ONLINE APPENDIX

Eberhardt, Markus, Christian Helmers and Hubert Strauss, "Do Spillovers Matter When Estimating Private Returns to R&D?", *The Review of Economics and Statistics*.

A Literature Overview

Table A-1 provides an overview of the literature on returns to own R&D and R&D-related spillovers based on the recent survey article on the measurement of returns to R&D by Hall et al. (2009). The selection reported here, however, is much smaller because we focus on articles that match our own approach as closely as possible. The selection criteria are as follows: (i) country or country-industry as the unit of observation (i.e. no firm-level studies); (ii) production function setup (as opposed to cost functions); (iii) samples of developed countries; (iv) studies featuring an explicit own-R&D variable for the business sector (as opposed to specifications using total R&D or confounding own and others' R&D); and (v) published after 1980. Our selection includes some 30 articles of which the 19 studies deemed most relevant are summarized in Table A-1. The full table including all studies as well as further information on the specifics of the underlying production function, the estimators, alternative specifications, additional variables and results is available from the authors upon request.

In Table A-1, we make a distinction between country-level and industry-level studies. The latter are further divided into those analysing *inter-industry* spillovers, whereby the sample may contain only one country (central part of the table), and articles with a particular — albeit not exclusive — interest in *international spillovers within the same industry*. As shown in the table, most studies first derive TFP indices from a standard growth accounting framework and regress this TFP index on own R&D, the R&D spillover variable and sometimes a set of control variables and dummies. When the R&D variables come as R&D capital stocks, results are to be interpreted as elasticities and reported in column 'Elasticity'. When R&D variables are intensities (R&D/value-added), results are interpreted as gross returns (assuming zero depreciation, see Hall et al., 2009) and are reported in column 'Gross return'. Column 'Modeling of Spillovers' summarises the different weighting schemes employed to aggregate R&D in other industries/countries into an R&D spillover variable. Studies can be broadly divided into employing spillover measures aimed at uncovering rent spillovers or knowledge spillovers. In the former case, input-output relations between industries and trade relations between countries are used. In the latter case, preference is given to patent flows across industries and countries and indicators of countries' similarity in research field composition among others. The spillover coefficients are reported in the final column.

Table A-1: Literature Review

Author(s) (year)	Sample	Years	Dependent variable	Modeling of spillovers	Estimated R&D coefficient: Elasticity	Estimated R&D coefficient: Gross return	Spillover coefficient
I. Cross-country studies (aggregate economy level)							
Coe & Helpman (1995)	22	1971-90	log(TFP)	FRDS (import-share-weighted) interacted with import/GDP	0.23 (G7), 0.08 (others)		0.29
Keller (1998)	22	1971-90	TFP	FRDS (random weights) interacted with import/GDP	0.13 (G7), 0.035 (others)		0.05 (G7 to others)
Kao, Chiang & Chen (1999)	22	1971-90	TFP	FRDS (import-share-weighted) interacted with import/GDP	0.21 (G7), 0.08 (others)		0.26
Van Pottelsberghe & Lichtenberg (2001)	13	1971-90	log(TFP)	FRDS weighted by imports, outw. or inw. FDI	0.05 0.06 0.08		0.067 (import weights) 0.039 (outw. FDI weights) [0.006] (inw. FDI weights)
Luintel & Khan (2004)	10	1965-99	log(TFP)	FRDS (import-share-weighted) interacted with import/GDP	0.29 (avg LR)		0.12 (avg LR)
Guellec & van Pottelsberghe (2004)	16	1980-98	TFP	FRDS technological-proximity weighted (technology-distance)	0.13		0.46
Coe, Helpman & Hoffmaister (2009)	24	1971-2004	log(TFP)	FRDS (import-share-weighted) interacted with import/GDP	0.20 (G7), 0.13 (others)		0.065
II.1. Industry studies: Inter-industry spillovers (one or more countries)							
Scherer (1982)	US, 87 m	1959-78	TFP	Product R&D of other industries, patent-flow weighted		1964-69: [0.13] 1973-78: 0.29	1964-69: 0.64 1973-78: 0.74
Griliches & Lichtenberg (1984)	US, 193 m	1959-78	Avg TFP growth of adjacent half-decades	Product R&D of other industries, patent-flow weighted		1959/63-1964/68: 0.29 1964/68-1969/73: 0.11 1969/73-1974/78: 0.31	1959/63-1964/68: 0.51 1964/68-1969/73: 0.90 1969/73-1974/78: 0.50
Odagiri (1985)	Japan, 15 m	1960-77	TFP growth	Sum of R&D expenditures of other industries, weighted by industry's share in total sales		1.57 to 3.15	-6.06 to 7.34
Goto & Suzuki (1989)	Japan, 50 m	1978-83	Avg annual TFP growth	Inter-industry transactions		0.25	0.80
Wolff & Nadiri (1993)	US, 50 i	1947/58/63/67/72/77	TFP growth rate	R&D in other industries i, weighted by 1) share of deliveries to ind. j in j's gross output 2) contributions to change of j's capital stock		1) 0.17 2) 0.21	1) [0.08] 2) 0.09
Griffith, Redding & Van Reenen (2004)	12 c, 12 i	1974-90	TFP growth rate	1) Industry's TFP gap from frontier 2) Own R&D intensity interacted with TFP gap		1) 0.67 2) 0.50	1) 0.07 2) 0.60
Cameron, Proudman & Redding (2005)	UK, 14 m	1970-92	TFP growth rate	1) Industry's TFP gap from frontier 2) Own R&D intensity interacted with TFP gap		1) 0.70 2) 0.64	1) 0.10 2) [0.66]

