation variables and performance measures.<sup>2</sup> To our knowledge this is the first example of the use of panel data for innovation variables to investigate a number of theoretical issues raised during the last decade.

2. Innovation surveys were “born” out of a growing concern about the following deficiencies of the traditional R&D surveys: 1) inputs into innovation were insufficiently covered by R&D expenditures only, 2) the lacking of more appropriate and direct measures of the output of the innovation process than indirect measures like patent applications and 3) the lacking of any data on the organisation of innovation process and the importance of knowledge flows between firms.

3. Linked to the R&D-productivity literature, it can be concluded that CIS has opened new routes for the assessment of the contribution of innovation to productivity (growth) along the following lines. Firstly, the use of a direct measurement of a firm’s innovation output enables an explicit estimation of the innovation production function (see e.g. Griliches, 1998). In addition, the data on the (firm specific) characteristics of the innovation process enhances a more direct analysis of the importance of knowledge flows between firms or between firms and other organisations, both for building up and maintaining internal knowledge bases or for the output of the innovation process. Secondly, with a direct measurement of innovation output available, we can circumvent some of the disadvantages of the widely used knowledge-capital-stock approach. Thirdly, the embedding of the innovation production function in a structural model enables a better understanding of the complex links between innovation and productivity growth. By allowing more structure (more equations) and by providing new instruments the new data sources enhance another step forward in the search for the identification of the contribution of innovation, or more specifically R&D, to productivity growth along the lines proposed in Griliches and Mairesse (1997).

4. Since the availability of the harmonised CIS data, only relatively few studies have tried to exploit the new data for the purpose of estimating the contribution of innovation to firm performance. Recent examples are presented in Crépon et al. (1998), Lööf and Heshmati (2001) and Klomp and van Leeuwen (2001a). The before mentioned studies have in common that only one wave of CIS could be used. In this paper we extend our previous cross-sectional analysis by using the two waves of CIS to incorporate recent lines of research in a structural modelling approach. We use adaptations of the model for knowledge-stock accumulation suggested e.g. by Hall and Hayashi (1989) and Klette (1996) and the revenue approach of Klette and Griliches (1996) to embed the innovation process in a model that aims at explaining differences in productivity growth. The model simultaneously takes into account the importance of innovation for the competitive environment of firms and uses the innovation panel to investigate the within-firm time interdependencies of innovation output and the importance of inter-firm knowledge flows.

5. The model adaptations yield a dynamic system for the innovation process, which – on the one hand may present a better description of the intricacies at work, but – on the other hand – also introduces a myriad of other problems. Our first results show that many firms that innovated in CIS2 were absent in CIS2,5. Nevertheless, the coverage of innovating firms was very similar in the two waves. This loss of data

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<sup>2</sup> In the Netherlands CIS1 (covering 1992 – 1994) and CIS2 (covering 1994 – 1996) were conducted by different institutions. As a consequence of the use of different sampling frames, it appeared to be virtually impossible to link these surveys at the micro level and to use the linked data for analysing the dynamics of innovation. An other difference between these two surveys concerns the questions asked and the reporting unit. From CIS2 onwards the CIS surveys are considered to be harmonised and are more or less conducted in the same fashion.

complicates the use of a dynamic innovation model severely, as this may be due to discontinuities of the innovation process itself (e.g. triggered by the depletion of technological opportunities). In the estimation procedure we have tried to control for this source of endogenous attrition as much as possible. Furthermore, we also compare the results of using the dynamic innovation model in the full model with the results obtained after implementing a static version of the innovation model that can be applied to a more extensive data set.

6. The plan of the paper is as follows. In sections (2) and (3) we discuss the derivation of the dynamic innovation model and the linking of this model to our model for productivity growth. Section (4) discusses the data construction. In this section we also present some descriptive measures that enable a comparison of the performance of innovating and non-innovating firms. The estimation results for the various models are presented in section 5. Finally, section 6 summarises and concludes.

## 2. The relation with previous research

### 2.1 *Adaptations of the basic framework*

7. In this section we discuss some adaptations of the basic framework proposed in recent literature (see appendix I for a summary of this framework). These adaptations concern 1) a modification of the model for the process of knowledge accumulation underlying the R&D production function framework and 2) the extension of the traditional reduced-form R&D models into the direction of a structural model as an attempt to exploit the CIS data. The first strand of research (which is the subject of subsection 2.1) discusses the separability of current R&D efforts and the internal knowledge base already acquired. The second strand of research (discussed in subsection 2.2) models innovation as a separate process and discusses how this process can be linked to the overall firm performance. We establish a link between the two strands of research by combining a (reduced-form) revenue model and a dynamic model for the innovation process.

### 2.2 *The process of knowledge accumulation*

8. Many discussions concerning the traditional R&D-productivity framework are centered around questions concerning the concept of knowledge production and how the usually applied procedure of constructing R&D-capital stocks fits into this concept. The disadvantages of using the capital-accumulation equation

$$K_t = (1 - \delta)K_{t-1} + R_t \quad (1)$$

as a model for knowledge production has been discussed extensively in the literature (see e.g. Griliches, 1998). In this paper we focus on the central point of criticism which concerns the separability of current R&D efforts and the level of innovativeness already achieved.

9. As the equation is homogeneous of degree one in current R&D, equation (1) implies constant returns of R&D to knowledge production. Thus (1) neglects any complementarity between current R&D and the knowledge already captured in the existing stock or the history of R&D investment. Griliches (1998) has been pointed out that the process of knowledge production of firms induced by their own R&D history may be different in this respect from other capital investment. A firm's R&D investment may depend nonlinearly not only on its current own R&D but also on (own) previously accumulated results

derived from R&D and – moreover – also on the absorption of knowledge sourced from its technological environment.

10. An alternative specification exploited by e.g. Hall and Hayashi (1989) and Klette (1996) to offend the core of this criticism is given by

$$K_{it} = K_{it-1}^{\rho-v} R_{it-1}^v, \quad (2a)$$

From equation (2a) it can be derived that the marginal product of R&D is inversely related to the current R&D effort and thus implies decreasing returns of R&D to knowledge capital.<sup>3</sup> Klette (1996) rationalises (2a) as follows: "... the complementarity in knowledge production may explain why firms with a high rate of *return to knowledge capital* may have little incentive to carry out R&D because they may have too little knowledge capital or too few R&D skills to get much knowledge out of its new R&D investment. Similarly, firms with a low rate of *return to knowledge capital* might prefer to carry out more R&D as the knowledge capital already acquired makes the current R&D effort more productive ...".

11. Taking logarithms of the variables and adding a constant term, then (2a) transforms into

$$k_{it} = \mu_3 + \theta_1 k_{it-1} + \theta_2 r_{it-1} \quad (2b)$$

The parameters of interest in (2b) are  $\theta_1$  and  $\theta_2$ . If  $\theta_1$  is larger (smaller) one, then we have increasing (decreasing) returns in the knowledge production function. The estimate of  $\theta_2$  represents the innovation opportunities of R&D. The estimate of  $\theta_1$  can be considered as a measure of the persistence of the knowledge capital already acquired. A high value signals significant scale economies in R&D. An estimate larger than one points to the case of a cumulative process, where an above-average firm departs more and more from the average firm, even if its R&D efforts are average.<sup>4</sup> By contrast, a small estimate of  $\theta_1$  signals a low persistence of knowledge capital. This may be due to the depletion of technological opportunities as a result of (unintended) spillovers and diffusion of knowledge to competitors. In this case we have a tendency to convergence, as a firm with an above average knowledge capital gravitates downwards to the average firm, even if it carries out the average amount of R&D.

