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Boris Lokshin

United Nations University - Maastricht Economic and social Research and training centre on Innovation and Technology
Keizer Karelplein 19, 6211 TC Maastricht, The Netherlands
Tel: (31) (43) 388 4400, Fax: (31) (43) 388 4499, e-mail: info@merit.unu.edu, URL: http://www.merit.unu.edu

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Boris Lokshin

Faculty of Economics and Business Administration
Maastricht University and UNU-MERIT
PO Box 616, 6200 MD Maastricht, The Netherlands

Abstract

This paper extends the LSDV bias-corrected estimator in [Bun, M., Carree, M.A. 2005. Bias-corrected estimation in dynamic panel data models, *Journal of Business and Economic Statistics,* 23(2): 200-10] to unbalanced panels and discusses the analytic method of obtaining the solution. Using a Monte Carlo approach the paper compares the performance of this estimator with three other available techniques for dynamic panel data models. Simulation reveals that LSDV-bc estimator is a good choice except for samples with small T, where it may be unpractical. The methodology is applied to examine the impact of internal and external R&D on labor productivity in an unbalanced panel of innovating firms.

Key words: Bias correction, unbalanced panel data, GMM; dynamic model
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1. Introduction

As is well-known, the within estimator (LSDV) is not consistent for large N and finite T in dynamic panel data models. Bun and Kiviet (2003) and Bruno (2005) derive the infeasible bias approximations of this estimator. The bias approximations can be estimated using an initial consistent estimator such as Anderson-Hsiao or GMM estimator. This proposed correction thus depends on initial consistent estimates. In a recent contribution, Bun and Carree (2005) proposed an alternative correction to the bias that directly uses LSDV estimator, obviating the need to resort to initial consistent estimates.

The purpose of this paper is to extend the method to implement the Bun and Carree (2005) estimator for unbalanced panels. An analytic solution is derived which allows to avoid the iterative methods. In the second part of the paper, Monte Carlo experiments are carried out to assess the performance of the LSDV-bias corrected estimator in the designs with various degrees of unbalancedness. The performance of LSDV-bias corrected is also compared to difference and system GMM estimators (Blundell and Bond, 1998) and to the additive bias-corrected estimator (Bruno, 2005; Bun and Kiviet, 2003).

The rest of the paper is organized as follows. Section 2 presents the model and discusses the analytic method of obtaining the solution. Section 3 reviews the results of the Monte Carlo experiments that assess the performance of the estimator. The methodology is applied to examine the impact of internal and external R&D on labor productivity in an empirical illustration in Section 4, finally, Section 5 concludes.

2. The model

We consider the dynamic fixed effects model

$$y_{it} = \gamma y_{i,t-1} + x_{it}'\beta + \eta_i + \varepsilon_{it}, \qquad i = 1,....,N; t = 1,....,T \tag{1}$$

The dependent variable, y_{it}, is determined by the one-period own lag $y_{i,t-1}$, the $((k-1)x1)$ vector of strictly exogenous explanatory variables, x_{it}, an unobserved individual effect η_i, and a random disturbance $\varepsilon_{i,t} \sim N(0,\sigma_\varepsilon^2), \sigma_\varepsilon^2 > 0$. We assume that x_{it} is not correlated with the general disturbance term, but could be correlated with the individual-specific term, η_i.

Bun and Carree (2005) formulate the expressions for the case of a balanced panel to correct the bias of the inconsistent LSDV estimator, reproduced for convenience here:

$$\gamma_{lsdv} = \gamma - (\sigma_\varepsilon^2 h(\gamma,T))/((1-\rho_{x,y_{-1}}^2)\sigma_{y_{-1}}^2) \tag{2}$$

$$\beta_{k,lsdv} = \beta_k - \varsigma_k(\gamma_{lsdv} - \gamma), \quad k = 1,\dots,K \tag{3}$$

$$\sigma_\varepsilon^2(\gamma,\mathbf{\beta}) = (y - \gamma y_{-1} - X\mathbf{\beta})' A(y - \gamma y_{-1} - X\mathbf{\beta})/(N(T-1)) \tag{4}$$

where $h(\gamma,T) = (T-1-T\gamma+\gamma^T)/(T(T-1)(1-\gamma)^2)$, $\rho_{xy_{-1}}^2 = \sigma_{xy_{-1}}/\sigma_x\sigma_{y_{-1}}^2$ and $\varsigma = \sigma_{xy_{-1}}/\sigma_x^2$. Bun and Carree (2005) use iterative methods on (2)-(4) to find the bias-corrected estimates. In our experiments the iterative method showed to be imprecise. In what follows we propose to solve the system of equations analytically with respect to γ and $\beta = (\beta_1,\dots,\beta_k)'$ as explained here.

