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Abstract

We use ONS micro data for large UK establishments in the production industries in the period 1997-2008 to study the relationship between their productivity and the presence of substantial R&D activities, either at the production unit itself, or at other UK reporting units owned by the same enterprise group. We estimate that total factor (revenue) productivity is on average about 14% higher at the establishments which have substantial R&D themselves, compared to those with no R&D. Among the establishments with no R&D themselves, we estimate that productivity is on average about 9% higher at those which belong to enterprise groups which do have substantial R&D elsewhere in the UK in the same sub-sector. For the establishments with substantial R&D themselves, we also estimate a significant positive relationship between current productivity and past R&D expenditure using dynamic specifications which allow for both establishment-specific 'fixed effects' and a serially correlated error component.

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1 Introduction

This paper uses micro data from the UK Office for National Statistics' (ONS) main surveys of research and development (R&D) and production activities to study the relationship between R&D spending and (revenue) productivity among large UK establishments in the production industries in the period 1997-2008. We focus on production units which are large enough to be surveyed each year in the Annual Business Inquiry,[1] and which have either no R&D activity or which have R&D activities that are substantial enough to be reported annually and in detail in the Business Expenditure on Research and Development (BERD) survey. We also use ownership information to link production units to substantial R&D activities that are conducted elsewhere in the UK within the same enterprise group. Our focus on larger production units which are surveyed annually allows dynamic models of production to be considered, thereby controlling for persistent unobserved influences on productivity which may be correlated with R&D spending. Our focus on substantial R&D operations allows R&D personnel and purchases to be excluded from the measures of labour and material inputs used in our analysis of productivity, and allows the sectoral composition of the enterprise group's UK R&D activity to be taken into account.

Our main findings can be summarised briefly. There is a strong association between the presence of substantial R&D activity and higher productivity, with (measured) total factor (revenue) productivity being about 14% higher on average in the production units that conduct significant R&D. This association remains after controlling for differences in size, age, ownership (domestic/foreign) and sub-sector of production activity. Within the sub-sample of production units which have substantial R&D activities, the evidence of a positive association between higher R&D spending and higher productivity is less strong. For a given production unit, however, we do find evidence that an increase in R&D spending tends to be followed by an increase in productivity; this suggests that the cross-sectional association may not be driven entirely by unobserved heterogeneity or establishment-specific 'fixed effects'. We also find that the presence of substantial R&D activity elsewhere in the UK within the same enterprise group is associated with higher productivity when that R&D is classed as being within the same sub-sector as the production unit, but not when the R&D elsewhere relates to a different sub-sector of production activity.

Earlier papers which have used these UK ONS micro datasets to study the

[1] This was formerly known as the Census of Production.

relationship between R&D and productivity include Rogers (2006), Harris and Li (2009), Sena and Higon (2014) and Harris and Moffat (2015). Our paper differs in its focus on the behaviour of larger establishments and in its consideration of R&D conducted by the same enterprise group but at different locations. Concerning this latter aspect, the closest precedent that we are aware of is the study by Adams and Jaffe (1996) for the chemicals sector in the USA.[2] We share the goals of the classic contribution by Crepon, Duguet and Mairesse (1998), using micro data on establishments and econometric methods which account for some sources of simultaneity bias; lacking data from innovation surveys, however, we consider the relationship between R&D and productivity using a more traditional reduced form approach.

Sections 2 and 3 describe the data and the econometric framework that we use in our analysis. Section 4 presents our main findings, first considering the relationship between productivity and substantial R&D activity at the same production unit, and then extending the analysis to consider substantial R&D activities by other reporting units that are owned by the same enterprise group. An accompanying online working paper provides more detail about both our sample and our results.

2 Data

Our sample is obtained from two ONS micro datasets, the Annual Respondents' Database (ARD) which provides information on production inputs and outputs, and the BERD survey. These are linked using the Inter-Departmental Business Register (IDBR), which also allows us to construct, for each production unit, measures of UK R&D conducted by the same enterprise group but at different locations. We use data for ONS *reporting units* ('establishments'), which is the most disaggregated level at which data on gross output and all production inputs is available in the ARD.[3] Multiple reporting units may be owned by an *enterprise*, and multiple enterprises may by owned by an *enterprise group*. The enterprise group is the most aggregated level to which reporting units can be matched using the IDBR, and corresponds to the UK component of corporate groups.[4]

[2] There is of course a much larger literature on externalities or 'spillover effects' from the R&D expenditures of other firms. See Hall et al. (2010) for a recent review, and Bloom et al. (2013) for a recent example.