12. The usual procedure to implement (2b) in the empirical model is to find some way to solve out the unobservable  $k$ . In Klette (1996) this has been achieved by combining a demand model with an equation for *productivity differences* relative to the reference firm (represented by the average over all firms). The empirical model finally obtained is a dynamic equation in *Solow-residual productivity differences* with the contribution of innovation represented by (the logarithm of) lagged R&D. Thus in essence this remains a (modified) reduced-form R&D model. Besides the drawback that these types of models remain based on measures of inputs into innovation<sup>5</sup> they also suffer from the disadvantage that the importance of knowledge flows between firms are not taken into account at all.

<sup>3</sup> Equation (2a) has the undesirable property that knowledge capital vanishes if R&D expenditure is zero. This problem can be taken into account in the estimation procedure by imputing one (guilder) for R&D and using a 'No-R&D' dummy variable in the regression model.

<sup>4</sup> This interpretation can be obtained after using deviations from the means of the variables included in (2b).

<sup>5</sup> A central problem related to the use of input measures remains the unknown relation between R&D investment and the output of the innovation process. This concerns – amongst others – the time delay between R&D investment and innovation success, or the depletion of technological opportunities build up by the history of R&D investment.

### 2.3 *Structural modelling approaches*

13. It is at this stage that the CIS data comes into play. The main feature of CIS is that the survey is directed to the innovation process itself. The CIS surveys aim at the description of this process by collecting data on the inputs into innovation (innovation investment disaggregated by type), innovation output (measured by the share of new or improved sales in total sales) and data to describe the technological environment of firms and the importance of inter-firm knowledge flows.

14. One of the new variables collected, and which seems to be most promising in view of the problems encountered in previous research, is the direct measurement of innovation output, represented by the share of new and of improved sales in total sales. It seems straightforward to use these variables and to use the data on the firm-specific characteristics of the innovation process for the estimation of a (enhanced) knowledge production function as an alternative for (2b).

15. Unfortunately, no new comes without a price. A first problem to note is that innovation output should be linked to the overall firm performance in some way in order to enable an assessment of the contribution of innovation to productivity (growth). The change from input to output measures would aggravate the endogeneity problem<sup>6</sup> as in this case the productivity equations will contain an output measure as one of the explanatory variable. A second point concerns the definition of innovation output. Which choice between the available alternatives should be made ? For instance, should we use (the share of) new products or new and improved products, products new to the firm or new to the market ? Secondly, is innovation output measured in this way equivalent to the output of a knowledge production or – stated more precisely – the result of applying the knowledge-capital accumulation equation given by (2b)?

## 3. *Adaptations of our previous model*

### 3.1 *The derivation of an enhanced productivity-growth equation*

16. Recent attempts (see e.g. Crépon et al., 1998, and Klomp and van Leeuwen, 2001b) have exploited the new CIS data in a structural modelling approach. These approaches claim that it is not differences in *innovation investment* (or, more specifically, the history of R&D investment) but differences in *innovation output* that determines the observable differences in productivity (growth). In this section we present an extension of the model used in van Leeuwen and Klomp (2001b). Our model aims at capturing the theoretical issues of the preceding section and also makes a more extensive use of the CIS data than the study of Crépon et al. (1998). Similar to Klette (1996) we also use a firm's total sales as the starting point for the model derivation, but contrary to his study we embed the sales performance of firms in a market-share model. Therefore, our model is more similar to the model of Klette and Griliches (1996). The difference is that we use an innovation output measure to capture the impact of “demand-shifts” on sales-per-employee growth. This adaptation can be argued as follows. Saying that innovation output is similar to relative product quality, by definition implies that innovating firms are operating on markets characterised with horizontal product differentiation. Thus, one may expect that successful innovators have the discretion of market power and this makes their relative prices endogenous.

17. Let the differential equation for the market share of firm  $i$  operating on market (industry)  $I$  be given by

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<sup>6</sup> This econometric problem also complicates the use of traditional R&D models as one may expect that the R&D investment decision may be dependent on firm performance.

$$\Delta q_i^d - \Delta \bar{q}_I = \Delta d_i + \eta \Delta(p_i - \bar{p}_I). \quad (3a)$$

In (3a)  $q_i^d$ ,  $p_i$  and  $\bar{q}_I$  denote respectively the demand and own price (index) of firm  $i$  and total sales of market (industry)  $I$ . Furthermore,  $\eta$  represents the demand elasticity with respect to relative prices (or stated otherwise: the “own” price index relative to the aggregate deflator for industry  $I$ ) and  $\Delta d_i$  summarises the contribution of “demand-shifting” variables to the growth rate of a firm’s own demand relative to the growth of exogenously given sales opportunities, represented by  $\Delta \bar{q}_I$ .

18. In our model we will adopt a parametrisation of the “demand-shifter” that uses the data on cross-sectional differences in relative product quality observed in CIS. More precisely, we use  $\Delta d_i = \phi S_i$ , with  $S_i$  the share of new (or new and improved) sales in total sales. Taking into account the definition of the growth rate of deflated revenues ( $\Delta r_i$ ), expressed as

$$\Delta r_i = \Delta(q_i + p_i) - \Delta \bar{p}_I, \quad (3b)$$

and combining (3a) and (3b) with a traditional gross-output-production-function model<sup>7</sup>, then yields

$$\Delta r_{it} = \varepsilon(\alpha \Delta c_{it} + \lambda \Delta m_{it} + \beta \Delta l_{it}) - \frac{1}{\eta} \Delta \bar{q}_{It} - \frac{\phi}{\eta} S_{it} + e_{1it}, \quad (3c)$$

where  $\varepsilon$  represents the inverse of the mark-up factor<sup>8</sup>,  $e_{1i}$  is a disturbance term and time subscript are added to distinguish between observation periods.

19. In the empirical application we use the productivity equivalent of (3c) after adding a constant term and dummy variables to capture a general trend and the impact of process innovation on a firm’s revenue-per-employee growth respectively.<sup>9</sup> Therefore, the empirical specification for revenue-per-employee equation of our model reads

$$\Delta r_{it} - \Delta l_{it} = \mu + \varepsilon \alpha (\Delta c_{it} - \Delta l_{it}) + \varepsilon \lambda (\Delta m_{it} - \Delta l_{it}) + \varepsilon (\alpha + \beta + \lambda - 1) \Delta l_{it} \quad (4)$$

$$- \frac{1}{\eta} \Delta \bar{q}_{It} + \gamma S_{it} + \xi D_{proc,it} + e_{2it}.$$

20. The estimation of (4) yields an implicate estimate of the contribution of innovation to multi-factor-productivity growth (MFP), given by  $\hat{\gamma} \bar{S} = -(\hat{\phi} / \hat{\eta}) \bar{S}$ , and also controls for biases in the returns-to-

<sup>7</sup> The model which uses as inputs into production ordinary physical capital (C), labour (L) and material inputs (M) (see appendix I).

