Innovation performance across Europe

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Abstract

The innovation performance of firms is primarily determined by their own innovative activities and the interaction with their innovation-related environment. This environment typically differs among countries. We assess empirically these differences on firms' innovation performance. To that end we first estimate the relationship between an aggregate innovation input measure and an aggregate innovation output measure, thereby explicitly controlling for structural differences between countries. We then consider the extent to which firms located in a particular country perform better or worse than this estimated benchmark performance. The analysis is based on a panel dataset that we have constructed from Eurostat's first and second Community Innovation Survey. In order to control for possible data contamination we employ an outlier-robust estimator. It appears that among the

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fourteen countries considered Italy, Germany and Ireland offer an environment that facilitates most the transformation of innovation-related inputs into commercial outputs while the environment in Denmark is the least facilitating.

Key words: Innovation performance; Community Innovation Survey; panel data; General M estimator.

JEL Classification: L16, O31

1 Introduction

The innovation performance of firms is primarily determined by their own innovative activities and the interaction with their innovation-related environment. Typically these environments differ across countries. For instance, central governments of some countries provide generous support for private R&D activities, others sustain the formation of R&D cooperatives while yet others, in addition, subsidize these agreements.[1] Schooling systems also differ across countries, hence affecting the supply of knowledge workers, while consumers' propensity to buy novel products might very well be related to cultural aspects, hence affecting the demand for innovative products. As a result, firms located in one country can easily have different returns on innovative inputs vis-à-vis identical firms located in another country using the same inputs.

The purpose of this paper is to assess empirically the influence of national innovation-related environments on firms' ability to transform innovation inputs into commercial outputs. To that end we first estimate the relationship between an aggregate innovation input measure and an aggregate innovation output measure, thereby explicitly controlling for structural differences across countries. The latter include differences in 'country dynamics' and the extent to which innovative activity is spread throughout the economy. This estimate is then interpreted as the benchmark of innovation-related output for a given level of inputs. Next, we consider for fourteen countries to what extent the innovation performance of firms receding in these countries is below or above this benchmark.[2] Based on this indication a ranking is

[1] For a theoretical assessment of R&D subsidies see e.g. Romano [1989]; related empirical research includes Busom [2000]. R&D cooperatives are analyzed theoretically in e.g. Hinloopen [2000b], while the 1998 June issue of the *Journal of Industrial Economics* is devoted to related empirical studies. A discussion on subsidized R&D cooperatives can be found in Hinloopen [1997, 2000a, 2000c and 2001].

[2] These countries are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, and United Kingdom. The choice

constructed which lists these countries according to the relative innovation performance of the firms they host.

This methodology is both simple and elegant. An alternative would be to provide a careful description of each country's innovation-related environment, followed by a microeconomic analysis of the interaction between this environment and firms operating within it. Although this procedure could give an adequate assessment of the environment with which innovating firms are confronted, it most likely is a formidably elaborate task yielding diverse (and possibly conflicting) results.

For the analysis use is made of the results from Eurostat's two Community Innovation Surveys (CIS1 and CIS2; see Eurostat [1997, 1999 and 2001] and Section 2 below). These surveys provide indicators for inputs and outputs of the innovation process at a national level for sixteen European countries, both in 1992 and 1996. Using the results from both surveys allows for the construction of a panel dataset. Accordingly, structural aspects (that is, developments over time) of the innovation process are captured. The unit of observation in these surveys is the individual firm. However, for strategic reasons only aggregate information is publicly available. Indeed, the regressions we carry out are based on aggregates at national levels of firm-level observations.

There is however much to comment on the comparability over time of the data from the Eurostat surveys (see e.g. Kleinknecht and Wunderink [1999]). Yet, these are the only (recent) data available that allow for a dynamic cross-country assessment of the type considered here. In any case, in our empirical analysis we explicitly control for possible differences between the first and second survey.

Another critique of the CIS-data relates to the quality of the observations as such. Because of the inherent difficulty of describing objectively aspects of the innovation process (for instance, when does one report that a product or production process is 'improved'?) it is difficult to obtain quantitative information that is without flaw. In particular, data could be recorded that in some sense are 'outlying'.[3] Estimates of conjectured relations based on these contaminated data are then easily blurred. To circumvent this problem we use an outlier-robust estimator, a so-called General M estimator, for our empirical analysis. Rather than removing outlying observations, this estimator accommodates these observations by bringing them in line with the majority of the data while not ignoring completely their influence. As shown by Hinloopen and Wagenvoort [1997], this estimator is both efficient and ro-

of countries is primarily dictated by the availability of appropriate data.

[3] In Section 5 below we define precisely what is meant by 'outlying'.

bust for several types and fractions of data contaminations (including those possibly present in the Eurostat surveys).

Given the broad range of countries participating in the surveys, the dynamic nature of the constructed dataset, the fact that we explicitly control for potential differences between countries as to their inherent dynamics and the fact that we rely on outlier-robust estimates, we conjecture that our estimates are an adequate approximation of the benchmark relation between the considered innovation inputs and outputs. Indeed, we are sufficiently confident to provide a country ranking based on the estimated benchmark.

Note in passing that we estimate the relation between 'country dynamics' and innovation performance. Our estimates show that an economically dynamic environment enhances the return to investments in innovative activities. Documenting this relation empirically is new to the literature. It implies that for innovations to be commercially successful governments should create an environment in which new opportunities can be pursued without innovators having to step over too many institutional thresholds.

Examining then the innovation performance of firms in the fourteen countries considered indicates that those located in Germany and Italy (and to a lesser extent Ireland) are best able to transform innovative inputs into commercial outputs, while those located in Denmark are least able to make this transformation. That German firms perform so well could be due to the fact that in Germany the dissemination and absorption of new knowledge takes place rather rapidly compared to several other countries (see Eaton and Kortum [1999]). Although this might reduce a firm's incentive to invest in R&D, it also enhances the effectiveness of such an investment. Indeed, innovation spending as a percentage of total turnover is not particularly high in Germany, but it is the percentage of total turnover attributable to new and/or improved products that stands out.[4]

The paper continues as follows. In the next section the innovation data are described while in Section 3 the benchmark model is presented. Our country dynamics indicator is introduced and computed in Section 4, followed in the next section by a discussion of the outlier-robust estimator. Section 6 contains the benchmark estimate while in Section 7 the and concomitant ranking of countries is presented. Section 8 concludes.