[3] For reporting units which have operations at more than one site, information on turnover and employment may be available at the more disaggregated *local unit* level.

[4] The IDBR definitions of enterprise and enterprise group follow the EU Regulation on Statistical Units (EEC 696/93). An enterprise group is an association of enterprises bound together by

2.1 Production data

We use annual observations on the production variables during the period 1997-2008, in which the source for the ARD was the Annual Business Inquiry. During this period, both the survey questionnaire and the sampling scheme remained constant. Reporting units with 250 or more employees were surveyed annually in all production industries, while the sampling probabilities for smaller reporting units depended on the sub-sector of production activity. We use data on reporting units which provide information on the production variables for 3 or more consecutive years,[5] which ensures that most of the reporting units in our sample are large enough to be surveyed annually. We also restrict our sample to reporting units in the production industries. Table S.1 summarises the main variables that we use in this paper. Nominal variables are expressed in constant prices using ONS price indices for the most disaggregated sub-sectors available. Observations with extreme high or low values for the growth rates or the ratios of any of these production variables are dropped from the sample used for estimation.[6] Table S.1 and its footnotes provide further details.

2.2 R&D data

The BERD survey is an annual census only for reporting units with at least 400 employees or those with substantial R&D activities. A subset of reporting units with the largest R&D expenditures are asked to provide more detailed information using a 'long-form' questionnaire. The number of long-form recipients increased over our sample period, from 352 in 1997 to 785 in 2008. These units accounted for around 80% of total UK BERD, and around 85% of manufacturing sector BERD. The number of these long-form recipients which also reported production data in the ARD was more stable over our sample period, fluctuating between 131 in 2003 and 159 in 2001; these long-form production units accounted for around 30% of total UK BERD. The number in our estimation sample fluctuated between 87 in 2000 and 114 in 2001.

legal and/or financial links. The ONS User Guide for the Business Structure Database provides further details.

[5]We require a minimum of 3 consecutive observations to estimate the dynamic production models reported in section 4.2 below.

[6]We removed the observations with materials or labour or capital cost shares that exceeded unity. We also removed the observations that fell in the lowest percentile in the distribution of materials or labour cost shares, or if the capital cost share was negative. We removed all observations on a firm if in any year, one of labour cost, capital stock, output or materials expenditure experienced an 'absolute growth rate' (negative or positive) of more than twice the prior years level.

In addition to total R&D spending, the long-form BERD survey reports data for the number and total salaries of R&D employees, and total purchases of R&D materials. We use this information to exclude R&D personnel and R&D purchases from the measures of employment and material inputs used in our analysis of production, as suggested by Schankerman (1981), and to exclude R&D employees from the average wage variable that we use as a measure of labour quality. Since we found that these 'double-counting' corrections had an important impact on our results, we omit from our sample production units which have R&D activities but do not report this more detailed information (i.e. they appear in the BERD survey but are not long-form recipients). For the remaining production units which have substantial R&D activities, we require that they report long-form R&D information for at least 4 consecutive years.[7]

R&D expenditure is converted to constant prices using an index which gives equal weight to the GDP deflator and the average earnings of scientists. For each production unit, we construct measures of UK R&D conducted by other members of the same enterprise group by summing over all reporting units which belong to the same group and which report long-form R&D information. The sectoral breakdown of R&D expenditure available for long-form recipients then allows us to restrict this measure to other UK R&D which relates to the same sub-sector as the production unit's own production.[8]

2.3 Sample

Our resulting sample contains 14,242 annual observations on 2,895 distinct establishments which are observed for 3 or more consecutive years between 1998 and 2008. Of these 14,242 observations, 603 were on production units which themselves reported detailed information on substantial R&D activities in the previous year, and 3,631 were on production units which belonged to enterprise groups in which at least one member reported detailed information on substantial R&D activities in the previous year.

The median age of the establishments in our sample is 23 years, with the lower quartile and upper quartile of the age distribution being 14 and 29 years respectively. 41.5% of our observations have more than 250 employees, and 8.6% have

[7]This arises because we relate production in year t to R&D expenditure in year $t-1$, but also require information in year t to correct the measures of labour and material inputs for 'double-counting'.