<sup>8</sup> The inverse of the mark-up factor is related to the price elasticity of demand as follows:  $\varepsilon = (\eta + 1) / \eta$ .

<sup>9</sup> This dummy variable takes on a value of one if firms stated to have implemented process innovation and zero otherwise.

scale estimates.<sup>10</sup> Notice that contrary to the basic framework (see appendix I), innovation investment is no longer interpreted as a separate input, but that the model assumes that differences in innovation intensities are transmitted to differences in revenue-per-employee growth to the extent that a firm's investment endeavour has been successful.

### 3.2 *Linking the revenue model to the innovation process*

21. The next step is to embed (4) in a structural model that is sufficiently flexible to capture important features of the innovation process and that takes into account the joint endogeneity of innovative sales and sales-per-employee growth. With sufficiently flexible we mean that this model should be able to account for within-firm time interdependencies of knowledge production as well as the various interactions between internal and external knowledge bases. However, this is a daunting task in view of the available data and the intricacies at work. Many variables collected in CIS are of a qualitative nature and how to use these data optimally together with the continuous variables for innovation investment and innovation output remains an open question. A related problem is that a firm's technological environment may affect its innovation investment and its level of innovation output achieved at the same time.

22. A recurrent conclusion of previous research (see e.g. Cohen and Levinthal, 1989, Leiponen, 2001, Veugelers, 1997, and Veugelers and Cassiman, 1999), is that the technological environment of a firm may affect its organisational arrangements. Firms absorb knowledge from the environment via supplier-producer-customer-interactions, the use of available information sources in addition to building up and maintaining their own knowledge bases via R&D investment and (R&D) co-operation. The choice between the "make", "buy" or "make and buy" option at the one hand, or between "formal" and "informal" R&D or – more general – innovation at the other hand, may have diverging impacts on the level and composition of innovation cost. Moreover, utilising the technological environment may also contribute to innovation output more directly. For instance, one can imagine that firms innovate by exploiting the available information sources or by relying on informal innovation co-operation even without spending one dollar on R&D.

23. In order to account for the complementarity between internal and external knowledge bases and knowledge flows between firms we assume that the R&D investment decision and the level of innovative sales achieved are jointly dependent on various firm-specific innovation characteristics.<sup>11</sup> In addition, we model the within-firm time interdependencies for the two stages of the innovation process by adopting a dynamic specification for the R&D intensities (denoted by R/Q) as well as for the (logarithm of the) share of new sales in total sales.<sup>12</sup> This yields the following two equations

$$(R/Q)_t = \pi_{10} + \pi_{11}(R/Q)_{it-1} + \pi_{12} \ln(S_{it-1}) + X'_{1t} \Pi_{13} + Z'_{1t} \Pi_{14} + e_{rt} \quad (5a)$$

$$\ln(S_{it}) = \pi_{20} + \pi_{21} \ln(S_{it-1}) + \pi_{22}(R/Q)_{it} + X'_{2t} \Pi_{23} + Z'_{2t} \Pi_{24} + e_{sit}, \quad (5b)$$

<sup>10</sup>  $\bar{S}$  represents the average share of innovative sales and the estimate for  $\alpha + \beta + \lambda - 1$  in (4) represents the deviation from constant-returns-to-scale.

<sup>11</sup> A description of all instrumental variables is given in appendix II.

<sup>12</sup> We use the R&D intensity form and the logarithmic transformation of  $S$  in (5a) and (5b) because this enables a comparison with e.g. Crépon et al. (1998) and van Leeuwen and Klomp (2001b). Furthermore, to be consistent with (5a) and (5b), we replaced  $S$  in (4) by  $\exp\{\ln(S)\}$ .

24. The capital  $\Pi$ 's in (5a) and (5b) denote vectors of parameters associated with the instrumental variables (other than the lagged dependent variables included). We collect these variables into two vectors  $X$  (for production survey data) and  $Z$  (the innovation survey data). The identification of our model rest on the partitioning of these vectors across the two equations. We have chosen to adopt a similar partitioning as used in van Leeuwen and Klomp (2001b). Therefore, we use

$$X = \{MS_{t-1}, \Delta\bar{q}_I, l_{t-1}, CF_{t-1}\};$$

$$Z = \{D_{pull1}, D_{pull2}, D_{push1}, D_{push2}, SCIENCE, OTHER, D_{co-op}, D_{R\&D}\},$$

$$Z_1 = \{Z, D_{subs}\}, X_1 = \{MS_{t-1}, \Delta\bar{q}_I, l_{t-1}, CF_{t-1}\},$$

$$Z_2 = \{Z, D_{proc}, PAVIT\} \text{ and } X_2 = \{\Delta\bar{q}_I, l_{t-1}\}.$$

25. Notice that (5a) generalises (2b) and that system (5) as a whole can be used to compare the differences between the persistence of the R&D endeavour and innovation output. In addition, we also obtain an estimate for the impact of the initial level of innovativeness (represented by  $\ln(S_{t-1})$ ) on the current R&D endeavour. Furthermore, system (5) can be adjusted to a static version by removing the lagged endogenous variables. Doing so, we enable a comparison with our previous research.

#### 4. The data

26. The data used in this paper are obtained by matching the two waves of CIS to the production surveys for manufacturing. The two innovation surveys are comparable in time and are also based on the same sampling frame that underlies the production surveys. Thus, in principle, the matching of the two different surveys is straightforward. However, an exception should be made for few enterprises that have their R&D function centralised in special units. As their innovation data for 1996 – 1998 were collected in a different way than the corresponding data for 1994 – 1996 (CIS2), we have chosen not to use these data.

27. Our model makes an extensive use of market (industry) variables. Therefore, we first constructed industry data on nominal sales for the years 1994, 1996 and 1998. Using the raising factors of the underlying production surveys we calculated the value of total sales on the ISIC three-digit level for each year. Subsequently, we linked to these data the corresponding industry price indices for total sales and material usage.<sup>13</sup> In the next step we constructed a clean set of complete firm-level production survey data for the two periods covered by the innovation surveys. In order to obtain two short panels, we selected firms with complete production survey data in 1994 and 1996 or 1996 and 1998. The cleansing rules applied thereafter, eliminated firms with a negative score for their value added or missing data on employment, the cost of material usage and depreciation costs. In addition, and to safeguard against a mismatch with our industry data, we also eliminated firms that showed a change of the (3-digit) ISIC classification.<sup>14</sup>

<sup>13</sup> The price indices represent the average change in prices compared to (base-year) 1990. Their level of detail varies between the two- and three-digit level of the ISIC industry classification of firms, with a greater level of detail for the sales deflators than for the price indices concerning material usage.

<sup>14</sup> A firm for which the 3-digit industry classification was changed in 1994 – 1996 has been eliminated from the panel for this period, but may be existent in the panel for 1996 – 1998.