Table A-1: Literature Review (continued)

Author(s) (year)	Sample	Years	Dependent variable	Modeling of spillovers	Estimated R&D coefficient: Elasticity	Estimated R&D coefficient: Gross return	Spillover coefficient
II.2. Industry studies: Cross-country intra-industry spillovers							
Braconnier & Sjöholm (1998)	6 c, 9 m	1979-91	TFP growth rate	Other industries' R&D weighted by 1) dom. intermediates 2) imported intermediates 3) Foreign R&D in same industry (FDI-weighted)	0.03		1)[-0.53] dom. inter-ind. 2) [1.09] int. inter-ind 3) 0.0006 int. intra-ind
Keller (2002a)	8 c, 13 m	1970-91	log(TFP index)	Other country-industry pairs' R&D stocks: i) dom. inter-ind., ii) int. intra-ind., iii) int. inter-ind.; Weights are based on 1) I/O relations/intermediate imports 2) Source & user industry for Canadian patents	1) 0.61 2) 0.15		1) i) 0.57; ii) 0.09; iii) 0.29 2) i) [0.39]; ii) 0.22; iii) [0.19]
Keller (2002b)	14 c, 12 m	1970-95	log(own TFP/ weighted avg foreign TFP)	Sum of cumulative R&D expenditure weighted by bilateral distance	0.078		0.84
Baldwin, Braconier & Forslid (2005)	9 c, 7 m	1979-91	(VA/employee) growth	Int. intra-industry spillover 1) FDI spillover 2) Marshall-Arrow-Romer spillover	0.001		1) 25.5 2) 0.63
López-Pueyo, Sanaú & Barcenilla Visús (2008)	6 c, 10 m	1979-2000	Level of TFP	Weighted sum of 3 R&D capital stocks: (i) same foreign ind; (ii) other foreign ind.	0.143		i) 0.107; ii) 0.213

Notes: Statistically insignificant estimates are reported in square brackets; FRDS: Foreign R&D stock; c: country; m: manufacturing; i: industry; I/O: input/output; LR: long-run; dom.: domestic; int: international; FDI: foreign direct investment; avg: average (unweighted unless indicated). Full literature review with additional information available on request. References for all studies reviewed here are provided in the main article.

B Variable construction

B.1 Output — Value-added

We use value-added as a measure of industry output in order to achieve comparability with the existing literature and because value-added is more closely related to profitability than sales. EU KLEMS reports both gross output and intermediate inputs in current prices. We therefore construct double-deflated value-added by subtracting real inputs from real output. This practice is preferable over using single-deflated value-added, i.e., deflated nominal value-added, as a measure for output, since it avoids the situation where differential price movements across countries generate the false impression of productivity changes. EU KLEMS also provides the necessary industry-level deflators which is a distinct advantage of this data as for some industries, expectations of price changes would likely be different to the general level of inflation. This is an important issue because if inadequate deflators are used, industry output may appear to grow slower. Since this is most likely in industries that are R&D-intensive, the contribution of R&D to output growth would be underestimated (Hall, 1996).[1]