[8]We combine the sub-sectors chemicals and pharmaceuticals for this purpose. The available classification of product groups is reported in Table S.2.a, corresponding to the two digit SIC level. Further details are provided in Table S.2.b of the supplementary material.

more than 1000 employees. 22.5% of the establishments are foreign-owned. Table S.2.a reports the sectoral distribution of our full sample of 14,242 observations on production units (93.3% of which are within the manufacturing sector) and our sub-sample of 603 observations on long-form BERD recipients (almost all of which are in manufacturing). Table S.3.a reports some basic descriptive statistics for the variables that are used in our cleaned dataset and empirical analysis.[9] The production establishments with substantial R&D activities tend to be much larger than those with no R&D activity; they account for less than 5% of our total number of observations, but almost one quarter of the total value added produced by the establishments in our sample. They also tend to employ more skilled workers than the non-R&D establishments, as suggested by average annual real wages that are about 50 percent higher at either the mean or the median. We present the sample characteristics for the combined set of R&D and production units in Table S.3.c.

3 Empirical framework

Our starting point is a 3 factor Cobb-Douglas production function which can be written in log-linear form as

$$y_{it} = \beta_L l_{it} + \beta_K k_{i,t-1} + \beta_M m_{it} + a_{it} \tag{1}$$

in which Y_{it} is a measure of the value of gross output for reporting unit i in year t, L_{it} is a measure of the number of employees during year t, $K_{i,t-1}$ is a measure of the capital stock at the end of year $t-1$, M_{it} is a measure of total purchases of materials during year t, and corresponding lower case notation denotes the natural logarithms of these variables. The residual term (a_{it}) then denotes the log of total factor (revenue) productivity, or the variation in the value of gross production which is not accounted for by the measured variation in these observed inputs (given the imposed functional form).

We allow the log of total factor (revenue) productivity to depend on measures of previous R&D activity. In the empirical analysis reported below we consider various functional forms for this relationship. Letting $r_{i,t-1}$ denote the log of R&D expenditure in year $t-1$, one simple example would be a linear relationship as in

$$a_{it} = \beta_R r_{i,t-1} + e_{it} \tag{2}$$

[9]We describe each of the data cleaning steps in the supplementary material and present the number of observations kept at each step in Table S.3.b.

which gives the augmented production function

$$y_{it} = \beta_L l_{it} + \beta_K k_{i,t-1} + \beta_M m_{it} + \beta_R r_{i,t-1} + e_{it}. \tag{3}$$

We also include the log of the average wage (W_{it}) paid to employees of reporting unit i during year t, which controls for variation in labour quality and/or hours worked, giving the extended specification

$$y_{it} = \beta_L l_{it} + \beta_K k_{i,t-1} + \beta_M m_{it} + \beta_R r_{i,t-1} + \beta_W w_{it} + u_{it}. \tag{4}$$

The restriction $\beta_W = \beta_L$ would imply that variation in labour quality/hours is fully reflected in the cost of labour, in which case the appropriate measure of labour input would be the wage bill rather than the number of employees; we investigate but do not impose this restriction.

Our empirical specifications all include a full set of year dummies and a full set of sector dummies, at approximately the two digit SIC level.[10] In some specifications, the R&D variable is a binary dummy which indicates whether the reporting unit had either substantial R&D expenditure or no R&D expenditure in year $t-1$. In other specifications, we use the level of R&D spending in year $t-1$. Since the level of R&D spending is zero for the majority of the reporting units in our sample, this precludes the use of the standard logarithmic transformation. Instead we use the inverse hyperbolic sine transformation, so that our lower case notation denotes[11]

$$x_{it} = \sinh^{-1} X_{it} = \ln(X_{it} + \sqrt{X_{it}^2 + 1}). \tag{5}$$

The choice between using natural logarithms or inverse hyperbolic sines made no noticeable difference to the results for baseline specifications with no R&D variables or for specifications with R&D dummies.[12]

The use of flow data on R&D expenditure also raises a different issue, since it is unlikely that productivity this year depends only on last year's R&D spending. A more plausible interpretation draws on the knowledge stock model of Griliches (1979), in which productivity this year depends on the stock of knowledge at the end of the previous year ($G_{i,t-1}$), given by cumulated R&D expenditures with the perpetual inventory formulation

$$\begin{aligned} G_{i,t-1} &= R_{i,t-1} + (1-\delta)R_{i,t-2} + (1-\delta)^2 R_{i,t-3} + ... \\ &= (1-\delta)G_{i,t-2} + R_{i,t-1} \end{aligned} \tag{6}$$

[10] Table S.2.a reports the full set of sector classifications that we consider.