The expressions (2) – (4) can be used to solve analytically for the bias-corrected estimates of γ and $\mathbf{\beta} = (\beta_1,\dots,\beta_k)$ as follows. Using (3) we can express $\beta_1,\dots,\beta_k$ as a function of γ and insert the resulting expression in (4). The resulting expression is a quadratic polynomial with respect to γ of the form $\sigma_\varepsilon^2 = c_0 + c_1\gamma + c_2\gamma^2$, where c_0, c_1, and c_2 are known constants. These constants have the following expressions: $c_0 = (y - X(\mathbf{\beta}_{lsdv} + \varsigma\gamma_{lsdv}))' A(y - X(\mathbf{\beta}_{lsdv} + \varsigma\gamma_{lsdv}))/(N(T-1))$, $c_1 = (y - X(\mathbf{\beta}_{lsdv} + \varsigma\gamma_{lsdv}))' A(X\varsigma - y_{-1}) + (X\varsigma - y_{-1})' A(y - X(\mathbf{\beta}_{lsdv} + \varsigma\gamma_{lsdv}))/(N(T-1))$,
and $c_2 = (X\varsigma - y_{-1})' A(X\varsigma - y_{-1})/(N(T-1))$.

The computed $\sigma_\varepsilon^2 = c_0 + c_1\gamma + c_2\gamma^2$ is inserted back to (2). The resulting expression is a polynomial of power T with respect to γ:

$$a_0 + a_1\gamma + a_2\gamma^2 + \dots + a_T\gamma^T = 0 \tag{5}$$

where $a_0,...,a_T$ are some known constants. For example, when T=3, these constants have the following expressions:

$a_0 = \gamma_{lsdv} + c_0/(3\xi)$, $a_1 = (c_0 + 2c_1)/(6\xi) - 1$, $a_2 = (c_1 + 2c_2)/(6\xi)$, $a_3 = c_2/(6\xi)$, where $\xi = (1-\rho^2_{x,y_{-1}})\sigma^2_{y_{-1}}$ is the conditional variance of $\tilde{y}_{it} = y_{it} - \bar{y}_i$ given $\tilde{x}_{it} = x_{it} - \bar{x}_i$.

The advantage of an analytical solution is in extra precision. When *T* is odd the polynomial (5) always has at least one real root, when *T* is even, it may have zero real roots and *T* complex roots. Having solved for γ, we use (3) to obtain the bias-corrected $\beta_1,...,\beta_k$.

The expressions (2) – (5) can be generalized to the case of unbalanced panel, when there are missing observations in the interval [0, T] for some individuals. The individuals can be ordered in terms of the length of their time period, $T_i - B_i + 1$, B_i denotes the beginning of the period and T_i the final time period for an individual i ($1 \le B_i \le T_i \le T$). The resulting unbalanced panel consists of at most T-1 balanced panels, with the number of observations n_p, with maximum length equal to T and the minimum possible length 2. Following Bun and Carree (2005) we introduce the $\varphi(p)$, the fraction of observations in each of the balanced sub-panels, i.e. $\varphi(p) = (p-1)\cdot n_p \Big/ \sum_{p=2}^{T}(p-1)n_p$. The bias-corrected estimates of γ and $\beta_1,...,\beta_k$ can then be obtained by solving the following system of equations:

$$\gamma_{lsdv} = \gamma - (\sigma^2_\varepsilon h_u(\gamma,T))/((1-\rho^2_{x,y_{-1}})\sigma^2_{y_{-1}}) \tag{6}$$

$$\sigma^2_\varepsilon(\gamma,T) = \sum_{p=2}^{T}\varphi(p)\sigma^2_\varepsilon(p) \tag{7}$$

where $h_u(\gamma,T) = \sum_{p=2}^{T}\varphi(p)(p-1-p\gamma+\gamma^p)/(p(p-1)(1-\gamma)^2)$. It can be shown that the last expression can be also written as $h_u(\gamma) = \sum_{p=2}^{T}\varphi_{2,p}((p-1)-p\gamma+\gamma^p)/p(1-\gamma)^2 \Big/ (\overline{T}-1)$, where $\varphi_{2,p} = n_p/N$.