To account for the 'expensing bias' discussed in Section 2 of the main text, we adjust intermediate inputs for R&D-related expenses. We use OECD data to construct the share of intermediate R&D inputs in total R&D expenditure to adjust the conventional measure of intermediate inputs. We then use this adjusted intermediate input measure to construct our double-deflated measure of value-added. In an alternative specification we include the measure for R&D intensity directly in our regression model. The sample for the Schankerman-adjustments (we only discuss the coverage for the final regression sample which is diminished primarily by the lack of industry-level data on R&D workers) covers 97 country-industries in 9 countries (SWE is missing, USA only has 5 observations in one industry) between 1987 and 2005 (with 1988, 1992, 1994, 1996 further missing) and has a total of 725 observations, thus less than 30% of the full sample analysed in the main section of the paper.

B.2 Labour input

As a measure of labour input, EU KLEMS provides the total number of hours worked by persons engaged. The availability of such information is an advantage of EU KLEMS over other datasets as usually the number of full-time equivalent employees has to serve as a proxy for labour input, possibly aggravating the problem of measurement error (see for example Hall and Mairesse, 1996; Wakelin, 2001).

In order to correct for 'double counting' of R&D in our measure of labour input as suggested by Schankerman (1981), we construct the ratio of R&D labour input and traditional labour. The data come from EUKLEMS and the OECD.

B.3 Capital input

Ideally, a measure of current capital services instead of capital stocks, i.e., a flow measure instead of a stock measure, should be used in productivity analysis (Jorgenson and Griliches, 1967).[2] The EU KLEMS dataset provides such a measure for capital services in index form. However, since we do not have any data on R&D capital services, we prefer to use physical capital stocks as a proxy for capital services.[3] This is acceptable under the assumption that the quantity of an asset held by an industry is proportional to the quantity of the corresponding service obtained from that asset. For this to be the case, the aggregate of an industry's capital holdings should represent an average over the various different vintages and age groups of the capital employed within the industry. That this assumption may approximately hold in practice is supported by empirical work, for example, by Wallis and Turvey (2009) for the UK.

Capital input is measured as total tangible assets by book value recorded annually. EU KLEMS provides several measures for tangible assets including total tangible assets, gross fixed capital formation (GFCF), ICT assets, and non-ICT assets. We use total tangible assets and deflate them using a industry-level producer price index.

We create a measure for the ratio of physical capital devoted to R&D and total physical capital to correct for 'double-counting' of R&D (Schankerman, 1981). The measure is constructed as the share of R&D spending on capital in total R&D spending where the data come from the OECD.

B.4 R&D expenditure and stocks

We use R&D stocks in our analysis. It is well known that R&D takes time to translate into innovation and it is therefore the ensemble of past and current R&D expenditures that should matter for productivity rather than merely current expenditure. At the same time past knowledge also depreciates, hence, simply specifying lagged *levels* of R&D expenditure to account for the dynamic nature of R&D may be misleading. The combination of knowledge accumulation and depreciation is also the underlying rationale for Equation (2) in the Griliches knowledge production framework: the notion that more recent vintages of R&D investment matter more for the knowledge stock than older ones is captured by the log polynomial specification.

EU KLEMS provides R&D stocks for 19 countries for the period 1980-2003. However, the overlap with the available tangible capital stock data is not perfect leaving us with 9 countries for which both R&D stocks and physical capital data are available. In order to increase the number of countries in the sample, we constructed R&D capital stocks for Portugal for which R&D data is readily available. These R&D stocks were computed using the OECD Analytical Business Enterprise Research & Development (ANBERD) data (update May 2009) which only accounts for business enterprise R&D.[4] EU KLEMS also uses ANBERD to construct R&D stocks and we followed their methodology for Portugal applying the perpetual inventory method (PIM):

$$R_{it} = (1-\delta)R_{it-1} + \mathrm{R\&D}_{it} \tag{1}$$

where R&D denotes real R&D flows and R the corresponding stock. In order to implement equation (1), δ has to be determined. In line with EU KLEMS, we assume a depreciation rate of 12% (Hall and Mairesse, 1995; Hall, 2007). The depreciation rate is assumed to be the same across industries and constant over time: as noted by Hall and Mairesse (1995), the actual rate chosen seems to be of little relevance for estimation. The reason is the same that also justifies the use of the following formula to compute the initial capital stock