[4]We can further only speculate as to why Italy, Ireland and Denmark are at the boundaries of the ranking.

2 Innovation data

The data we use for our empirical assessment are taken from the first and second Community Innovation Survey (CIS) conducted by Eurostat. The aim of these surveys is to "set up a database that (can) be used for analysis of innovation from academic and policy making perspectives" (Eurostat [1997, word in parentheses added]). The first survey - CIS1 - relates to 1992 data while the second - CIS2 - relates to 1996 data. The countries participating in CIS1 were Belgium, Denmark, Germany, Spain, Greece, France, Ireland, Italy, Luxembourg, The Netherlands, Portugal (i.e. the EU12 excluding the United Kingdom) and Norway. For CIS2 Austria, Finland, Sweden and the United Kingdom were added. A distinguishing feature of the survey is that for each country information is obtained through an identical set of core questions and that this information is processed according to the same methodology. This makes the results directly comparable between countries.[5]

In Table 1 some of the results of CIS1 and CIS2 are presented. The observations relate to an aggregate input indicator of the innovation process (the innovation spending as percentage of GDP - x_1), an indicator for the extent to which innovative activity is widespread in the economy (the percentage of innovating enterprises - x_2) and an aggregate output indicator (the percentage of total turnover on new and improved products - y). There appear to be substantial differences in innovation activity in the sample. In 1996 the percentage of innovating enterprises varies between a low 26 percent for Portugal to a high 73 percent for Ireland. Likewise, in 1996 in Portugal only 0.57 percent of GDP was spent on innovation, a fraction that is more than six times higher in Spain and Sweden. Also, in 1996, the percentage of total turnover attributable to new and improved products varies substantially, ranging from 14 percent for Belgium to 45 percent for Germany.

In addition to these cross-sectional differences in dynamic developments can be observed. On average, innovation spending as percentage of GDP increased by 0.13 percentage-points in only four years. One of the reasons for this dramatic increase is that CIS1 is only concerned with product innovations while CIS2 also takes process innovations into account (see also footnote 4). At the same time the percentage of total turnover attributable to new and improved products fell, on average, from 37.1 percent in 1992 to 25.4 percent in 1996. Yet, as our regression results below show, statistically there is a positive relation between innovation spending and turnover

[5] According to Eurostat, the information obtained in CIS1 is not directly comparable with that obtained in CIS2. In the regression analyses we control for these possible differences by including an appropriate dummy variable. This dummy variable appears to be highly significant (see Section 6 for details).

Country	Innovation spending as a percentage of GDP (x_1)		Percentage of innovating enterprises (x_2)		Percentage of total turnover on new and improved products (y)	
	1992	1996	1992	1996	1992	1996
Belgium	1.64	1.82	61	27	39	14
Denmark	1.74	1.85	56	71	45	21
Germany	2.45	2.26	67	69	51	45
Greece	n.a.	n.a.	n.a.	48	n.a.	n.a.
Spain	2.87	3.47	37	29	52*	27
France	2.43	2.30	39	43	27	21
Ireland	1.01	1.42	72	73	36	32
Italy	1.20	1.01	34	26	29	27
Luxembourg	n.a.	n.a.	37	42	31	n.a.
Netherlands	1.99	2.03	57	62	37	25
Portugal	0.63	0.57	n.a.	26	29*	14
Austria	1.47	1.60	n.a.	67	n.a.	31
Finland	2.18	2.54	n.a.	36	n.a.	25
Sweden	2.87	3.47	n.a.	54	n.a.	31
United Kingdom	2.11	1.93	n.a.	59	n.a.	23
Norway	1.65	1.71	53	48	32	20
Minimum	0.63	0.57	34	26	27	14
Maximum	2.87	3.47	72	73	52	45
Mean	1.87	2.00	51.3	50.7	37.1	25.4
Median	1.87	1.89	54.5	48.0	36.0	25.0
Variance	0.45	0.65	187.3	245.9	77.9	63.8

Table 1: Community Innovation Survey results - manufacturing (NACE codes 15 - 36); Source: Eurostat [1997, 1999]; all numbers are percentages; * Observation relates to 1991.

attributable to new and improved products. The reason for this seemingly conflicting finding is that in 1992 in general the level of the percentage of total turnover attributable to new and improved products was higher than in 1996 (in particular, about 19 percentage points).[6]

In principle the variables in Table 1 allow for an empirical assessment of the differences between countries as to the innovation-related environment they offer to firms. The academic interest is mainly in the structural relation between inputs and outputs of the innovation process. The policy interest is mainly in the influence of the environment countries offer to (innovating) firms on their performance. To meet these two interests, given the data at hand, we have used the complete sample for the regression analyses in order to obtain an estimate of the structural relation which is as reliable as possible, while using only CIS2 results for ranking the countries according to the innovation performance of the firms they host in order to avoid out-dated assessments. Indeed, the countries for which CIS2 has no observations are excluded from this comparison.[7]

3 An empirical model

In order to assess the extent to which firms perform better or worse than can be expected on the basis of their innovation-related inputs, a model is estimated that relates the aggregate input indicator of the innovation process to the aggregate output indicator of that process, thereby controlling for structural differences between countries. The following linear model is considered:

$$y_{i,t} = \alpha_0 + \alpha_1 x_{1,i,t} + \alpha_2 m_{i,t} + \alpha_3 D_t + \varepsilon, \tag{1}$$

$t = 1992, 1996$, $i = 1, ..., N$, with N equal to the number of countries, where ε is iid $N(0,\sigma^2)$, $\sigma^2 < \infty$, where $\boldsymbol{\beta} = \{\beta_0, ..., \beta_p\}$ is the unknown parameter vector with p equal to the number of explanatory variables, where $D_t = 1$ for $t = 1992$, zero otherwise, and where x_1 and y are as given in Table 1. Indeed, equation (1) relates an innovation output measure (the percentage of total turnover on new and improved products) to an input measure (innovation spending as a percentage of GDP) and a variable that proxies a country's industrial structure (m, to be defined in Section 4 below). The dummy variable is included to control for differences in total turnover attributable to new and improved products between 1992 and 1996 which are not due to

[6] See Section 6. If anything, these results illustrate that relying on simple descriptive statistics could easily yield erroneous conclusions.