28. To estimate the parameters of the productivity growth equation of our model we also need data for the inputs of labour, material usage and physical capital. The first two variables are readily available, although for labour inputs we can only rely on “head counts” (the number of employees). Unfortunately, and not uncommon for this type of data, our measure of capital inputs raises more problems. The capital input measure used to estimate the models is approximated by the depreciation costs (deflated with the price index for total sales) available in the production surveys.<sup>15</sup> Similarly we deflated the other nominal variables in the data set after linking the industry data to the firm-level data and by applying the industry sales - or material price indices to all firms within the corresponding industry. In the final stage of the data construction we linked the two innovation surveys to the corresponding production survey panels and removed the firms with a suspicious high innovation intensity.<sup>16</sup>

Table 1: **Summary of the data sets available for manufacturing**

	1994-1996	1996-1998	1994-1998
Complete PS data	4134	5087	3180
Covered in CIS	2516	3012	1160
• Innovative	1428	1618	758
• Non-innovative	1088	1394	402

29. A summary of the data available after the before mentioned steps is given in table 1. It should be noted that the second period covers many more very small firms than the first period. This applies to the production survey as well as to the innovation survey. Nevertheless, the CIS coverage ratios for the two periods are more or less equal (about 60 %). For the coverage with respect to innovating firms we have a similar result: the share of innovating firms as a percentage of all firms covered by CIS only differs slightly between the periods covered by CIS2 and CIS2,5. However, if we use a balanced innovation panel, then the coverage ratio of CIS decreases to 36 % (see the last column of table 1). This unexpected result may have different causes and deserves further investigation. On the other hand, it can be seen that the use of a balanced innovation panel may invoke another selectivity problem, as the percentage share of innovating firms is largest for the balanced innovation panel (65 % compared to 57 % in 1994 – 1996 and 54 % in 1996 – 1998). The latter result may be due to the combined effect of a higher probability of survival and a higher persistence of innovativeness for larger firms. In closing, we also note that our definition of “innovativeness” differs from the one used in CBS (2001). In our application firms that responded to CIS are labelled “innovative” if we have a complete set of data on its innovation investment, innovation output and the qualitative data referring to their technological environment. By contrast CBS (2001) uses a broader definition as firms are classified “innovative” if they have carried out innovative activities in some way. In the latter definition firms are considered “innovative” even if they did not actually implement any product or process innovation in the period considered. For these firms we do not have available the variables that are included in the model.

<sup>15</sup> This financial measure is related to the capital stock but does not reflect directly the capital service flow. Tax laws, vintage structures and type distribution of the assets, and cyclical capital utilisation all cause differences between the depreciation data and the desired measure of real capital input.

<sup>16</sup> Firms covered in CIS2 or CIS2,5 were removed from the data if their innovation intensity (total innovation cost scaled by nominal sales) exceeded 50 %.

4.1 *A comparison of the performance of innovating and non-innovating firms*Table 2a: **Descriptive statistics for selected variables in 1994 - 1996**

<b>Variable</b>	<b>Median</b>	<b>Q1</b>	<b>Q3</b>	<b>SD</b>
<i>Growth rate of :<sup>1</sup></i>				
• Employment (I)	0.0	-3.8	4.6	11.0
• Employment (N)	0.0	-4.6	4.6	13.5
• Value added per employee (I)	2.0	-4.5	8.6	15.8
• Value added per employee (N)	1.4	-5.6	8.9	19.2
• Sales per employee (I)	3.3	-2.6	9.6	13.8
• Sales per employee (N)	2.6	-3.9	9.7	16.2
• Industry sales (I)	3.6	1.2	6.9	7.7
• Industry sales (N)	3.5	1.4	5.8	6.7
<i>Levels:</i>				
• Market share 1994 (%) (I)	0.6	0.2	1.9	7.6
• Market share 1994 (%) (N)	0.2	0.1	0.6	4.1
• Employment 1994 (I)	89	53	175	1152.8
• Employment 1994 (N)	42	28	73	224.9
• Profitability 1996 (%) (I)	9.8	5.1	16.5	13.9
• Profitability 1996 (%) (N)	8.4	3.3	14.9	14.4
• Value added per employee 1996 (I) <sup>2</sup>	97.0	76.5	131.7	82.2
• Value added per employee 1996 (N) <sup>2</sup>	84.4	66.3	109.6	82.3
• Sales per employee 1996 (I) <sup>2</sup>	251.1	184.3	373.8	422.0
• Sales per employee 1996 (N) <sup>2</sup>	212.6	151.7	317.5	565.4

<sup>1</sup> Annualised growth calculated over the period 1994 – 1996.<sup>2</sup> In 1000 Dfl.

Table 2b: **Descriptive statistics for selected variables in 1996 - 1998**

<b>Variable</b>	<b>Median</b>	<b>Q1</b>	<b>Q3</b>	<b>SD</b>
<i>Growth rate of :<sup>1</sup></i>				
• Employment (I)	1.3	-2.5	7.0	14.0
• Employment (N)	0.4	-3.2	7.7	17.6
• Value added per employee (I)	2.3	-4.8	9.8	17.8
• Value added per employee (N)	1.7	-6.7	10.3	21.9
• Sales per employee (I)	3.2	-3.3	9.7	17.4
• Sales per employee (N)	2.2	-5.5	10.1	21.6
• Industry sales (I)	5.4	2.3	6.9	5.3
• Industry sales (N)	5.4	1.4	6.9	5.9
<i>Levels:</i>				
• Market share 1996 (%) (I)	0.4	0.1	1.6	6.8
• Market share 1996 (%) (N)	0.2	0.1	0.5	4.1
• Employment 1996 (I)	74	34	159	1077.5
• Employment 1996 (N)	30	15	57	170.7
• Profitability 1998 (%) (I)	10.1	4.8	16.4	13.7
• Profitability 1998 (%) (N)	9.9	4.3	18.0	16.6
• Value added per employee 1998 (I) <sup>2</sup>	99.0	77.7	133.4	138.9
• Value added per employee 1998 (N) <sup>2</sup>	88.4	67.4	118.8	72.3
• Sales per employee 1998 (I) <sup>2</sup>	264.7	187.5	394.6	834.6
• Sales per employee 1998 (N) <sup>2</sup>	218.1	150.5	337.9	1751.3

<sup>1</sup> Annualised growth calculated over the period 1996 – 1998.

<sup>2</sup> In 1000 Dfl.

30. Tables 2a and 2b present some simple descriptive measures for the key variables used in this study that enable a comparison of the performance of innovating (I) and non-innovating (N) firms for 1994 – 1996 as well as for 1996 – 1998. Taken on the whole the tables confirm our previous result (see Klomp and van Leeuwen, 2001a) that innovating firms are performing better than non-innovating firms. This conclusion applies to all performance measures included, except for the industry variables. The latter result expresses that general business conditions did not favour innovating firms in particular. The most striking difference between the two periods concerns the growth rate of employment. The accelerating growth of industry sales in 1996 – 1998 shows up in a positive employment growth in this period, in particular for innovation firms. However, we do not observe a similar acceleration of sales-per-employee growth and the acceleration of labour productivity growth (measured as value-added-per-employee) also appeared to be modest.