[11] Thus we have $x = 0$ for $X = 0$, and x approaches $\ln 2X = \ln 2 + \ln X$ for large X.

[12] See Table S.5 in the supplementary material.

in which $R_{i,t-1}$ is R&D spending in year $t-1$, and δ is the rate at which knowledge acquired through R&D depreciates. Along a steady state path in which both knowledge and R&D spending are growing at the constant rate g, we have the relation

$$R_{i,t-1} = \left(\frac{g+\delta}{1+g}\right) G_{i,t-1}. \tag{7}$$

Close to such a steady state path, the log (or inverse hyperbolic sine) of the measured flow variable provides an approximation to the log (or inverse hyperbolic sine) of the unobserved stock of knowledge.[13]

3.1 Some econometric issues

There are numerous reasons why ordinary least squares (OLS) estimates of production function models like equation (4) above may be inconsistent. With panel data on reporting units, the residual component of (transformed) total factor productivity (u_{it}) may have time-invariant, persistent and transitory components. Explanatory variables like the capital stock at the end of last year, and last year's R&D spending, which are quasi-fixed in the sense of being determined before the start of year t, may nevertheless be correlated with time-invariant or persistent components of u_{it}. Explanatory variables like labour and material inputs, which are flexible in the sense that they can be adjusted during year t, may also be correlated with transitory components of u_{it}. Intuitively, establishments with higher productivity are likely to be larger, and the levels of more flexible inputs are likely to be more sensitive to temporary fluctuations in productivity. Measurement error may be a further source of inconsistency, and this may also be more important for some of the inputs. The net effect of these different sources of simultaneity bias on the behaviour of the OLS estimates is difficult to characterise.[14]

To investigate the reliability of our OLS estimates of the relationship between R&D and productivity, we also consider generalised method of moments (GMM) estimates of a dynamic production function specification, following the approach suggested by Blundell and Bond (2000). We allow the error term (u_{it}) to have a time-invariant component (η_i, i.e. an establishment-specific 'fixed effect') and an

[13]Construction of a knowledge stock measure from the flow data on R&D spending requires an initialisation and an assumption about the appropriate rate of depreciation. We experimented with standard approaches, finding broadly similar results to those obtained with the flow measure of R&D that are reported here. These results are reported further in the supplementary material, with a comparison presented in Table S.6.

[14]See Griliches and Mairesse (1998) for a thorough discussion of these and other issues in the estimation of production functions.

autoregressive component (v_{it})

$$\begin{aligned} u_{it} &= \eta_i + v_{it} \\ v_{it} &= \alpha v_{i,t-1} + \varepsilon_{it}. \end{aligned} \tag{8}$$

This formulation allows for both permanent and persistent components of (transformed) total factor productivity, with productivity shocks represented by ε_{it}. Quasi-differencing equation (4) then gives the dynamic specification

$$y_{it}^* = \beta_L l_{it}^* + \beta_K k_{i,t-1}^* + \beta_M m_{it}^* + \beta_R r_{i,t-1}^* + \beta_W w_{it}^* + \eta_i^* + \varepsilon_{it} \tag{9}$$

in which $x_{it}^* = x_{it} - \alpha x_{i,t-1}$, $v_{it}^* = \varepsilon_{it}$ and $\eta_i^* = \eta_i(1-\alpha)$. Conditional on the value of the autoregressive parameter α, this is a linear panel data model with explanatory variables which may be correlated with the time-invariant component of the error term (η_i^*) and with current or past values of the productivity shocks (ε_{it}). The parameters ($\beta_L, \beta_K, \beta_M, \beta_R, \beta_W$) can be estimated consistently using GMM. Assuming that the ε_{it} are serially uncorrelated, ($l_{i,t-2}, k_{i,t-3}, m_{i,t-2}, r_{i,t-3}, w_{i,t-2}$) and longer lags of these variables are valid instruments for the equations in first-differences

$$\Delta y_{it}^* = \beta_L \Delta l_{it}^* + \beta_K \Delta k_{i,t-1}^* + \beta_M \Delta m_{it}^* + \beta_R \Delta r_{i,t-1}^* + \beta_W \Delta w_{it}^* + \Delta\varepsilon_{it}. \tag{10}$$

Assuming that the first-differenced variables ($\Delta l_{i,t-1}, \Delta k_{i,t-2}, \Delta m_{i,t-1}, \Delta r_{i,t-2}, \Delta w_{i,t-1}$) are uncorrelated with the time-invariant unobserved heterogeneity (η_i), these lagged first-differences are also available as instruments for the equations in levels (9). Both sets of moment conditions can be combined using the 'system GMM' estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), and implemented in Stata by Roodman (2009). Standard tests of instrument validity can then be used to check the maintained assumptions.