[7] Being Greece and Luxembourg.

differences in the (possible) relation between the innovation input indicators and the indicator for innovative output.

Observe however that if spending on innovative activities as a fraction of GDP is poorly correlated with the fraction of firms being innovative, the extent to which innovative activity is spread within the economy is not captured adequately by the innovation input indicator x_1. If a relatively small number of large firms is engaged in innovative activities, indicator x_1 overestimates the spreading of innovative activity. Likewise, if a relatively large number of small firms is innovative, the indicator could easily underestimate the infiltration of innovative activity in the economy. It appears that the correlation between x_1 and x_2 is rather low indeed (0.34). To control for this possible bias we therefore consider as benchmark model:

$$y_{i,t} = \beta_0 + \beta_1 x_{1,i,t} \times x_{2,i,t} + \beta_2 m_{i,t} + \beta_3 D_t + \varepsilon, \tag{2}$$

$t = 1992, 1996$, $i = 1, ..., N$.

4 Country dynamics

In order to capture structural differences between countries we could opt for a wide array of variables. Given the very nature of the innovation process we focus on a structural measure that captures 'country dynamics'. To that end we follow Hinloopen and van Marrewijk [2001], who approximate these dynamics by considering the extent to which for a particular country the distribution of industries according to their comparative advantage evolves over time.

If a country specializes in the production of particular commodities (meaning that it has a comparative advantage in the production of these commodities, as measured by the Balassa index) and sticks to this specialization over time, it is said to have a low mobility of sectors. On the other hand, if the production of commodities in which a country specializes change over time, it is said to have a high mobility of sectors. Indeed, the latter countries are considered to be more dynamic than the former; sectors more often realize and loose their comparative advantage.

In this section we first formalize this notion of country dynamics (Section 4.1), after which the resulting mobility indices are calculated for the countries in our sample (Section 4.2), thus constructing the explanatory variable m.

4.1 Construction of a dynamics indicator

If $X^j_{i,t}$ are country i's export in industry j in period t, and define $X_{i,t} = \sum_j X^j_{i,t}$ as country i's total export in period t, $X^j_{t,ref} = \sum_{i \in ref} X^j_{i,t}$ as total export in industry j within a group of reference countries (including country i) in period t, and $X_t = \sum_j X^j_{t,ref}$ as total exports of all countries in period t. The index of revealed comparative advantage, or Balassa index, is then defined as (see Balassa [1965]):

$$BI^j_{i,t} = \frac{X^j_{i,t}/X_{i,t}}{X^j_t/X_t} \tag{3}$$

In general, whenever the Balassa index exceeds 1 country i is said to have a comparative advantage in the production of good j (see Hinloopen and van Marrewijk [2001] for details as to the interpretation of particular values of the Balassa index)

The construction of the dynamics indicator evolves along 3 steps. First we compute for a particular country and two particular time periods, say t and $t + 1$, the Balassa index for a number of industries (our choice of industries and group of reference countries is explained below). Second, we order the industries in both periods according to their Balassa-index and examine how many of the industries that are in the first quintile of the industry distribution in period t are in the first, second, third, fourth and fifth quintile of the industry distribution in period $t + 1$.[8] Likewise, we examine how many of the industries that are in the second quintile of the industry distribution in period t are in the first, second, third, fourth and fifth quintile of the industry distribution in period $t + 1$, etc. This yields a transition or Markov matrix, P, where each entry represents the probability of going from some particular quintile in period t (row entry) to another in period $t + 1$ (collum entry). The final step is to collapse the properties of the transition matrix into one number by computing the following mobility index (see Geweke et al. [1986]):[9]

[8] In principle we could devide up the distribution of industries into any number of cells of equal size, provided the that number of cells is at most as large as the number of industries that make up the distribution. Increasing the number of cells yields an (almost one-to-one) increase in the derived mobility indices. Indeed, using either of these mobility indices in our empirical analysis yield almost identical results.

[9] There are different ways to collapse the information contained in a transition matrix into one number (see Geweke et al. [1986]). For a discussion of these alternatives see Hinloopen and Van Marrewijk [2001]. Using either of these alternatives does not have any qualitative impact on our empirical results. Given the theoretical superiority of (4) over its alternatives (see Geweke et al. [1986]) we only report the results obtained with this mobility index.

$$M = (n - tr(P))/(n - 1) \tag{4}$$

It is this mobility index that we have used as an explanatory variable in (2) to capture the differences between countries as to their inherent dynamics.

4.2 Mobility

For the calculation of the mobility indices for the countries in our sample we have used the world trade data from Statistics Canada, as compiled by the Centre for International Data at the University of California (see Feenstra [2000]). This comprehensive data set contains bilateral annual export flows among some 160 countries, classified into some 1200 4-digit SITC industries, for the years 1970 through 1997. Rare are the years however that a country realizes an export flow in all 1200 industries. Indeed, the number of industries for which a positive Balassa index is registered typically is about 500. Accordingly, each quintile of the concomitant distribution in most contains about 100 observations.

We have computed (4) both for the transition from 1991 to 1992 and from 1995 to 1996.[10] In Table 2 the resulting values for the countries in our sample are summarized. It appears that mobility changes quite substantially over our sample period. For 12 out of 14 countries mobility has increased in 1996 compared to 1992, the exceptions being Ireland and Finland. This is also reflected in the increase in average and median mobility; in 1996 average mobility is some 19% higher than in 1992. At the same time the spread in mobility has increased by 25%.

Next, there are substantial differences in mobility between countries. In 1992 Irish sectors are the most mobile in terms of acquiring and losing comparative advantage while those in Italy are in this respect the least mobile. Four years later Italian sectors are still the least mobile (although mobility as such within the Italian economy has increased) but it is now Spain that heads the group.

The countries in our sample can be roughly divided in three groups: high mobility, medium mobility and low mobility. In 1996 Germany and Italy form the group of low mobility countries while Spain, Austria and Portugal comprise the high mobility group. The remaining nine countries all fall in the

[10] We could consider other, possibly longer transition periods as well. However, both CIS surveys were conducted in the years directly before the years the results were published. Indeed, our chosen transition periods are as much as possible in concordance with the period the surveys were conducted. In any case, estimates of (2) using mobility indices that are based on different transition periods yield quite similar results as those reported below.