31. The simple descriptive measures used for the level data also point to some well-known stylized facts as the tables show that size distributions are very skew and that innovating firms are smaller and have higher median values for the market shares. It can also be seen that the different survey design for the period 1996 – 1998 shows up in a lower median value for employment, both for innovating and non-innovating firms.

## 5. Estimation results

### 5.1 *Selectivity issues*

32. In this section we present the estimation results for the various implementations of the full model. In all implementations the estimated system contains the productivity-growth equation (4), but we shall iterate on the functional form of the equations that refer to the innovation process. In any case the estimation of the system takes into account the simultaneity of innovation investment, innovation output and productivity growth. The data allow a break down for the total of innovation cost and we can also choose between different measures of innovative sales. In order to keep things tractable, and to preserve the link with previous R&D-productivity research, we have chosen to use the R&D intensity as the measure of inputs into innovation. As to the output side of the innovation process, we have chosen to compare the model estimates obtained after using two alternative measures: the share of new sales (new to the firm) in total sales or the share of new and improved sales in total sales. We begin by using the second measure<sup>17</sup> and then recalculate our models using the first definition of innovation output.

33. In the estimation procedure we also try to correct for possible biases due to selectivity problems. A priori reasoning suggests that the emergence of such problems may be dependent on the adopted specification for the innovation model. For instance, if we (5a) and (5b) as the model for the innovation process, then we can only estimate the complete system using the firms that were innovative in the two periods considered. In this case we encounter a severe loss of information. This problem can be overcome by transforming (5a) and (5b) into a static version by removing the lagged dependent variables from the equations.

34. However, this change of modelling strategy seems not be trivial in view of the very nature of the process of “knowledge production” and the measure used for the output of this “production process”. It may be the case that part of the sample attrition is due to discontinuities in knowledge creation (or more precisely the generation of new or improved products) at the firm level. Put simply: “having achieved new or improved sales in 1994 – 1996 may reduce the incentive to innovate in 1996 – 1998, as the technological opportunities may be depleted”. All this is tantamount to saying that we may encounter a problem of endogenous attrition if we use a dynamic innovation model. Notice that the selectivity issue can be carried over to the use of a static version of (5a) and (5b). Then, we can have the situation that firms that are facing favourable sales opportunities may have less incentives to be engaged in innovation.

35. The usual way to account for this type of problems is to apply Generalised Tobit models to the equations of the dynamic or static innovation model. These models have been applied as a first step in the estimation procedure. Doing so, we can assess the joint dependence on the explanatory variables of the probability of being innovative and the dependent variables of the innovation equations. To save space we will not discuss the results here in much detail (see appendix III for the model estimates). The main conclusion is that the selectivity problem is more severe for innovation inputs than for innovation output.

36. The next step consists of finding a way to control for possible selectivity biases of the estimates of the full model. This has been achieved as follows. Dependent on the results of the Tobit analysis, we added selectivity-correction terms derived from Heckman’s two-step method. Furthermore, and only for the full model that uses the static innovation equations, we added time dummy variables to all equations of the full model to control for period specific effects. We recall that the dynamic version of the full model covers the period 1996 – 1998, and thus uses the data for the 758 firms that were innovative in 1994 –

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<sup>17</sup> This measure has also been used in our previous research (see van Leeuwen and Klomp, 2001b).

1996 as well as in 1996 – 1998 (see table 1). The full model, with the static version of the innovation equation included, uses the 3046 firms that were innovative either in 1994 – 1996 or in 1996 – 1998.

37. The two versions of the full model are estimated with the help of the method of Full Information Maximum Likelihood (FIML). The FIML estimates are presented in two tables. First we look at the estimates for the equations of the innovation process, thereby focusing on two central themes: 1) the persistence of innovativeness and 2) the returns to R&D investment.

Table 3: Results of the innovation input - and innovation output equation<sup>1</sup>

Type of model	Dynamic model		Pooled model	
	Est.	T	Est.	T
Number of firms	758		3046	
<b>A) Inputs into innovation</b>				
Constant	2.792	2.0	6.269	7.2
R&D intensity lagged	0.434	24.2		
Innovation output lagged	-0.014	-0.2		
$I_{t-1}$	-0.255	-2.0	-0.784	-7.4
$MS_{t-1}$	0.042	5.8	0.034	8.2
$D_{SUBS}$	0.269	1.1	0.582	3.9
$CF_{t-1}$	-0.004	-0.6	-0.005	-1.7
$D_{R\&D}$	0.505	1.6	0.895	4.7
$D_{co-op}$	0.156	0.8	0.258	2.1
Science	0.247	2.9	0.544	13.5
Other	0.062	0.5	0.150	2.3
$D_{pull1}$	-0.108	-0.2	-0.155	-1.0
$D_{pull2}$	0.029	0.1	0.023	0.1
$D_{push1}$	0.182	1.0	-0.181	-1.6
$D_{push2}$	-0.016	-0.1	-0.220	-2.0
$\Delta \bar{q}_I$	0.001	0.7	0.042	6.2
Period dummy			-0.294	-2.4
Heckman's selectivity correction	-2.912	-1.9	-2.250	-6.3
Pseudo $R^2$	0.522		0.169	
<b>B) Innovation output</b>				
Constant	-5.624	-1.5	-4.790	-16.6
Innovation output lagged	0.295	2.9		
R&D intensity	0.067	0.5	0.615	3.9
$I_{t-1}$	0.135	0.5	-0.036	-0.9
$D_{R\&D}$	0.490	3.0	0.237	1.1
$D_{co-op}$	0.174	1.1	0.002	0.0
Science	0.056	0.6	-0.025	-0.5
Other	0.230	3.2	0.237	4.0
$D_{pull1}$	2.025	9.9	0.839	6.7
$D_{pull2}$	2.159	9.8	0.838	6.6
$D_{push1}$	0.033	0.2	-0.063	-0.6
$D_{push2}$	-0.267	-1.9	-0.114	-1.1
$\Delta \bar{q}_I$	0.003	0.2	-0.026	-2.7
$D_{proc}$	0.252	1.6	0.601	7.6
Period dummy			0.512	4.4
Heckman's selectivity correction <sup>2</sup>	1.096	0.3	x	
Pseudo $R^2$	0.354		0.088	

<sup>1</sup>The model uses the R&D intensity as the dependent variable in the innovation input equation and the (logarithm of the) share of new and improved products in total sales as the dependent variable in the innovation output equation.

<sup>2</sup>We did not include a selectivity correction for the pooled model as the preliminary Tobit-selectivity analysis did not indicate a selectivity problem.