The expression for $\sigma^2_\varepsilon(p)$ becomes $\sigma^2_\varepsilon(p) = (y-\gamma y_{-1} - X\boldsymbol{\beta})' A_s (y - \gamma y_{-1} - X\boldsymbol{\beta})/(n_p(p-1))$. Idempotent matrix A_s wipes out the individual means and selects usable observations and is defined as $A_s = S(I - D(D^{'}SD)^{-1}D^{'})S$, where $D = I_N \otimes i_p$ (*Np* x *N*) is matrix of individual dummies (i_p is the (*p* x 1) vector of unity elements), matrix $S = diag(S_i)$, (*Np* x *Np*) block-diagonal, and $S_i = diag(s_{it})$, (*p* x *p*) diagonal matrix for each i are such that s_{it}=1 if ($obs_{i,t}$ and $obs_{i,t-1}$)=(1,1). Finally, vector $\beta = (\beta_1,...,\beta_k)^{'}$ is solved for as explained in (2)-(4). To increase the precision of the estimates, this system and the polynomial of power T with respect to γ in (5) is solved analytically with respect to γ and $\beta = (\beta_1,...,\beta_k)^{'}$.

3. Monte Carlo experiments

In our Monte-Carlo experiments we follow Bun and Kiviet (2003) and Bruno (2005). Data for y_{it} are generated by model (2.1) and the data for x_{it} by

$$x_{it} = \rho x_{i,t-1} + \xi_{it}, \qquad \xi_{it} \sim N(0,\sigma_\xi^2), \quad i = 1,...,N \text{ and } t = 1,...,T \tag{8}$$

Initial observations y_{i0} and x_{i0} are generated using a procedure that allows to avoid small sample non-stationary problems[1] (Kiviet, 1995). The individual effects η_i are generated by assuming $\eta_i \sim N(0,\sigma_\eta^2)$ and $\sigma_\eta = \sigma_\varepsilon(1-\gamma)$, while σ_ε^2 is normalized to unity. In addition to β and σ_ξ^2, ρ also determines the correlation between y_{it} and x_{it} and is set at values 0.8 and 0.2. In Kiviet (1995) it is argued that the relative bias of the estimators is significantly influenced by σ_s^2, the signal-to-noise ratio of the regression. In our experiments we use a combination of relatively high σ_s^2=9 with high and low correlation and relatively low σ_s^2=2 with high and low ρ . The parameter γ is set at values 0.8 and 0.2. We also choose $\beta = 1 - \gamma$ so that a change in γ impacts the short-run and not the long-run dynamic relationship between x and y .

To investigate how the bias-corrected estimator performs for unbalanced data, we select for the Monte Carlo experiments T-patterns ranging from slightly to badly unbalanced. Following

[1] We implemented a Fortran code for the LSDV-bc estimator, available upon request. For the additive LSDV bias corrected estimator we used -xtlsdvc- module for Stata discussed in Bruno (2005) and for GMM routine -xtabond2- written by David Roodman, Center for Global Development, Washington, DC. To generate the data we used Stata 9.0 program -xtarsim- developed by G. Bruno, and described in Bruno, 2005. We performed 10000 replications with a fixed seed.

Baltagi and Chang (1995) we control for the extent of unbalancedness as measured by the Ahrens and Pincus (1981) index: $\omega = N \Big/ [\bar{T}\sum_{t=2}^{T}(n(t)/t)]$, where $\bar{T} = \sum_{t=2}^{T}[n(t)t] \Big/ N$, $N = \sum_{t=2}^{T} n(t)$, and $n(t)$ is the number of observations in a sub-panel t. Note that $0 \le \omega \le 1$ and $\omega = 1$ when the panel is balanced.

We vary $n(t)$ from 20 to 160 for the different T-patterns (4, 10, 15, 20). For each of the T-patterns we consider three cases from mild unbalancedness ($\omega = 0.9$) to medium ($\omega = 0.6$) and severe unbalancedness ($\omega = 0.3$).