Country	Country dynamics indicator (m)	
	1992	1996
Belgium	0.19	0.24
Denmark	0.18	0.23
Germany	0.16	0.19
Spain	0.31	0.32
France	0.18	0.22
Ireland	0.32	0.28
Italy	0.16	0.16
Netherlands	0.17	0.23
Portugal	0.24	0.34
Austria	0.17	0.36
Finland	0.25	0.24
Sweden	0.20	0.23
United Kingdom	0.18	0.23
Norway	0.22	0.28
Minimum	0.16	0.16
Maximum	0.32	0.36
Mean	0.21	0.25
Median	0.19	0.23
Variance	0.003	0.003

Table 2: Value of the economic dynamics indicator for the sample countries.

group of medium mobility. The largest increase in mobility is recorded for Austria, going from the low mobility group in 1992 to the high mobility group in 1996. The runner-up in this sense is Portugal, being in the group of high mobility in 1996 while belonging the medium mobility group in 1996. The largest fall in mobility is recorded for Ireland, although its loss in mobility over the sample period is substantially smaller than the increase in mobility of several other countries.

On the whole mobility has increased over the sample period, both in terms of the level of mobility as in terms of the mobility spread. Observe that in the same period also the relative spending on innovation-related activities has increased (see Table 1). Moreover, countries recorded as having a low mobility among sectors also spend relative little on innovation. But before we explore these economically very interesting issues further we first indicate how we deal with outlying observations in our empirical analysis.

5 Outlier robust estimation

Given the perceived quality of the CIS data it is desirable to control for possible obscure observations when estimating (2). To that end in this section we discuss and outlier-robust estimator. Do note that the estimator we use yields exactly the same estimates as conventional (OLS-like) estimators if data are not contaminated. However, in the more probable event of data contamination our estimator yields much more reliable estimates, both as to the sign and size of estimated coefficients as well as to the concomitant significance levels (see Hinloopen and Wagenvoort [1995] for various illustrations).

Consider the linear model:

$$y_i = \mathbf{x}_i \boldsymbol{\beta} + e_i, \quad i = 1, ..., n, \tag{5}$$

where $\mathbf{y} = \{y_1, ... y_n\}$ is an observable dependent variable, where $\mathbf{x}_i$ is a row vector of length p of observable explanatory variables and where the errors, e_i, are independently and identically distributed with zero mean and bounded variance. Our focus is on the effect that outlying observations have on the estimate of the unknown parameter vector $\boldsymbol{\beta}$.

Following Rousseeuw and Van Zomeren [1990] we distinguish **leverage points** and **vertical outliers** (see Figure 1). That is, leverage points are data for which the explanatory variable lies far from the bulk of explanatory observations (according to some measure of distance, to be defined below), while vertical outliers (or regression outliers) are observations that are positioned

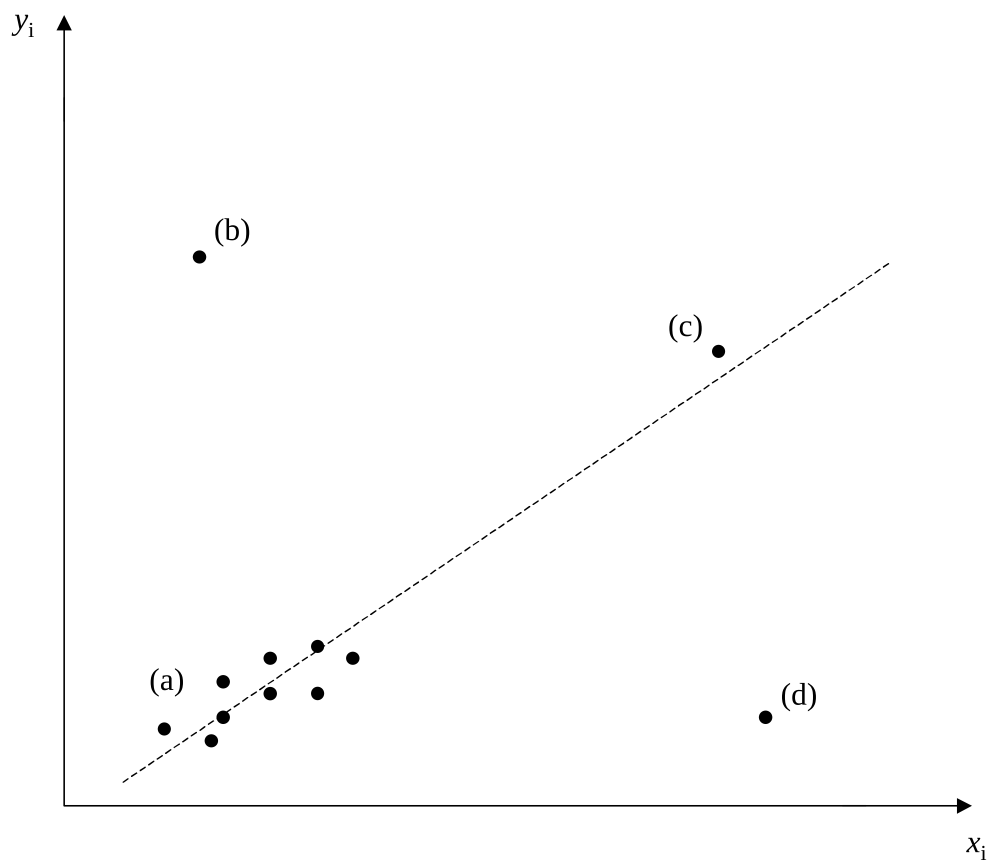

Figure 1: Simple regression example with (a) regular observations, (b) vertical outlier, (c) leverage point, and (d) vertical outlier and leverage point.

far from the majority of the data but whose explanatory variable is not necessarily a leverage point. Of course an observation can be both a leverage point and a vertical outlier. The robust estimator to be derived is designed to control for the impact of these two types of outlying observations on the final estimate of the unknown parameter vector $\boldsymbol{\beta}$.