## 5.2 The estimates for the innovation equations

38. The first, and most notable, point to observe is that the estimates for the two lagged dependent variables are statistically significant and that the estimate is higher (and estimated with more precision) for the R&D-intensity equation than for the innovation-output equation. This result suggests that we have less persistence if we measure innovation from the output side rather than from the input side of the innovation process. Apparently, the often quoted stylized fact that differences in R&D intensities across industries are persistent cannot be carried over to the output of knowledge production. Moreover, the coefficient of the lagged R&D intensity presented in table (3) may be considered too low to make a very strong statement about its persistence on the basis of our data.<sup>18</sup> Anyway, the obtained estimates indicate that – at least for innovative sales – we have a strong tendency to convergence if we use firm level data.<sup>19</sup> As mentioned before, the results for innovative sales may be due to a depletion of technological opportunities. One can imagine that this source of non-persistence is much more valid at the firm level than in the aggregate, where the decrease of innovative sales of a particular firm is counterbalanced by an increase of innovative sales of other firms. This leads to the conclusion that we have to do not only with much turbulence of firms, but also to do with much turbulence at the product level behind the observed regularity of aggregate statistics.<sup>20</sup>

39. From this point of view it is equally understandable that the returns to innovation investment to innovation output (represented by the coefficient of the contemporaneous R&D intensity in the innovation output equation of the model) are small and statistically insignificant in the dynamic model. If the level of product quality achieved captures the history of a firm's R&D endeavour (and the technological opportunities of this are depleted), then the innovation opportunities of the most recent R&D investments may be small. This is the basic conjecture of the models of Hall and Hayashi (1989) and Klette (1996).<sup>21</sup> In the dynamic model we control for the initial level of “innovativeness” in terms of innovation output. Thus, the estimate of the contemporaneous R&D intensity in the innovation output equation of the dynamic model seems to corroborate Hall and Hayashi (1989) and Klette (1996).

40. However, this point deserves further reflection for two reasons. Firstly, how can we understand this result given that we also obtained a much higher estimate for the returns of innovation investments to innovative sales in the static model, where it is about 0.6 and, moreover, rather significant? Secondly, how can we explain the pattern of the estimates for the variable  $D_{R\&D}$  in the two equations? We recall that the latter variable controls for the presence of permanent R&D. Thus, in the dynamic model, we have two different “forms of control” that are related to the same phenomena. First, let us now compare the corresponding estimates for the two versions of the innovation-input equation. The significance of the estimate for the variable that controls for the presence of permanent R&D facilities is much smaller in the dynamic version of the model than in the “static” equivalent. However, this should not surprise us, as the dynamic model is aimed at an estimation of R&D persistence and this persistence has also been captured in the estimate of the lagged R&D intensity.

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<sup>18</sup> We note that this stylized facts has been often found after using other types of data, e.g. time series data for industry aggregates or long R&D time series data of very large enterprises.

<sup>19</sup> It should be remembered that the models use the broadest definition of innovative sales available, i.e. the share of new and improved products in total sales.

<sup>20</sup> To give an example: the simple arithmetic average share of new and improved sales in total sales for 1994 – 1996 (calculated using the 1428 firms of table 2a) was about 26 %. This almost equal to the corresponding average for 1996 – 1998 (calculated using the 1618 firms of table 2b). The same regularity can be observed after weighting the data (see e.g. CBS, xxx, and, CBS, yyy).

<sup>21</sup> See the summary of their models given in section 2.1.

41. Next, we look at the innovation-output equation. The most striking difference between the two versions of the model is that we have a low and insignificant estimate for the R&D intensity in the dynamic model and a much higher (and rather significant) estimate in the static model. By contrast we see that the impact of performing R&D on a permanent basis is small and insignificant in case of the static version but larger and rather significant in the dynamic model. Thus, these estimates seem to represent contradictory results. However, there are reasons to question this interpretation. One can imagine that the level of R&D-knowledge stocks achieved are dependent on the nature of R&D investment. A firm that performs R&D on a permanent basis may have fewer difficulties in building up knowledge stocks than firms that perform R&D incidentally. Furthermore, one can imagine that the initial level of innovative sales has captured the history of R&D investment to the extent that knowledge-stocks were productive in terms of innovative sales. In the static model we do not control for the past. Therefore, it is not very surprising that “performing R&D on a permanent basis” is a better predictor for differences in R&D intensities than for differences in innovative sales. However, in the dynamic model we do control for the past at both sides of the innovation process. Nevertheless, we obtained a significant contribution to innovative sales of performing R&D permanently.

42. Another – and perhaps more interesting – explanation for the estimated differences in returns to the current R&D endeavour may be related to the fact that the static model uses many more firms. As a result of the non-rivalry of innovation and (non-intended) “spillovers” to competitors we also have “new innovators” or “innovation imitating” firms that were not observed earlier. Such a mixture of “old” and “new” innovators – by definition – can be taken into account more properly in the static model. Furthermore, the emergence of “new” innovators may explain – in line with the conjecture of Klette (1996) – why the returns to current R&D endeavour are higher in the static innovation model than in the dynamic version of this model.

43. All in all, these results make a very strong plea for the importance of performing R&D on a permanent basis. They also clarify why we cannot simply rely on R&D intensities only. But – at the same time – the results also stress that the use of firm-level innovation panel data may not be able to capture all salient features of the innovation process. Anyway, the results presented in table 3 underline the benefits of using variables that refer to the organisation aspects of innovation processes and a firm’s interaction with its technological environment. As to the latter, it can be seen that our previous results are confirmed for other explanatory variables: we obtained a similar pattern for the impact of the technological opportunity variables *SCIENCE* and *OTHER* in the two equations as in Klomp and van Leeuwen (2001b). Again, and in line with the “absorptive-capacity” hypothesis of Cohen and Levinthal (1989), *SCIENCE* appears to be more important for predicting differences in R&D intensities and *OTHER* for predicting differences in innovative sales.<sup>22</sup> Furthermore, the correspondence with the conclusions of our previous research also applies to other results:

- Conditional on selection there appears to be a negative relation between firm size and R&D intensities (see also Cohen and Klepper, 1996).
- Large firms do not show a better innovation performance in terms of innovation output than small firms.
- The implementation of process innovation contributes positively to innovation output (see also Bartelsman et al., 1998).
- Innovation seems to be a “demand-driven” process merely (see the estimates for the variables that refer to the objectives underlying innovation).

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<sup>22</sup> The decrease in significance for the estimated impact of *SCIENCE* to innovation investment when using a dynamic model can be explained by the fact that the contribution of this variable has already been captured in the estimate for the lagged dependent variable.