The results for the Monte Carlo experiments for T-patterns (4, 10, 20) are summarized in tables 1 and 2. As expected, the bias for both γ and β decreases in $\bar{T}$. The bias of γ slightly decreases in unbalancedness for additive bias-corrected estimator and increases for GMM estimators. With respect to σ_s^2, γ, and ρ the patterns reported by Bruno (2005) and Bun and Kiviet (2003) are confirmed. Last column reports the number of no-solution cases for the LSDV-bias corrected estimator. When T is odd the polynomial in (5) always has at least one real root, when T is even, it may have zero real roots and T complex roots. In our Monte Carlo experiments, for the designs we count the number of cases when the polynomial has no real roots, and when there is at least one real root, we count as non-convergence those solutions that are smaller than γ-LSDV. While the bias-corrected estimator may produce superior results in terms of bias, it is not always practical. When the signal-to-noise ratio σ_s^2 is low and the $\bar{T}$ is relatively small (designs 1, 2, 5, 6) there is a large percentage of cases with no solution for high values of γ. Overall, LSDV-bc has the smallest bias, but the advantage over the additive bias-corrected estimator becomes negligible as $\bar{T}$ increases. For relatively small $\bar{T}$, high values of γ GMM-system is the preferred choice.

4. Empirical Application

In this section we apply the estimators discussed in this paper to a dynamic model of firm productivity and R&D investment. The empirical illustration makes use of the data from the annual R&D surveys in the Netherlands in combination with the data from the Netherlands census of manufacturers, both provided by Statistics Netherlands. The R&D surveys contain information on type and amount of R&D expenditures, and the census data contain information on value added, labor, and fixed capital investments. These merged establishment level databases provided us with an unbalanced panel of firms covering the years 1996-2001.

Our empirical model of firm productivity is derived from an augmented Cobb-Douglas production function that allows estimating labor productivity as a function of internal and external R&D. A semi-translog approximation of the production function with a second-order polynomial in R&D investment is used. Such a specification allows for decreasing returns to scale in internal and external R&D with a non-linear approximation of changes in the knowledge stock. There are a priori strong reasons to allow for (dis)economies of scale at the same time as (dis)economies of scope in R&D investment if the process of augmentation of the knowledge capital stock is characterized by declining returns to scale and if high R&D intensive firms engage in both internal and external R&D. Cohen and Klepper (1996) among others argued that R&D productivity is to decline with firm size.

The dependent variable, firm labor productivity, is net value added per employee at constant prices. Internal R&D is defined as a firm's expenditure on intramural R&D while external R&D is the expenditure on contracted R&D. Investment growth is the percentage growth in gross fixed capital investments between *t-1* and *t*, and employment growth is the percentage growth in employment.

Table 3 provides descriptive statistics on the variables used in estimation. The results of the dynamic panel estimation using difference and system GMM as well as two bias-corrected estimators are reported in Table 4. The four consistent estimators agree on the signs and magnitudes of most of the coefficients, while the system GMM estimator generates a higher F-value than difference GMM.[2] The Hansen test of over-identifying restrictions does not reject at 1% the validity of the instruments for the GMM models, with the exception of the system GMM model in column (2). Arellano-Bond AR tests also indicate that there are no problems relating to serial correlation of the error terms.

[2] GMM results are from the two-step variant of the estimator, which is more efficient than the one-step. The two-step estimates of the standard errors tend to be downward biased (Arellano and Bond 1991; Blundell and Bond 1998). The standard errors are corrected via a finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005).

Overall the results clearly suggest that there are diseconomies of scale in both internal and external R&D with the squares term of both internal and external R&D negative and significant. Allowing for diseconomies of scale leads to a positive, although insignificant estimate for the coefficient of the interaction term between internal and external R&D.

5. Conclusion

In this paper we enlarged on the results obtained in Bun and Carree (2005) on the bias of LSDV-corrected estimator for dynamic panel data models. We considered the analytical formulas to derive the bias, which obviate the need to resort to the iterative methods of obtaining the solution. We have extended the formulas to include the unbalanced panels and assessed the performance of the estimator using a Monte Carlo approach. Simulation reveals that LSDV-bc estimator is a good choice compared to difference and system GMM as well as the additive bias-corrected estimator except for samples with small T, where it may be unpractical.