An M-estimator b of the unknown parameter vector $\boldsymbol{\beta}$ is defined by the objective

$$\min_{\mathsf{b}} \sum_{i=1} \rho(r_i), \tag{6}$$

where $r_i = y_i - \mathsf{x}_i\boldsymbol{\beta}$, and where $\rho(\cdot) : \Re \rightarrow \Re_+$ (in case of OLS we have that $\rho(r_i) = r_i^2$). The corresponding first-order condition is

$$\sum_{i=1} \mathsf{x}_i^T r_i w_r(r_i) = 0, \tag{7}$$

where x_i^T is the transpose of x_i, and where the weight function $w_r(\cdot) : \Re \rightarrow \Re_+$ is given by $w_r(r_i) = [\partial\rho(r_i)/\partial r_i]/r_i$. Observe that $w_r(\cdot)$ downweighs vertical outliers.

Generalized M-estimators were first proposed by Mallows [1975] who generalized (7) to

$$\sum_{i=1} \mathsf{x}_i^T w_x(\mathsf{x}_i) r_i w_r(r_i) = 0, \tag{8}$$

where $w_x(\cdot) : \Re \rightarrow \Re_+$ downweighs leverage points (for OLS both $w_x(\cdot)$ and $w_r(\cdot)$ are the identity function). A particular GM estimator is then defined by the specific choice of the weight functions (see Simpson et al. [1992] for regularity conditions that are imposed on both $w_r(\cdot)$ and $w_x(\cdot)$). Our choice is defined below.

In order to approximate the solution to (8) we use the Newton-Raphson (NR) algorithm. Observe that $w_x(\mathsf{x}_i)$ is independent of $\boldsymbol{\beta}$ (see also Figure 1). That is, weights based on leverage points are computed before starting the NR-iterations. On the other hand, since the identification of vertical outliers does depend on the estimate of $\boldsymbol{\beta}$, which in turn depends on the weights based on vertical outliers, $w_r(r_i)$ is updated every NR-iteration.

To obtain a high breakdown point (HBP), which is the minimum fraction of data contamination that causes an estimator to take on any value (see Donoho and Huber [1983])[11] with the procedure outlined above we have to use

[11] The breakdown point of OLS is 0%: any single observation can cause this estimator

HBP estimators to (i) compute $w_x(x_i)$ and (ii) to have a preliminary estimate of $\boldsymbol{\beta}$ to start the NR-iterations. For these purposes we use Rousseeuw's [1984] Least Median of Squares (LMS) estimator as an initial approximation of (8) and base $w_x(x_i)$ on the Minimum Volume Ellipsoid (MVE) estimates of location and scale, the latter being described in the Appendix. Observe that both the LMS estimator and the MVE estimator have a breakdown point of 50%. Given our construction of $w_r(r_i)$ and $w_x(x_i)$, as described below, the GM estimator we employ also has a breakdown point of 50% (see Hinloopen and Wagenvoort [1997] for the formal proof of this claim). In addition, as shown in Hinloopen and Wagenvoort [1997], our GM estimator is also efficient under different types and fractions of data contaminations.

For the computation of weights based on leverage some measure of distance is needed. A natural candidate is the Mahalanobis distance, $MD(\cdot)$, for design x_i, defined as

$$MD(x_i) = \sqrt{[x_i - m(X)]\, C(X)\, [x_i - m(X)]^T}, \tag{9}$$

with $X = \{x_1^T, ..., x_n^T\}$ where $m(\cdot)$ is the arithmetic mean and where $C(\cdot)$ is the sample covariance matrix (observe that the Mahalanobis distance is often referred to as the z-score, and that it follows a χ^2-distribution with p degrees of freedom). However, as shown by Rousseeuw and Van Zomeren [1990], the Mahalanobis distance suffers from a masking effect: mild leverage points remain undetected if severe leverage points are present as the latter corrupt both $m(\cdot)$ and $C(\cdot)$ such that the former remain unnoticed.

To overcome this masking problem we use robust estimates of the Mahalanobis distances, RD_i. These estimates are based on the MVE approximations of location and scale (see the Appendix). Weights based on leverage points are then computed as (see also Simpson et al. [1992, p. 440])

$$w_x(x_i) = \min\left\{1, \frac{\sqrt{\chi^2_{0.975}(p)}}{RD_i}\right\}. \tag{10}$$

Further, we use Tukey's bi-square function to construct weights based on vertical outliers. In particular we set

$$w_r(r_i) = \begin{cases} [1 - (r_i/2)^2]^2 & |r_i| < c, \\ 0 & |r_i| \geq c. \end{cases} \tag{11}$$

to yield any particular estimate (and/or any level of significance). The highest breakdown point possible is 50% since beyond this limit the distinction between 'good' and 'bad' observations becomes arbitrary.

Variable	Constant	$x_1 \times x_2$	m	1992-dummy
	2.54	0.09**	0.19*	18.51**
	(0.87)	(7.15)	(2.41)	(13.88)
$\overline{R}^2$	0.91			

Table 3: GM regression results; France, Portugal, Austria, Finland, Sweden and the United Kingdom are not included in the 1992 sample; Greece is not included in either sample; Total number of observations is thus 22; Heteroskedasticity-consistent t-values are in parentheses (Hinloopen and Wagenvoort [1997]); * indicates that the estimated coefficient is statistically significant at the five-percent level; ** indicates that the estimated coefficient is statistically significant at the one-percent level; $\overline{R}^2$ is based on the weighted sample.

A common choice for c is 4.685 under the assumption of standard normally distributed residuals (see Beaton and Tukey [1974]). We approximately achieve this by scaling model (5) with the initial LMS estimate of scale (see Rousseeuw and Leroy [1987]).

6 Estimation results

Table 3 depicts the GM regression result of (2). All estimated coefficients have the expected sign and are statistically significant at the 5 percent level, with some estimates being statistically significant at the one-percent level. In particular, if the percentage of innovating firms increases, given the level of innovation spending as a percentage of GDP, the return to innovative activities increases. Likewise, if relative innovation spending increases, given the fraction of firms that innovate, the percentage of total output that is attributable to innovative activities increases.