5.3 *The contribution of innovation to productivity growth*Table 4: The results for the revenue-per-employee equation<sup>1</sup>

Use of innovative sales	New sales		New and improved sales	
	Est.	T	Est.	T
<b>A) Dynamic model</b>				
Number of firms	510		758	
Constant	0.518	0.5	-0.046	-0.0
Physical capital	0.017	1.2	0.006	0.5
Labour	0.076	1.7	0.132	3.3
Material inputs	0.781	10.7	0.761	11.4
Dummy process innovation applied	-1.155	-1.7	-0.754	-1.0
Share of innovative sales	0.055	1.7	0.015	1.0
Returns to scale	-0.126	-1.5	-0.101	-1.2
Inverse of mark-up	0.896	10.9	0.913	12.3
Share of innovative sales in total sales	10.1		27.5	
Contribution of innovation to MFP	0.6		0.4	
R <sup>2</sup>	0.630		0.550	
<b>B) Pooled model</b>				
Number of firms	1929		3046	
Constant	-1.001	-2.1	-0.317	-0.9
Physical capital	0.020	4.1	0.014	3.5
Labour	0.117	10.5	0.142	15.0
Material inputs	0.747	28.1	0.749	36.2
Dummy process innovation applied	-0.196	-0.4	-0.245	-0.7
Share of innovative sales in total sales	0.115	6.8	0.030	3.8
Returns to scale	-0.116	-3.8	-0.095	-3.9
Inverse of mark-up	0.966	29.0	0.946	38.2
Share of innovative sales	8.2		26.4	
Contribution of innovation to MFP	0.9		0.8	
R <sup>2</sup>	0.714		0.683	

<sup>1</sup>All models use annualised growth rates.

44. In this subsection we discuss the estimation results of the revenue-per-employee model presented in table 4. In particular we pay attention to the contribution of innovation to multi-factor-productivity (MFP) growth. According to the theoretical exposition of section 3, this contribution is given by

$\hat{\gamma}\bar{S} = -(\hat{\phi}/\hat{\eta})\bar{S}$ . Therefore, by focusing on innovative sales, we have derived a measure for the contribution of innovation to productivity growth along the quality ladder or product variety model of Grossman and Helpman (1991). Indeed, looking at our firm-level data, it can be observed that many innovations are incremental. It can be verified, that a substantial part of the innovating firms only have implemented product improvements. Furthermore, our discussion of the patterns for the estimates of the two versions of the innovation model presented in table 3 point to the presence of different forces. We have a rather low persistence of innovativeness (in terms of having achieved new and improved sales) when tracking the innovation performance of individual firms across time. On the other side, we also estimated a higher return to the current R&D endeavour if we also take into account “new” innovators’ or “innovation imitating” firms.

45. Unfortunately, and by construction, we do not have data on the innovation-investment history of these “new” innovators.<sup>23</sup> We have tried to circumvent this problem by using two alternative measures for innovation output. We recalculated the full model after redefining innovation output as the share of new sales in total sales and then compared the results for the MFP-contribution to productivity growth of the two measures of innovation output. Furthermore, we also applied the two definitions of innovativeness to the innovation panel as well as to the complete sample (including the firms that were only existent in one wave of CIS). It goes without saying that the different models applied yield different estimates for the innovation-output variable of the productivity-growth model and that the differences between the averages for the innovative output measure chosen should also be taken into account.<sup>24</sup>

46. Doing so, we obtain an estimate for the contribution of innovation to MFP growth that lies in between 0.3 % and 0.9 %. It can be seen, in table 4, that these estimates are highest for innovation output defined as the share of new sales in total sales. It is also interesting to see that the latter model version yields the best “fit” to the data. In the variant that use new sales we obtained a higher precision of the corresponding estimates as well as a higher coefficient of determination ( $R^2$ ) than in the variant that uses a less discriminating definition of innovation output, and irrespective of specification for the innovation model used. On the basis of these criteria – and because it covers many more firms – we adopt the model that uses the new sales performance of all available firms as the preferred model.

47. In closing, we also look at the other estimates of the revenue model. It can be observed that the precision of the production elasticities of the model increases with the sample size used and that we have a tendency to decreasing returns to scale. However, this conclusion should be interpreted with care as we have – in general – a rather low (and in some cases insignificant) estimate for the production elasticity of ordinary physical capital. The latter result is expected to be due to our approximate measure used for this variable, taking also into account that we have used firm-level data of a times series type rather than cross-sectional differences in levels.<sup>25</sup> Furthermore, it should be noted that our estimates control for the importance of process innovation. In general, the contribution of process innovation to sales-per-employee growth appears to be insignificantly. Comparing this result with the estimates of the corresponding variable found in the innovation-output equation, then we have to conclude that process innovation contributes relatively more to innovative sales than to non-innovative product lines. A final notable result concerns the estimate for the mark-up factor included in the models. Here, we obtain the most sensible results for the model that uses new sales as the measure of innovativeness and that has been applied to the panel of

<sup>23</sup> This a consequence of the fact that only the current innovation cost are collected if firms stated to have implemented product or process innovation.

<sup>24</sup> If we change of the definition of innovation output to cover new sales only, then we can use 510 firms in the dynamic model and 1929 firms in the model that uses all available data.

<sup>25</sup> See e.g. Mairesse (1990) for a detailed account of this phenomenon.

innovative firms. This result seems in line with the a priori expectation that the underlying market-share model yields the most sensible representation for those firms that are continuously engaged in innovation.

## 6. Summary and conclusions

48. In this paper we have presented the first results of an attempt to assess the importance of innovation for inter-firm differences in productivity growth using two similar CIS surveys and after linking these surveys to the Production surveys of the same firms. We have exploited the innovation panel to investigate a number of theoretical issues. We combined recent lines of research in a structural modelling approach that allows the contribution of innovation to multi-factor-productivity (MFP) growth to be interpreted as a “demand-shifting effect”. The model rests on the basic assumption that innovation is a “demand-driven” process merely, and that its contribution to productivity growth thus should be measured along the quality ladder or product variety model of Grossman and Helpman (1991). Our model also accounts for the joint endogeneity of R&D investment, innovation output and sales-per-employee growth. Moreover, we have also tried to control for the interaction between internal and external knowledge bases, the within-firm time interdependencies for R&D and innovation output, and the biases in estimates as a consequence of endogenous panel attrition or endogenous selection. Two important points that were touched upon concerned 1) a comparison of the persistence of R&D investment and innovation output, and 2) a comparison of the contribution to MFP growth obtained after using the innovation panel with the same contribution obtained after using all data.

49. The dynamic model employed offers an intuitive form of “controlling” for the past innovation history, and, – moreover – also enables a comparison of the importance of other firm-specific innovation characteristics after having applied this form of “control”. The results of this model show that the innovation persistence is smaller when measured from the output side of the innovation process, than when judged from R&D intensities. This outcome seems to confirm the conjecture of earlier research, that the returns to current R&D endeavours are much lower after controlling for the level of innovativeness already achieved. Our result also points to a (private) rate of depreciation of “knowledge”, which is much higher than usually applied when constructing R&D-capital-stocks in the traditional way. Furthermore, and in line with the previous result, we also observed a rather small return to the current R&D endeavour for the firms included in the innovation panel. Nevertheless, the estimates of the dynamic innovation model underline the importance of being active in R&D permanently. Controlled for the past of innovation inputs as well as innovation output we observed a significant contribution to innovation output of performing R&D on a permanent basis.

50. On the other hand, we have found that the returns to the current R&D endeavour are very different if we relax the dynamic specification and apply a restricted and static model to all available CIS data. For this restricted model we obtained a much more pronounced and rather significant estimate for the returns of the most recent R&D investment endeavour. Conditional on the assumption that many of the additional firms used in the static model are “new innovators” with relatively short innovation histories, then this result also seems to corroborate the conjecture that the returns to R&D are highest for the firms that have low initial knowledge-capital-stocks.