Our main conclusion is that for samples with $T>5$ the LSDV-bias corrected estimator performs well in terms of bias relative to all other estimators, including the LSDV additive bias-corrected technique. This finding effectively updates an earlier recommendation by Judson and Owen (1999) in favor of the new bias-corrected estimator. For samples with $T<5$ the LSDV-bias corrected estimator relatively often does not have a solution, especially around the unity circle (cf. Hahn, Hausman and Kuersteiner, 2001).

It is useful to note a number of caveats in the proposed results. The LSDV inconsistency derived in the paper is not robust to the presence of gaps in the data because of the function h which is derived on the assumption of balanced sub-panels. This is, however, immaterial for the Monte Carlo designs considered in the paper, but may be of importance in the applications with real-life data sets. The exogeneity of the selection rule S is a required assumption in the proposed results. Situations when the unbalanced nature of the data is caused by self-selection or attrition are not considered in this extension and are left for future work.

When applying the estimator to the dynamic model of firm productivity and R&D investment we find a convergence parameter of -0.27, implying that about a fourth of the productivity lead is neutralized by the next period. The implied by LDVC-bias corrected estimator convergence in productivity in Dutch firms is much faster than that implied by the additive bias-corrected or difference GMM estimators.

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Table 1 Bias Results, σ_s^2=2

$\bar{T}$	ω	γ	ρ	γ LSDV-BC	γ LSDV-AD	γ GMM-SYS	γ GMM-DIF	β LSDV-BC	β LSDV-AD	β GMM-SYS	β GMM-DIF	non con-verged cases, %
4	0.9	0.8	0.8	-0.0560	-0.1132	-0.0126	-0.1132	0.0003	-0.0001	0.0004	-0.0046	30.0
			0.2	-0.0468	-0.1049	-0.0128	-0.1051	-0.0025	-0.0080	-0.0011	-0.0098	27.0
		0.2	0.8	-0.0023	-0.0105	0.0181	-0.0264	-0.0014	0.0015	-0.0105	-0.0008	
			0.2	-0.0014	-0.0040	0.0080	-0.0095	-0.0008	-0.0009	-0.0009	-0.0027	
	0.6	0.8	0.8	-0.0279	-0.0583	0.0111	-0.1559	-0.0021	0.0080	-0.0076	0.0201	16.2
			0.2	-0.0207	-0.0482	0.0125	-0.1421	0.0003	-0.0010	-0.0001	-0.0077	13.9
		0.2	0.8	-0.0024	-0.0077	0.1438	-0.0489	-0.0012	0.0015	-0.0935	0.0172	
			0.2	-0.0009	-0.0024	0.0808	-0.0212	-0.0005	-0.0005	-0.0054	-0.0014	
10	0.9	0.8	0.8	-0.0029	-0.0255	-0.0008	-0.0504	-0.0005	0.0038	-0.0006	0.0097	1.7
			0.2	-0.0013	-0.0228	-0.0008	-0.0456	0.0001	-0.0006	-0.0000	-0.0025	1.0
		0.2	0.8	-0.0013	-0.0018	0.0298	-0.0146	0.0004	0.0009	-0.0185	0.0056	
			0.2	-0.0005	-0.0006	0.0133	-0.0058	-0.0000	-0.0000	-0.0011	-0.0002	
	0.6	0.8	0.8	-0.0054	-0.0195	0.0039	-0.0606	0.0040	0.0071	-0.0011	0.0189	1.0
			0.2	-0.0033	-0.0170	0.0040	-0.0551	0.0003	-0.0001	-0.0002	-0.0024	0.6
		0.2	0.8	-0.0014	-0.0019	0.0609	-0.0182	0.0024	0.0028	-0.0404	0.0095	
			0.2	-0.0004	-0.0005	0.0289	-0.0079	0.0003	0.0003	-0.0031	-0.0005	
	0.3	0.8	0.8	-0.0024	-0.0061	0.0231	-0.0658	-0.0021	0.0004	-0.0129	0.0214	
			0.2	-0.0016	-0.0045	0.0225	-0.0612	-0.0005	-0.0001	-0.0012	-0.0016	
		0.2	0.8	-0.0015	-0.0019	0.1554	-0.0258	-0.0001	0.0002	-0.1080	0.0151	
			0.2	-0.0011	-0.0012	0.0898	-0.0129	-0.0003	-0.0003	-0.0101	0.0003	
20	0.9	0.8	0.8	-0.0005	-0.0049	0.0025	-0.0383	0.0009	0.0022	0.0003	0.0166	
			0.2	0.0002	-0.0039	0.0024	-0.0348	0.0005	0.0005	0.0004	-0.0008	
		0.2	0.8	-0.0002	-0.0003	0.0444	-0.0126	0.0008	0.0009	-0.0289	0.0083	
			0.2	0.0002	0.0002	0.0211	-0.0051	0.0004	0.0004	-0.0019	0.0004	
	0.6	0.8	0.8	-0.0050	-0.0035	0.0067	-0.0214	0.0051	0.0009	-0.0040	0.0103	
			0.2	-0.0040	-0.0027	0.0064	-0.0195	0.0009	-0.0002	-0.0005	-0.0006	
		0.2	0.8	0.0108	0.0004	0.0476	-0.0070	-0.0058	-0.0001	-0.0328	0.0053	
			0.2	0.0071	0.0003	0.0227	-0.0030	-0.0008	-0.0002	-0.0026	0.0002	
	0.3	0.8	0.8	-0.0020	-0.0040	0.0135	-0.0333	-0.0018	-0.0010	-0.0077	0.0155	
			0.2	-0.0018	-0.0035	0.0129	-0.0307	-0.0007	-0.0006	-0.0010	-0.0009	
		0.2	0.8	-0.0009	-0.0009	0.0909	-0.0132	-0.0003	-0.0002	-0.0644	0.0087	
			0.2	-0.0007	-0.0008	0.0469	-0.0062	-0.0004	-0.0004	-0.0062	-0.0001	