Interpreting the estimated coefficient of interacted explanatory variables deserves some attention. According to (2) the effect of innovation spending as a percentage of GDP (x_1) on the percentage of total turnover attributable to new and improved products (y) is given by

$$\frac{\partial y}{\partial x_1} = \hat{\beta}_2 x_2. \tag{12}$$

Observe that (12) differs at any point in the sample.[12] Evaluated at the mean of x_2 (12) yields for $\partial y / \partial x_1$ a value of 4.78. This means that if innovation

[12] For a more elaborate discussion of this issue, see Hinloopen and Martin [1997].

spending as a percentage of GDP increases with one percentage point, the percentage of total turnover that is attributable to new and improved products increases with almost 5 percentage points, or 15.5 percent. Note that an increase of one percentage point in x_1 corresponds on average to an increase of almost 32 percent in innovation spending as a percentage of GDP.

Most interesting is the documentation of the empirical relation between economic dynamics and the percentage of innovative turnover. It appears that in more dynamic countries a larger fraction of total turnover is attributable to new and improved products. In particular, if the dynamics indicator m increases by one percentage point, the fraction of innovative turnover increases with 0.19 percentage points, or, on average, by 0.63 percent. For instance, on the basis of the difference in economic dynamics alone, in 1996 the fraction of total turnover attributable to new and improved products in Austria is expected to be 3.88 percentage points or, on average, 12.6 percent higher than in Italy.

Documenting empirically the positive relation between economic dynamics and innovation-related performance is new to the literature. Obviously there is ample room for a more detailed empirical analysis of this relation, possibly along the lines of our analysis. For the present exercise we note that our (preliminary) empirical findings imply that authorities should foster economic dynamics (as defined in Section 3 above) if it is desired that the firms their respective countries host invest in innovation-related activities.

Finally, the dummy variable appears to be highly significant with an estimated coefficient around 19. Given the relation between the input indicator of the innovation process and the percentage of total turnover attributable to new and improved products (while controlling for economic dynamics across countries), the latter appears to be, on average, some 19 percent higher in 1992 than in 1996. One explanation for this level shift could be that CIS2 is carried out more carefully. Revenue flows are more accurately traced back to the responsible product and/or service, yielding a more precise determination of the fraction of total turnover due to innovative activities.

7 Innovation performance across countries

The estimation results of Section 6 show a positive and consistently statistically significant relation between the innovation input indicator and output indicator. One could then ask what the innovation score is of individual countries. That is, given the input in the innovation process, what is the (deviation from the) expected output attributable to innovative activity based on the estimated structural model of the previous section.

Country	Scaled residual
Belgium	1.04
Denmark	-11.90
Germany	8.29
Spain	8.92
France	-1.00
Ireland	1.08
Italy	10.06
Netherlands	-2.61
Portugal	0.51
Austria	-0.28
Finland	2.20
Sweden	-7.53
United Kingdom	-1.08
Norway	-0.09
Bera-Jarque*	0.53
Doornik-Hansen*	3.20

Table 4: Regression residuals; the computed residuals are based on the (not rounded) estimates presented in Table 3 and relate to 1996 only; * The critical value for both the Bera-Jarque and Doornik-Hansen test statistic for normality of the residuals is 5.99 and 9.21 at the five and one percent significance level respectively; computations for both test statistics are based on the whole sample.

In Table 3 the scaled regression residuals are depicted.[13] These residuals indicate that in terms of innovative output some countries consistently perform worse than can be expected on the basis of the input into the innovation process, while other countries consistently perform better than expected. In particular, for Denmark, France, The Netherlands, Austria, Sweden, United Kingdom and Norway the percentage of total turnover on new and improved products is lower than can be expected on the basis of the relative amount spent on innovative activities in these countries and their inherent economic dynamics. On the other hand, Belgium, Germany, Spain, Ireland, Italy, Portugal and Finland perform better in terms of the fraction of total turnover attributable to new and improved products, given these countries' inherent economic dynamics and what they spend on innovative activities. This exercise immediately shows its usefulness. For instance, a country like Portugal is not spending much on innovative activities and the percentage of innovating firms is low. Yet on the basis of what it does its return to innovative activities is more than what could be expected.

We now construct an overall ranking based on the regression residuals in Table 4 as to the influence of the innovation-related environment offered by any country and firm's innovation-related performance. Such a ranking is inevitably arbitrary. For instance, a different structural model yields different residuals and, accordingly, a possibly different ranking. On the other hand, the benchmark estimate of Section 6 appears to be a rather good approximation for the structure that is in the data. In addition, the estimates are outlier-robust, whereby small differences in the data are not likely to (strongly) affect the estimates (and hence, the ranking). In any case, given the broad range of countries in our sample, the fact that we use both the 1992 and 1996 surveys, and that we have explicitly controlled for differences between countries as to their inherent dynamics, we are confident enough to provide a country ranking based on our approximation of the benchmark relation between the considered innovation inputs and outputs.

In Table 5 the ranking is presented. According to this methodology Italy offers an environment that facilitates most the transformation of innovative inputs into commercial outputs while the environment in Denmark is the least facilitating.

To give more insights as to the order of the countries in Table 5, consider Figure 2. This is a useful graphical aid for identifying leverage points and vertical outliers. It plots the robust Mahalanobis distances, RD_i, against the concomitant standardized residuals.[14] This plot then allows for an exact

[13] As mentioned before, only the countries for which results of the CIS2 are available are considered in this section.

[14] The residuals are defined as $r_i = y_i - \mathbf{x}_i \mathbf{b}_{GM}$, where $\mathbf{b}_{GM}$ is the GM estimate of $\boldsymbol{\beta}$.