The dynamic model (9) can also be written in the form

$$\begin{aligned} y_{it} = {} & \alpha y_{i,t-1} + \beta_L l_{it} - \alpha\beta_L l_{i,t-1} + \beta_K k_{i,t-1} - \alpha\beta_K k_{i,t-2} + \beta_M m_{it} \\ & -\alpha\beta_M m_{i,t-1} + \beta_R r_{i,t-1} - \alpha\beta_R r_{i,t-2} + \beta_W w_{it} - \alpha\beta_W w_{i,t-1} + \eta_i^* + \varepsilon_{it} \end{aligned} \tag{11}$$

and can be estimated without imposing the non-linear 'common factor' restrictions which link the coefficients on the current and lagged values of each explanatory variable to that on the lagged dependent variable.[15] Estimates of this unrestricted specification are useful for assessing the validity of the dynamic structure implied by (8), and for providing consistent estimates of the persistence parameter α.

[15]For example, denoting the unrestricted coefficient on the lagged labour input ($l_{i,t-1}$) by γ_L, equation (11) implies the restriction $\gamma_L = -\alpha\beta_L$.

4 Results

4.1 Static specifications

We begin by presenting OLS estimates of static production function specifications for our sample of large UK establishments, initially without any R&D variables. The first column of Table S.4 reports the results for a specification with only the basic employment, capital and material inputs, as in equation (1). The estimated partial elasticity parameters for each of these inputs is positive and significantly different from zero. The three parameters sum to 1.016, suggesting that the production technology is very close to displaying constant returns to scale.[16] For comparison, the average shares of labour costs and material costs in gross output are 0.25 and 0.59 in our sample.

The second column of Table S.4 reports the results for an extended specification which includes the average wage paid to employees as a control for variation in labour quality and/or hours worked. The estimated coefficient on the average wage is very close to the estimated coefficient on the number of employees in this and subsequent specifications.[17] This suggests that workers who were 10% more (less) productive than the average were also paid 10% more (less) than the average in these large UK establishments during our sample period. Given this, the effective labour input could be measured more parsimoniously using the log (or inverse hyperbolic sine) of the wage bill.[18]

The remaining columns of Table S.4 report the results for augmented specifications with various measures of R&D activity, as illustrated in equation (4). Column (iii) includes a binary dummy variable which takes the value one (in year t) for production units which had substantial R&D activity in the previous year (i.e. they were long-form recipients in the BERD survey), and zero (in year t) for production units which had no R&D activity in the previous year (i.e. they were not included in the sampling framework for the BERD survey). On average, we estimate that total factor (revenue) productivity was 14.4% higher in the subsample of large establishments which themselves had substantial R&D activity. This result is not found if we do not correct the measures of labour and materials at the production units with R&D activity for the inclusion of R&D personnel

[16]Although the constant returns to scale restriction is strongly rejected by a standard F test.

[17]The restriction that these two coefficients are equal is not rejected by a standard F test at conventional significance levels.

[18]Denoting the wage bill by B and the average wage by $W = B/L$, this follows from $\ln L + \ln W = \ln L + \ln B - \ln L = \ln B$.

and purchases in the standard measures of employment and material costs.[19] This contrast suggests that spending on labour and materials engaged in R&D on average generated a similar contribution to revenue as spending the same amount on labour and materials engaged directly in production. This in turn suggests that the typical allocation of resources between R&D and production activities may have been broadly efficient, at least within these establishments.

Column (iv) replaces the binary indicator of substantial R&D activity by the inverse hyperbolic sine of total R&D expenditure reported by the long-form recipients in year $t-1$. This specification also indicates that total factor (revenue) productivity is significantly higher in the sub-sample of establishments with significant R&D activities. For this sub-sample, the mean of the transformed R&D expenditure variable is 9.95, so this specification also suggests that their productivity is about 14% higher on average compared to the production units with no R&D.

The two specifications considered in columns (iii) and (iv) of Table S.4 differ in their implications for whether higher spending on R&D is associated with higher productivity, within the sub-sample of establishments which have large R&D operations. Our sample provides only weak evidence in favour of this association. The specification reported in column (v) includes both the dummy variable and the continuous measure of R&D spending. In this case, the hypothesis that the two coefficients on these R&D variables are both zero can be strongly rejected, but neither of the individual coefficients is significantly different from zero. Thus we have strong evidence that establishments with substantial R&D activity tend to have a productivity advantage over establishments with no R&D activity, but not that this productivity advantage increases with the level of R&D expenditure.