Table 2 Results, σ_s^2=9

$\bar{T}$	ω	γ	ρ	γ LSDV-BC	γ LSDV-AD	γ GMM-SYS	γ GMM-DIF	β LSDV-BC	β LSDV-AD	β GMM-SYS	β GMM-DIF	non con-verged cases, %
4	0.9	0.8	0.8	-0.0242	-0.0634	0.0161	-0.1469	-0.0006	0.0011	-0.0081	-0.0039	0.02
			0.2	-0.0140	-0.0318	-0.0103	-0.0674	-0.0013	-0.0029	-0.0000	-0.0059	
		0.2	0.8	-0.0022	-0.0025	0.0148	-0.0168	-0.0004	-0.0001	-0.0084	-0.0004	
			0.2	-0.0011	-0.0012	0.0022	-0.0032	-0.0005	-0.0005	-0.0003	-0.0011	
	0.6	0.8	0.8	-0.0176	-0.0207	0.0049	-0.1125	0.0011	0.0054	-0.0036	0.0083	

			0.2	−0.0078	−0.0085	0.0035	−0.0508	−0.0004	−0.0006	0.0001	−0.0029	
		0.2	0.8	−0.0021	−0.0018	0.0814	−0.0224	−0.0001	−0.0002	−0.0525	0.0069	
			0.2	−0.0010	−0.0008	0.0277	−0.0063	−0.0003	−0.0003	−0.0017	−0.0004	
10	0.9	0.8	0.8	−0.0147	−0.0183	0.0098	−0.0571	0.0012	0.0018	−0.0040	0.0029	
			0.2	−0.0053	−0.0080	−0.0028	−0.0223	−0.0002	−0.0005	0.0001	−0.0014	
		0.2	0.8	−0.0012	−0.0011	0.0191	−0.0070	0.0005	0.0005	−0.0116	0.0024	
			0.2	−0.0004	−0.0004	0.0042	−0.0017	−0.0000	−0.0000	−0.0004	0.0000	
	0.6	0.8	0.8	−0.0122	−0.0125	0.0050	−0.0503	0.0019	0.0024	−0.0023	0.0059	
			0.2	−0.0038	−0.0055	−0.0004	−0.0201	−0.0001	−0.0002	−0.0000	−0.0011	
		0.2	0.8	−0.0008	−0.0007	0.0343	−0.0079	0.0012	0.0012	−0.0222	0.0037	
			0.2	−0.0001	−0.0001	0.0095	−0.0024	0.0001	0.0001	−0.0010	−0.0002	
	0.3	0.8	0.8	−0.0069	−0.0050	0.0112	−0.0393	0.0009	0.0013	−0.0056	0.0087	
			0.2	−0.0029	−0.0029	0.0069	−0.0202	−0.0001	−0.0002	−0.0002	−0.0005	
		0.2	0.8	−0.0010	−0.0009	0.0799	−0.0115	0.0002	0.0001	−0.0548	0.0064	
			0.2	−0.0007	−0.0006	0.0308	−0.0042	−0.0001	−0.0001	−0.0031	0.0001	
20	0.9	0.8	0.8	−0.0066	−0.0067	0.0033	−0.0322	0.0012	0.0013	−0.0012	0.0052	
			0.2	−0.0019	−0.0024	−0.0007	−0.0134	0.0001	0.0000	0.0001	−0.0004	
		0.2	0.8	−0.0005	−0.0004	0.0239	−0.0058	0.0006	0.0006	−0.0152	0.0032	
			0.2	0.0000	0.0000	0.0069	−0.0016	0.0002	0.0002	−0.0005	0.0001	
	0.6	0.8	0.8	−0.0191	−0.0058	0.0039	−0.0183	0.0098	0.0010	−0.0020	0.0040	
			0.2	−0.0080	−0.0020	0.0011	−0.0075	0.0015	−0.0001	−0.0000	−0.0002	
		0.2	0.8	0.0004	0.0000	0.0249	−0.0032	0.0012	0.0001	−0.0166	0.0021	
			0.2	0.0009	0.0000	0.0074	−0.0010	0.0001	−0.0001	−0.0008	0.0001	