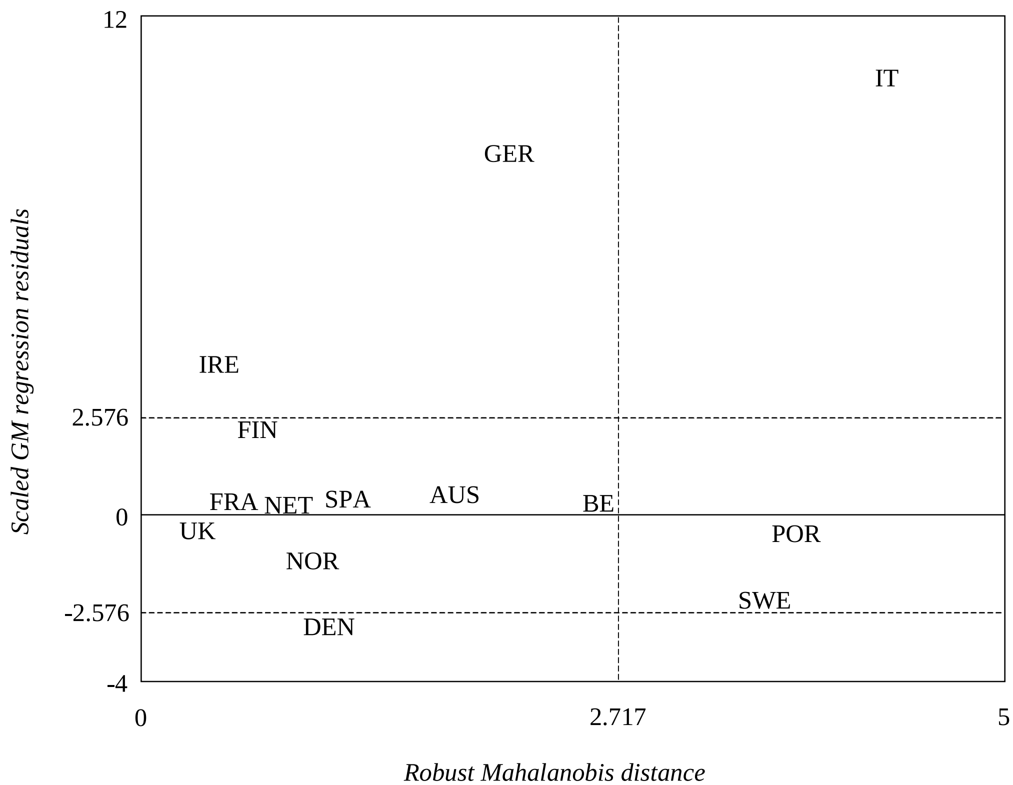

Figure 2: Scatter plot of robust Mahalanobis distances versus scaled GM regression residuals; critical value for vertical outliers is $N_{0.99} = 2.576$; critical value for leverage points is $\sqrt{\chi^2_{0.975}(2)} = 2.717$.

Position	Country
1.	Italy
2.	Germany
3.	Ireland
4.	Finland
5.	Austria
6.	Spain
7.	France
8.	Belgium
9.	Netherlands
10.	Portugal
11.	United Kingdom
12.	Norway
13.	Sweden
14.	Denmark

Table 5: Ranking of countries according to the innovation performance of firms located in these countries; Italy, Germany and Ireland statistically perform better than the benchmark estimate; Denmark statistically performs worse than the benchmark estimate.

identification of observations as in Figure 1. Observations to the right of the vertical line through 2.717 ($=\sqrt{\chi^2_{0.975}(2)}$; recall that RD_i follow a χ^2-distribution with p degrees of freedom) are leverage points (like observations (c) and (d) in Figure 1), while points outside the horizontal strip bounded by 2.576 and -2.576 (which corresponds to the 99% confidence interval of the standard normal distribution for a two-tailed test) are vertical outliers (as points (b) and (d) in Figure 1). Dots in the North-East and South-East rectangles of Figure 2 refer to observations that are both leverage points and vertical outliers (like point (d) in Figure 1).

In terms of innovation-related output Germany and Ireland perform significantly better and Denmark significantly worse than can be expected on the basis of their inherent country dynamics and what is spend on innovation related inputs. For these three countries the explanatory part of the benchmark estimate does not stand out. That is, Germany, Ireland and Denmark are vertically outlying but do not constitute leverage points. Portugal and Sweden on the other hand are leverage point but their innovation performance is well within what can be expected. For Sweden innovation spending

The (robust) estimate of scale is defined as $\sigma_{GM} = [1 + 5/(n-p)]\sqrt{median\{r_i^2\}}/0.6745$ (see Rousseeuw and Leroy [1987]). Standardized residuals then equal r_i/σ_{GM}.

as a percentage of GDP is relatively high, thus becoming a leverage point. Portugal is a leverage point as well but for quite the opposite reason; both innovation spending as a percentage of GDP and the percentage of innovating enterprises is relatively low.

The country that in this respect stands out most is Italy. It is a leverage point because of its very low mobility of sectors and because both innovation spending as a percentage of GDP and the fraction of innovation enterprises is relatively low. At the same time, the fraction of total output that is attributable to new and improved products is considerable, and much higher than can be expected on the basis of what is spend on innovation, of how many firms are innovative and of the economic dynamics of the Italian economy. Indeed, Italy is both a leverage point a vertical outlier.

One explanation for the ranking could be the differences in speed of diffusion and absorption of technological innovations across the countries considered here. Recently, Eaton and Kortum [1999] have examined these issues for five OECD countries (being Germany, France, the United Kingdom, Japan and the United States).[15] They find the fraction of potentially useful ideas that are ever adopted to be higher in Germany (99 percent) than in France (97 percent) and the United Kingdom (95 percent). Also, the speed at which ideas generated in a domestic country are ready for adoption in a foreign country appears to differ markedly across countries, being in Germany much higher than both in France and the United Kingdom. These findings could (partly) explain why firms located in Germany are better able to transform innovation inputs into commercial outputs than firms located in both France and the United Kingdom.

8 Conclusions

For fourteen countries we have assessed empirically the influence of national innovation-related environments on firms' ability to transform innovation inputs into commercial outputs. This assessment yields a ranking of these countries that is based on a benchmark relation between an aggregate input measure and an aggregate output measure of the innovation process. According to this ranking Italy, Germany and, to a lesser extent, Ireland offer an environment that statistically facilitates more the transformation of innovation-related inputs into commercial outputs than can be expected on the basis of our benchmark estimate. Based on the same estimate the environment in Denmark statistically facilitates less than can be expected the

[15]We restrict the discussion of Eaton and Kortum [1999] to those countries which are also in our sample.

transformation of innovation-related inputs into commercial outputs.

Note that in passing we have documented empirically the positive relation between the fraction of firm's total revenue that is attributable to new and improved products and the inherent economic dynamics of the country where these firms reside. This very interesting result opens up a number of avenues for future research, also because our empirical analysis is only a preliminary exploration of this relation. Future research includes (i) a repetition of the empirical analysis with industry-level or firm-level data, (ii) an investigation of the possible simultaneity of the relation between country dynamics and innovative returns and (iii) an exploration of the possible non-linearity of the empirical relation between the fraction of sales attributable to innovation-related activities and the mobility of sectors over time.