$$\begin{aligned} R_{i1} &= \mathrm{R\&D}_{i0} + (1-\delta)\ \mathrm{R\&D}_{i-1} + (1-\delta)^2\ \mathrm{R\&D}_{i-2} + \ldots \\ &= \sum_{t=0}^{\infty}(1-\delta)^t\ \mathrm{R\&D}_{i-s} = \mathrm{R\&D}_{i0}\sum_{t=0}^{\infty}\left[\frac{1-\delta}{1+g_i}\right]^t = \frac{\mathrm{R\&D}_{i0}}{\delta+g_i} \end{aligned} \tag{2}$$

where g_i denotes the industry-specific growth rate of R&D capital stock. Contrary to other authors, such as Hall and Mairesse (1995), we do not assume a value for g_i but compute it using the first seven years for which R&D expenditure is observed. As long as the growth rate and the depreciation rate do not change dramatically within industries over time, they will be captured by industry-specific effects in any regression. Hence, the elasticity of output with respect to R does not depend on the choice of δ.

In addition to constructing R&D capital stocks for Portugal, we extended the R&D stocks computed by EU KLEMS for all other countries to cover 2004 and 2005 as well, using ANBERD data and PIM described above. We used GDP deflators as proxies for R&D-specific deflators to obtain real R&D expenditures prior to computing the stock variables. We acknowledge a potential measurement problem arising from this choice (see Edworthy and Wallis, 2007) but at present no viable alternative data are available.

Despite efforts undertaken by the OECD to produce internationally comparable R&D data, important differences across countries in their attribution of R&D across industries remain, including data collection, changes in classification and annual data coverage (OECD, 2009). For our data, the problem in international comparability arises from the fact that countries do not report R&D data uniformly by product field but some rather by main activity. Countries also differ in their treatment of R&D conducted in the 'R&D services' industrial sector ISIC 73. Our set of countries contains countries that follow either the product field or main activity approach: Denmark, Germany, Italy, Japan, Netherlands, Portugal and the US follow the main activity approach, whereas Finland, Sweden, and the UK follow the product field approach. This difference in the allocation of R&D spending across industries still contaminates cross-country comparability of R&D expenditures and stocks.[5]

C Variable Properties

Table C-1: Time-Series Properties

Panel A: Variables in Levels

Maddala and Wu (1999) Fisher Test

	Constant					Constant and Trend			
lags	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}	lags	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}
0	377.10 (.00)	195.89 (.98)	475.55 (.00)	821.56 (.00)	0	237.33 (.50)	165.30 (1.00)	218.26 (.82)	113.11 (1.00)
1	387.37 (.00)	318.94 (.00)	353.65 (.00)	376.22 (.00)	1	448.85 (.00)	405.17 (.00)	381.98 (.00)	585.53 (.00)
2	329.96 (.00)	184.69 (1.00)	277.02 (.04)	373.42 (.00)	2	337.86 (.00)	233.73 (.57)	254.39 (.22)	210.84 (.90)
3	292.94 (.01)	211.53 (.89)	329.64 (.00)	361.32 (.00)	3	272.38 (.06)	280.36 (.03)	481.75 (.00)	429.02 (.00)

Pesaran (2007) CIPS Test

	Constant					Constant and Trend			
lags	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}	lags	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}
0	2.33 (0.99)	3.46 (1.00)	8.01 (1.00)	9.45 (1.00)	0	1.11 (0.87)	3.45 (1.00)	8.01 (1.00)	10.26 (1.00)
1	2.50 (0.99)	-0.24 (0.41)	8.43 (1.00)	7.13 (1.00)	1	-3.30 (.00)	-1.60 (0.06)	-2.62 (.00)	0.57 (.72)
2	10.36 (1.00)	8.39 (1.00)	10.27 (1.00)	14.58 (1.00)	2	8.47 (1.00)	9.88 (1.00)	6.98 (1.00)	9.52 (1.00)
3	15.22 (1.00)	12.55 (1.00)	11.63 (1.00)	16.51 (1.00)	3	18.73 (1.00)	17.61 (1.00)	14.65 (1.00)	17.53 (1.00)