	0.3	0.8	0.8	−0.0054	−0.0052	0.0068	−0.0229	0.0006	0.0007	−0.0035	0.0056	
			0.2	−0.0022	−0.0024	0.0032	−0.0107	−0.0001	−0.0002	−0.0002	−0.0003	
		0.2	0.8	−0.0006	−0.0006	0.0457	−0.0057	0.0000	−0.0000	−0.0315	0.0033	
			0.2	−0.0005	−0.0004	0.0156	−0.0020	−0.0002	−0.0002	−0.0020	−0.0001	

Table 3 Descriptive statistics

Variable	Mean	S.D.	Description
Productivity	3.88	.52	Net value added divided by employees in constant prices, in logarithm
ΔLabor	.01	.29	Log growth in the number of employees
ΔInvestment	.03	4.01	Log growth in Fixed Capital Investment in constant prices
R&DINT	.07	.20	Expenditure on in-house R&D divided by net value added
R&DEXT	.01	.06	Expenditure on contracted R&D divided by net value added

Table 4 Dynamic model of labor productivity

	GMM (difference)	GMM (system)	Bias-corrected additive	LSDV-bias corrected
	(1)	(2)	(3)	(4)
$Productivity_{-1}$	0.821*** (0.124)	0.535*** (0.065)	0.566*** (0.035)	0.743*** (0.194)
ΔLabor	-0.507*** (0.075)	-0.400*** (0.069)	-0.498*** (0.023)	-0.551*** (0.060)
Δinvestment	-0.001 (0.002)	0.005* (0.003)	0.001 (0.002)	0.002 (0.002)
R&DINT	0.943*** (0.266)	0.161 (0.101)	0.293** (0.117)	0.518** (0.207)
R&DINT squared	-0.103*** (0.037)	-0.005 (0.014)	-0.021 (0.016)	-0.046* (0.025)
R&DEXT	1.748*** (0.616)	0.783** (0.340)	0.775*** (0.238)	1.182*** (0.326)
R&DEXT squared	-1.339** (0.634)	-0.739* (0.379)	-0.667*** (0.192)	-0.867*** (0.207)
R&DINT * R&DEXT	0.257 (0.521)	0.228 (0.371)	0.030 (0.059)	0.008 (0.091)
Wald(df)	79.62	161.6		
Hansen test (df), p-value	21.85(21) 0.40	45.34(29) 0.04		
AR(1) test (p-value)	-5.01(0.00)	-5.49(0.00)		
AR(2) test (p-value)	0.14(0.89)	0.45(0.65)		
N. Obs.	1032	1032	1032	1032

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%.
All models include year dummies. Instruments for the difference GMM equations are lagged values of the right hand side variables in levels; Instruments for the level equations are differenced values of the right hand side variables. Robust standard errors are in parentheses. For GMM estimates, the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005) is used.

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