To explore this further, the specification reported in column (vi) divides the observations with substantial R&D activity (in year $t-1$) into 4 quartiles according to their level of R&D spending (also in year $t-1$), and includes 4 dummy variables which indicate whether or not an observation is in the corresponding quartile of the R&D expenditure distribution.[20] This specification indicates that establishments in each quartile of the R&D spending distribution have a significant productivity

[19] Using input measures which are not corrected for double-counting, the estimated coefficient on the R&D dummy falls to 0.026, with a standard error of 0.023. These results are reported in detail in the supplementary material, Table S.10.

[20] Observations with the lowest R&D spending are classed as being in the first quartile (Q1), and observations with the highest R&D spending are classed as being in the fourth quartile (Q4). All four dummy variables are zero for observations with no R&D spending. Note that R&D spending in the bottom quartile is only 'low' in the context of establishments whose R&D activity is substantial enough to be among the long-form recipients for the BERD survey.

advantage compared to establishments with no R&D activity. Formally we do not reject the restriction that these 4 coefficients are all equal, which again indicates no statistically significant difference between the productivity of the highest spenders and the lowest spenders within our sample of establishments with substantial R&D activities.[21] However the point estimates here do suggest some tendency for the productivity advantage to increase with the level of R&D expenditure, at least up to the third quartile. Moreover none of these R&D quartile dummies has a coefficient which is significantly different from zero when added as an additional explanatory variable to the specification in column (iv), with our continuous R&D spending measure.These results are reported in column (vii) of Table S.4. Thus neither of the more parsimonious functional forms considered in columns (iii) and (iv) is rejected by this consideration of more flexible specifications.

The finding that production units with substantial R&D activity have higher total factor (revenue) productivity than production units with no R&D activity could of course reflect other differences between these sub-samples of large UK establishments which happen to be correlated with the presence of R&D. Among the observable candidates, we can rule out size, age and ownership differences as being important contributors to the relationship between R&D and productivity that we have reported in this section. In the supplementary material, Table S.6, we report results for extended specifications, based on both column (iii) and column (iv) of Table S.4, with additional controls for size (using employment size band dummies), age (using age quartile dummies) and foreign ownership.[22] We find evidence that productivity tends to be somewhat higher in the larger establishments, lower in the older establishments, and higher in the establishments owned by foreign firms.[23] In all cases, however, we continue to find a highly significant difference between the establishments with and without substantial R&D activities, and the average size of this difference is stable at around 14%.

4.2 Dynamic specifications

We now consider specifications which allow for unobserved differences between establishments. The approach outlined in section 3.1 allows for both time-invariant and persistent unobserved components of total factor (revenue) productivity, with the latter assumed to follow a first-order autoregressive process. Any approach

[21]The F test of the restriction that these four coefficients are equal has a p-value of 0.53.

[22]We present some descriptive statistics on these additional controls in Tables S.7, S.8 and S.9.

[23]These differences are all quite modest. For example, we estimate the average difference between foreign-owned and UK-owned establishments to be about 4%.

which allows observed explanatory variables to be correlated with establishment-specific 'fixed effects' relies on variation over time within the set of observations on a given production unit. Since we observe almost no variation over time in the binary R&D status indicator for our sample of establishments, we focus in this section on models which use the continuous measure of R&D spending, as in column (iv) of Table S.4.

Table S.11 presents our system GMM estimates of quasi-differenced production functions of the form of equation (9), both with and without the R&D expenditure variable. The instruments used for the equations in first-differences are the second, third and fourth lags of each of the included explanatory variables, and the instruments used for the equations in levels are the first lag of the first difference of each of these variables. We impose the value of the autoregressive parameter (α) to be 0.5, based on preliminary estimates of the unrestricted version of equation (11).[24] These GMM estimates of the coefficients for the labour, capital and material inputs are broadly similar to the OLS estimates in, for example, column (ii) of Table S.4. The estimated coefficient on the R&D expenditure variable is positive and significantly different from zero at the 10% level. The point estimate here is larger than the OLS estimate reported in column (iv) of Table S.4, although we caution that the GMM approach estimates this parameter imprecisely. This imprecision reflects the limited variation over time in the level of R&D spending reported by individual establishments. The main conclusion that we draw from this section is that there is no indication that the association between R&D and productivity suggested by the OLS estimates of static specifications is likely to be seriously biased upwards by the neglect of either permanent or autoregressive differences in productivity between establishments.