51. Finally, we explored the sensitivity of the estimated for the implied contribution of innovation to MFP by iterating on the specification for the innovation model and the measures of innovation output available. The results of this sensitivity analysis show that, in most cases, we obtained a significant estimate for the contribution of innovation to MFP. The model that uses all data and the share of new products in total sales as the measure for innovation output, yields the preferred estimate of 0.9 % for the contribution on innovation to MFP.

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## APPENDIX I: THE BASIC FRAMEWORK FOR R&D-PRODUCTIVITY MODELS

1. This appendix summarises two well-known specifications for the production model that have been used extensively in the R&D-productivity literature (see e.g. Mairesse and Sassenou, 1991, and Griliches, 1999 chapter 4, for an overview). The model with output ( $Q$ ) and the inputs physical capital ( $C$ ), labour inputs ( $L$ ), material inputs ( $M$ ) and knowledge capital ( $K$ ) is approximated by a Cobb-Douglas function. Denoting the logarithms of variables with lower case letters, adding firm subscripts  $i$  and omitting time subscripts for the time being, then we have the following difference equations, where the contribution of R&D to output growth is represented either by the growth of R&D-capital (or equivalently knowledge-capital) stocks (1a) or by the R&D intensities (1b):

$$\Delta q_i = \mu_1 + \alpha_1 \Delta c_i + \lambda_1 \Delta m_i + \beta_1 \Delta l_i + \gamma \Delta k_i + \varepsilon_{1i} \quad (\text{Ia})$$

$$\Delta q_i = \mu_2 + \alpha_2 \Delta c_i + \lambda_2 \Delta m_i + \beta_2 \Delta l_i + \rho(R/Q)_i + \varepsilon_{2i} \quad (\text{Ib})$$

The knowledge-capital stocks ( $K$ ) underlying (1a) are constructed using the Perpetual-Inventory Method (PIM), usually applied to ordinary capital investment

$$K_t = (1 - \delta)K_{t-1} + R_t, \quad (\text{II})$$

and assuming no depreciation of knowledge-capital stocks ( $\delta = 0$ ).<sup>26</sup>

2. It is well-known that (1a) yields an estimate ( $\gamma$ ) of the elasticity of output with respect to innovation capital stocks, whereas (1b) yields an estimate ( $\rho$ ) of the (gross) private returns to innovation investment or, more specifically, R&D. The relation between these two estimates can be expressed as

$$\rho \equiv \frac{\partial Q}{\partial K} = \gamma \frac{Q}{K}. \quad (\text{III})$$

3. Both specifications have the advantage of providing a control for firm-specific and time-invariant differences in production levels, but (Ia) can only be estimated if we have firm-level time-series data for  $K$ . However, the construction of R&D-capital stocks at the firm level can only be accomplished at the cost of a severe loss of information.<sup>27</sup> In the CIS surveys we have a much larger sample of firms available. Moreover, our data are of a cross-sectional type and this implies that our model should be able to account for the well-known and persistent differences in R&D intensities across industries. For this reason we prefer to use specification (Ib).

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<sup>26</sup> The precise relation between (Ia) and (Ib) is given by  $\gamma \Delta k_i = \frac{\rho \Delta K}{Q} = \frac{\rho(R - \delta K_{-1})}{Q} \approx \rho \frac{R}{Q}$ .

<sup>27</sup> Similar to other countries R&D surveys in the Netherlands have a long tradition. Nevertheless, the linking across time of R&D data at the firm-level is severely hampered, by changes in the survey design or by the difficulty to track firms in time as a consequence of mutations in the sampling frame, e.g. due to the merging or the splitting-up of firms.

## APPENDIX II: THE EXOGENOUS VARIABLES FOR THE INNOVATION EQUATIONS

1. For the identification of the model it is necessary to assign exogenous variables to the jointly endogenous variables. The selection of the exogenous variables has been guided by the following considerations. We make a distinction between 1): variables that reflect the objectives underlying innovation, the organisational aspects of a firm's innovation process and its technological environment, 2): financial variables and 3): predetermined firm-specific variables and industry-specific variables that can be considered as exogenously given to the firm.

2. The first group of variables refer to the objectives underlying innovation. If the replacement of old products or the improvement of the quality of existing products or the extension of market shares and product ranges were rated as important, the dummy variable  $D_{pull1}$  takes on a value of one (and zero otherwise), whereas the rating "very important" is captured by  $D_{pull2}$ . Similarly, we constructed two "cost-push" dummy variables for the objectives "economising on production costs" (labour cost, cost of material inputs and energy) were considered "important" ( $D_{push1}$ ), or "very important" ( $D_{push2}$ ). The variables representing the organisational aspects of the innovation process are  $D_{R\&D}$  (indicating the presence of permanent R&D facilities),  $D_{co-op}$  (referring to innovating in partnership) and two continuous variables "SCIENCE" and "OTHER" derived from a principal components analysis in order to represent the use of technological opportunities.

3. The relation between the presence of permanent R&D facilities, "innovation in partnership" and the two technological opportunity variables ("SCIENCE" and "OTHER") can be outlined as follows. One may expect a "cost-push" effect on innovation expenditure of the technological opportunity factor "SCIENCE" due to the absorptive capacity argument (see e.g. Cohen and Levinthal, 1989). A co-operation between R&D firms and research institutes or universities requires relatively high internal research skills in order to assimilate the fruits of the co-operation and to internalise and commercialise the knowledge created during the co-operation. Contrary, R&D co-operation with e.g. suppliers, customers and competitors is expected to have lower research competence requirements, a smaller impact on the organisation of firms, and thus a lower "cost-push" effect on innovation expenditure than the technological opportunity factor "SCIENCE". On the other hand, as mentioned before, informal innovation co-operation may affect innovation output more directly.

4. The second category of instruments for the modeling of the innovation process consists of financial indicators. For many firms the innovation expenditures consist to a large extent of investment components, e.g. expenditures on in-house R&D, and/or licenses and patents and equipment purchased for the implementation of process innovation. We assume that these investment type expenditures are affected by the availability of financial resources and for this reason we include in the model two financial variables: the ratio of cash-flow to total sales at the start of the observation period ( $CF_{t-1}$ ) and a dummy variable that refers to the awarding of innovation subsidies ( $D_{subs}$ ).

5. The final category mentioned above consists of the variables derived from the Production surveys and that are assumed to be predetermined or exogenous to the firm. The variables used to serve as an instrument for the endogenous inputs into innovation and innovation output are (the logarithm of) initial employment ( $l_{t-1}$ ), the initial market shares of firms ( $MS_{t-1}$ ) and the growth rate of industry sales annual sales ( $\Delta \bar{q}_t$ ), already introduced in the main text of the paper. The first variable enables us to test whether the stylized facts of Cohen and Klepper (1996) concerning the relation between R&D and size also apply to our data. The two other instrumental variables are used to capture differences in initial states of competitiveness and exogenously given potentials for sales growth.

**APPENDIX III: THE RESULTS FOR THE GENERALISED TOBIT MODELS**

**To be added**