Panel B: Variables in First Difference (with Drift)

	Maddala and Wu (1999) Fisher Test					Pesaran (2007) CIPS Test			
lags	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}	lags	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}
0	1674.68 (.00)	1140.05 (.00)	579.39 (.00)	395.02 (.00)	0	-22.96 (.00)	-16.84 (.00)	-10.22 (.00)	-3.25 (.00)
1	1245.59 (.00)	879.13 (.00)	460.91 (.00)	537.31 (.00)	1	-14.83 (.00)	-11.54 (.00)	-5.27 (.00)	-6.37 (.00)
2	750.23 (.00)	469.34 (.00)	386.03 (.00)	308.01 (.00)	2	-2.19 (.01)	2.16 (.98)	1.66 (.95)	3.79 (1.00)
3	460.06 (.00)	422.29 (.00)	582.17 (.00)	356.46 (.00)	3	12.23 (1.00)	13.42 (1.00)	14.64 (1.00)	10.56 (1.00)

Notes: For the Maddala and Wu (1999) test we report the Fisher statistic and associated p-value, for the Pesaran (2007) test the standardised Z-tbar statistic and its p-value. The null hypothesis for both tests is that all series are nonstationary. Lags indicates the lag augmentation in the Dickey Fuller regression employed. In Panel A we augment the Dickey Fuller regression for variables in levels with a constant or a constant and trend; in Panel B for the variables in first differences we only employ a drift (constant). We used Stata routines `xtfisher` and `pescadf` written by Scott Merryman and Piotr Lewandowski respectively.

Table C-2: Cross-Section Correlation

Panel A: Levels	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}	Panel B: First Differences	Δln Y_{it}	Δln L_{it}	Δln K_{it}	Δln R_{it}
avg ρ	0.29	0.30	0.55	0.40	avg ρ	0.17	0.17	0.20	0.03
avg $\lvert\rho\rvert$	0.59	0.57	0.77	0.78	avg $\lvert\rho\rvert$	0.26	0.28	0.34	0.34
CD	110.44	105.45	199.00	149.64	CD	58.78	59.08	68.53	12.50
p-value	0.00	0.00	0.00	0.00	p-value	0.00	0.00	0.00	0.00
Panel C: Pooled AR(2)	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}	Panel D: Country-industry AR(2)	ln Y_{it}	ln L_{it}	ln K_{it}	ln R_{it}
avg ρ	0.00	0.00	0.00	0.02	avg ρ	0.13	0.12	0.09	0.02
avg $\lvert\rho\rvert$	0.23	0.26	0.24	0.25	avg $\lvert\rho\rvert$	0.25	0.25	0.25	0.23
CD	-0.55	-1.42	-1.03	7.05	CD	45.46	42.20	33.78	8.44
p-value	0.58	0.16	0.30	0.00	p-value	0.00	0.00	0.00	0.00

Notes: We present the average and average absolute correlation coefficients across the $N(N-1)$ sets of correlations. CD reports the Pesaran (2004) cross-section dependence statistic, which is distributed $N(0,1)$ under the null of cross-section independence. Panels A and B test the variable series in levels and first differences respectively. In Panel C each of the four variables in levels is entered into a pooled panel regression $z_{it} = \pi_{0,i} + \pi_1 z_{i,t-1} + \pi_2 z_{i,t-2} + \pi_t + \varepsilon_{it}$ where π_t indicates $T-1$ year dummies and $\pi_{0,i}$ N country-industry fixed effects. In Panel D each of the four variables in levels is entered into a time-series regression $z_{it} = \pi_{0,i} + \pi_{1,i} z_{i,t-1} + \pi_{2,i} z_{i,t-2} + \pi_{3,i} t + \varepsilon_{it}$, conducted separately for each country-industry i. The correlations and cross-section dependence statistic in Panels C and D are then based on the residuals from these AR regressions. We used the Stata routine `xtcd` written by Markus Eberhardt.