The construction of any ranking is, of course, arbitrary. Yet, given that we have used the data from both CIS surveys, that we employ an outlier-robust estimator and that we explicitly control for cross-country differences in economic dynamics, we think it unlikely that rankings based on a similar approach as that followed in this paper would be very much different. Indeed, a welcome validity check of our results is the formidable task referred to in the introduction.

References

[1] Beaton, A. E. and Tukey, J. W., 1974, "The fitting of power series, meaning polynomials, illustrated on band-spectro-scopic data", Technometrics, 16, pp. 147 - 185.

[2] Busom, I., 2000, "An empirical evaluation of the effects of R&D subsidies", Economics of Innovation and New Technology, 9, No. 2, pp. 111 - 148.

[3] Donoho, D. L. and Huber, P. J., 1983, "The notion of breakdown point", in Bickel, P. J., Doksum, K. A. and Hodges Jr., J. L. (editors), A festschrift for Erich L. Lehmann, Bellmont, C. A. : Wadsworth, pp. 157 - 184.

[4] Eaton, J. and Kortum, S., 1999, "International technology diffusion: theory and measurement", International Economic Review, 40, No.3, pp. 537 - 570.

[5] Eurostat, 1997, The first Community Innovation Survey, Brussels: European Commission.

[6] Eurostat, 1999, "Community Innovation Survey 1997/1998", *Statistics in Focus, Research and Development*, No. 2/99.

[7] Eurostat, 2001, "R&D statistics", *Statistics in Focus, Science and Technology*, No. 1/2001.

[8] Feenstra, R. C., 2000, "World trade flows; 1980-1997", Institute of Governmental Affairs, University of California, Davis.

[9] Geweke, J., Marshall, R. C. and Zarkin, G. A.,1986, "Mobility indices in continuous time Markov chains", Econometrica, **54**, No. 6, pp. 1407 – 1423.

[10] Hinloopen, J., 1997, "Subsidizing cooperative and noncooperative R&D in duopoly with spillovers", *Journal of Economics*, **66**, No.2, pp. 151 - 175.

[11] Hinloopen, J., 2000a, "Subsidizing cooperative and noncooperative R&D: an equivalence result?", *Economics of Innovation and New Technology*, **9**, No. 4, pp. 317 - 329.

[12] Hinloopen, J., 2000b, "Strategic R&D cooperatives", *Research in Economics*, **54**, No. 2, pp. 153 - 185.

[13] Hinloopen, J., 2000c, "More on subsidizing cooperative and noncooperative R&D in duopoly with spillovers", *Journal of Economics*, **72**, No.3, pp. 295 - 308.

[14] Hinloopen, J., 2001, "Subsidizing strategic R&D cooperatives", *De Economist*, **149**, No. 3, pp. 313 – 345.

[15] Hinloopen, J. and van Marrewijk, C., 2001, "On the empirical distribution of the Balassa index", *Weltwirtschaftliches Archiv*, **137**, No. 1, pp. 1 – 35.

[16] Hinloopen, J. and Martin, S., 1997, "Market-structure determinants of national brand-private label price differences of manufactured food products: comment", *Journal of Industrial Economics*, **XLV**, No.2, pp. 219 - 224.

[17] Hinloopen, J. and Wagenvoort, J.L.M., 1995, "Robust estimation: an example", Working Paper ECO 95/2, Florence: European University Institute.

[18] Hinloopen, J. and Wagenvoort, J. L. M., 1997, "On the computation and efficiency of a HBP-GM estimator: some simulation results", Computational Statistics & Data Analysis, 25, No. 1, pp. 1 - 15.

[19] Kleinknecht, A. and Wunderink, S. R., 2001, "Sales of innovative products: a problematic innovation indicator?", manuscript.

[20] Mallows, C. L., 1975, "On some topics in robustness", Technical Memorandum, Murray Hill, NJ: Bell Telephone Laboratories.

[21] Rousseeuw, P. J., 1984, "Least median of squares regression", Journal of the American Statistical Association, 79, No. 388, pp. 871 - 880.

[22] Rousseeuw, P. J. and Leroy, A. M., 1987, Robust regression and outlier detection, New York: Wiley.

[23] Rousseeuw, P. J., and Van Zomeren, B. C., 1990, "Unmasking multivariate outliers and leverage points", Journal of the American Statistical Association, 85, No. 411, pp. 633 - 639.

[24] Romano, R.E., 1989, "Aspects of R&D subsidization", Quarterly Journal of Economics, CIV, No.4, pp. 863 - 873.

[25] Simpson, D. G., Ruppert, D. and Carroll, R. J., 1992, "On one-step GM estimates and stability of inferences in linear regression", Journal of the American Statistical Association, 87, No. 418, pp. 439 – 450.

9 Appendix The Minimum Volume Ellipsoid estimator

The MVE estimator of location and scale is based on the hyper ellipsoid of minimum area containing at least half of all observations. The estimate of location corresponds to the centre of this hyper ellipsoid while the corresponding covariance estimate is the hyper ellipsoid multiplied by some factor to obtain consistency.

Recall that the determinant of a scatter matrix (that is, a positive definite symmetric matrix) is proportional to the squared volume of the corresponding tolerance ellipsoid. Accordingly, the MVE estimator is defined as the pair (m, C) that

$$\min_{(\mathsf{m},C)} \det(C) \tag{13}$$

subject to

$$\#\left\{i; [\mathbf{x}_i - \mathbf{m}]C^{-1}[\mathbf{x}_i - \mathbf{m}]^T < \delta^2\right\} \geq h, \tag{14}$$

where $h = int[(N + p + 1)/2)]$. If it is assumed that the majority of the data comes from a standard normal distribution, δ^2 is set equal to the 50_{th} percentile of the $\chi^2(p)$-distribution. We then denote

$$RD(\mathbf{x}_i) = \sqrt{[\mathbf{x}_i - \mathbf{m}]C^{-1}[\mathbf{x}_i - \mathbf{m}]^T} \tag{15}$$

as the robust distance of case $\mathbf{x}_i$.

See Hinloopen and Wagenvoort [1997] for details as to the algorithm used for computing the MVE distances in practise.