In the supplementary material, we report the corresponding system GMM estimates of the unrestricted version of equation (11) (Table S.12). We also find a significant positive long-run effect of R&D expenditure on total factor (revenue) productivity using this more general dynamic specification. Individually, none of the non-linear 'common factor' restrictions, which are imposed in the specifications reported in Table S.11, are rejected for any of the included explanatory variables.[25] This suggests that the persistence in the residual component of total

[24]Similar results were obtained using values of α in the range 0.4-0.6. For comparison, the OLS estimates of the coefficient on the lagged dependent variable in this specification are about 0.85, while the Fixed Effects (Within) estimates are about 0.2. The former are expected to be biased upwards in the presence of establishment-specifc 'fixed effects', while the latter are expected to be biased downwards due to the small number of time series observations available for individual establishments (Nickell, 1981).

[25]Although Wald tests formally reject the joint validity of these non-linear common factor

factor (revenue) productivity can be approximated well using the combination of time-invariant and first-order autoregressive components considered in equation (8).

4.3 R&D at affiliated establishments

Our sample also allows us to investigate the relationship between productivity at large UK establishments and substantial R&D activity conducted by other UK reporting units within the same enterprise group. The latter include R&D facilities which themselves have no significant production operations.

In the first column of Table S.13, we augment the specification from column (iii) of Table S.4 by including an additional binary dummy which takes the value one (in year t) for production units which themselves have no substantial R&D activity (i.e. they are not long-form recipients in the BERD survey) but which belong to enterprise groups which have substantial R&D activity elsewhere in the UK (i.e. they own one or more reporting units that were long-form recipients in the BERD survey, in year $t-1$). This dummy takes the value zero (in year t) both for production units owned by enterprise groups which have no substantial R&D activity in the UK (i.e. they have no members that are long-form recipients in the BERD survey) and by enterprise groups whose only substantial UK R&D activity is conducted at the production unit itself.[26] We find a significant association between higher productivity and the presence of substantial R&D activity elsewhere in the UK within the same enterprise group, although the average productivity gain associated with the presence of substantial R&D at affiliated UK establishments is lower than the average productivity gain associated with the presence of substantial R&D at the production unit itself. The estimated coefficient on the dummy for the presence of substantial R&D at the production unit itself suggests an average difference of 15.7% between the total factor (revenue) productivity of the establishments which have substantial R&D activities and the establishments which have no R&D activities and which belong to enterprise groups with no substantial R&D activities in the UK.[27]

restrictions.

[26]For the production units which themselves have substantial R&D activity, we found no further productivity advantage associated with the presence of additional substantial R&D activity elsewhere in the UK by other members of the same enterprise group. Indeed we found some weak evidence that additional substantial R&D within the same group at other locations may have a small negative effect on the productivity of such reporting units. These results are reported in the supplementary material, Table S.14.

[27]This estimate is naturally higher than we found in Table S.4, since the specification used in Table S.13 removes establishments owned by enterprise groups with substantial R&D activity

In the second column of Table S.13 we distinguish between the presence of substantial R&D at affiliated UK establishments which is reported to be in the same sub-sector as the production unit, and the presence of substantial R&D at affiliated UK establishments which is reported to be in different sub-sectors, or outside the production industries. We find a significant positive association only with substantial R&D by other members of the same enterprise group which is related to the production unit's sub-sector of production activity, and not with substantial R&D by other members of the same enterprise group which is related to other sub-sectors of production industries, or to non-production or service sector activities.

Columns (iii) and (iv) of Table S.13 report the results for otherwise similar specifications which use continuous measures of R&D spending. In column (iii), we add to the specification from column (iv) of Table S.4 the inverse hyperbolic sine of total R&D expenditure in year $t-1$ reported by all other long-form recipients owned by the same enterprise group. In column (iv), we decompose this measure into R&D spending by affiliated establishments which is related to the production unit's sub-sector of production industries, and that which is not. The results here are qualitatively and quantitatively similar to those found for the specifications in columns (i) and (ii) of Table S.13, using the binary R&D indicators.[28] Similar results were also found in extended specifications with additional controls for the size, age and ownership (domestic/foreign) of the production unit.[29]

5 Conclusions

We have used ONS micro data for large UK establishments in the production industries in the period 1997-2008 to study the relationship between their productivity and the presence of substantial R&D activities, either at the production unit itself, or at other reporting units in the UK that are owned by the same enterprise group. Correcting the measures of labour and material inputs for the inclusion of R&D personnel and purchases at the establishments which have substantial R&D activities, we estimate that total factor (revenue) productivity is on average about 14% higher at these establishments, compared to those which have no R&D activity. This estimate increases to about 16% when we compare

elsewhere in the UK from the comparison group.