D Schankerman (1981) Correction/Augmentation

We carry out variable adjustments to account for excess return bias due to double-counting (DC) and model augmentation to account for expensing bias (EB), following Schankerman (1981). Since our data coverage for s (share of R&D workers in total workforce), δ (share of R&D investment in total investment) and θ (R&D intensity) is relatively limited (we lose over 70% of observations) we are unable to estimate dynamic model specifications and limit our analysis to static models. Furthermore, the augmentations with cross-section averages in the (standard, augmented) CCEP estimators necessitate a sample reduction such that the number of country-industries would drop to a mere 33 ($n = 395$ observations). In addition, these estimators rely on the time-series dimension of the panel to estimate the country-specific coefficients on the cross-section averages and therefore cannot be expected to perform well in the resulting sample setup where T ranges from 8 to 13. We therefore drop these estimators from this robustness exercise.

We present results for a Griliches knowledge production function where input variables are adjusted for *observed values* of s & δ and with *observed* θ included as additional regressor. Alternatively, we use unadjusted input variables and add s, δ, and θ to the standard Griliches knowledge production function to account for the omitted variable bias. We also experimented with adjusting value-added directly by correcting the intermediate input measure for R&D expensing. Results showed very similar patterns to those presented in Table D-1, Panel A, and are therefore not presented here.

The results for the pooled models where k and l are adjusted and R&D intensity is added as covariate (Table D-1, Panel A) largely follow the direction of the bias suggested by Schankerman (1981): in all but the POLS models correcting for double-counting raises the coefficient on R&D capital. Further, adjusting for expensing can be seen to have an ambiguous effect across empirical models. When we instead add measures for s and δ to the regression equation with unadjusted k and l (same Table, Panel B) the coefficient on R&D capital hardly moves at all and the tests for the constraints linking the coefficients (see Schankerman (1981) footnote 4) reject in all models.

We further experimented with some data imputations, replacing missing observations with country-industry time-series averages (this yielded $n = 2,292$ observations), but these results proved not to be particularly insightful, following the patterns described in the smaller sample for observed data only.

In conclusion, given all the data constraints experienced we can merely highlight the seemingly limited change in the R&D coefficients once we adjust for expensing and double-counting. From an econometric perspective we believe there are good grounds to suggest that other data properties, first and foremost nonstationarity and cross-section dependence, play an important role in this type of data and that the empirical bias derived by Schankerman (1981) in a cross-section regression of firm-level data may be conflated with a failure to address these more salient macro panel data issues in the present case. For the empirical models which explicitly account for cross-section dependence there is furthermore a theoretical argument that they can address the double-counting and expensing problem (see Section 3.2.2 in the main text).

Table D-1: Schankerman Correction/Augmentation — Pooled Models

PANEL A: ADJUSTMENT using observed data for s, δ and θ

	POLS			2FE			FDOLS		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\ln R_{it}$	0.135	0.132	0.138	0.121	0.163	0.162	-0.005	0.041	0.043
	[14.19]**	[13.26]**	[13.77]**	[1.29]	[1.57]	[1.53]	[0.09]	[0.59]	[0.61]
Correction		DC	DC, EB		DC	DC, EB		DC	DC, EB
Year dummies	included	included	included	included	included	included	included	included	included
Observations	725	725	725	725	725	725	306	306	306
Aveage T	7.3	7.3	7.3	7.3	7.3	7.3	3.1	3.1	3.1

PANEL B: AUGMENTATION using observed data for s, δ and θ

	POLS			2FE			FDOLS		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\ln R_{it}$	0.135	0.127	0.131	0.121	0.101	0.099	-0.005	-0.007	-0.005
	[14.19]**	[12.90]**	[13.35]**	[1.29]	[1.09]	[1.07]	[0.09]	[0.11]	[0.08]
Augmentation		DC	DC, EB		DC	DC, EB		DC	DC, EB
Year dummies	included	included	included	included	included	included	included	included	included
Observations	725	725	725	725	725	725	306	306	306
Aveage T	7.5	7.5	7.5	7.5	7.5	7.5	3.2	3.2	3.2
Restricton F-test (s,δ)		5.37	4.45		22.16	22.24		7.13	7.13
p-value		0.005	0.012		0.000	0.000		0.001	0.001

Notes: DC — double-counting (correct variable for/augment model with s, δ), EB — expensing bias (augment model with θ). Year dummies included in all models. Constraint refers to an F-test linking coefficients on s and δ to those on $\ln L$ and $\ln K$ respectively. See text above for more details on these exercises. $*$, $**$ indicate statistical significance at the 5% and 1% level respectively. $N = 99$ country-industries in all regressions.