[28]The sample mean of the transformed R&D expenditure variable by other members of the same enterprise group in the production unit's sub-sector, for production units which themselves have no R&D, is 10.289.

[29]These results are reported in the supplementary material, Table S.15.

establishments with substantial R&D to establishments which have no R&D and which belong to enterprise groups which have no substantial R&D activity within the UK. Among the establishments which have no R&D activity themselves, we estimate that productivity is on average about 9% higher at those which belong to enterprise groups which have substantial R&D activity elsewhere in the UK in the production unit's sub-sector of production activity. For the establishments which have substantial R&D activity themselves, we also estimate a significant positive relationship between current productivity and past R&D expenditure using dynamic specifications which allow for both establishment-specific 'fixed effects' and for a serially correlated unobserved component of total factor (revenue) productivity.

There are several ways in which the research presented here can be refined and extended. Information on the location of production units and the location of affiliated establishments with substantial R&D activity can be used to investigate whether geographical proximity has an important effect on the relation between productivity and substantial R&D conducted by other members of the same enterprise group within the UK. More accurate measures of the connections between the nature of the production activity and the nature of the R&D activities at affiliated establishments can also be considered, perhaps using the distance measures suggested by Bloom et al. (2013). The rich information on the composition of R&D expenditure for all UK establishments with substantial R&D activities that is available for long-form recipients in the BERD survey will also allow the nature of spillover effects from substantial R&D spending by other firms to be explored.

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Datasets

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Supplementary material

for

R&D and Productivity:

Evidence from Large UK Establishments with Substantial R&D Activities

Table S. 1. Production Variables

Variable	Description	Variable names as they appear in the micro ARD dataset
Gross output (Y)	Turnover plus change in stocks of finished goods and raw materials	**go**
Number of employees (L)	Average of quarterly survey reports within year *t* (ARD data provided by ONS through the Secure Lab already contains the averaged value)	**empment**
Average wage (W)	Total salaries/Number of employees	**totlabcost/empment**
Capital stock (K)	Constructed from the data on capital expenditures, using a perpetual inventory formula with a 6% annual depreciation rate; initial values allocate a share of the ONS capital stock estimate for each two digit sub-sector to individual reporting units, in proportion to total purchases of materials (including energy)	Constructed using the total net capital expenditure (**ncapex_pm** + **ncapex_v** + **ncapex_b**) information. Initial values are based on the Volume Index of Capital Services (VICS) data provided by the ONS. Further details are provided below this table.
Material inputs (M)	Total purchases of materials (including energy)	**totpurch**

Variables:

The UK Data Service provides information on the construction of the standard variables listed in Table S**. 1** at: https://discover.ukdataservice.ac.uk/catalogue?sn=6644

We constructed the capital stock variable from the flow measures on capital spending and the information on sectoral aggregates. There are three variables readily available in the ARD dataset which we have used in constructing the investment flow. These are **ncapex_pm** (net capital expenditure on plant and machinery), **ncapex_b** (net capital expenditure on buildings) and **ncapex_v** (net capital expenditure on vehicles). We added these three variables to obtain a single "net capital expenditure" variable. To obtain the initial values for the stock measure, we used the Volume Index of Capital Services (2009) dataset of the ONS through the UK Data Service. We thank the ONS and the UK Data Service for providing this information.

The 2009 release of VICS contains data for the period 1995-2009 on aggregate annual investment, investment deflators (based on gross fixed capital formation in nominal and constant prices) and estimates of aggregate capital stock.

We first obtain the total investment amount made by the firms in our micro dataset and take the share of this total in aggregate UK investment reported in VICS for each year. We assume that, in each period, this share is equal to the ratio of total capital stock of the firms in our dataset to the UK's aggregate capital stock. We also assume that each firm's share in the total materials spending in their respective two-digit industry is proportional to their share in the capital stock of that particular sector in a given year. This allows us to allocate a portion of the aggregate capital (in constant price) to each firm in the data. The firm-level capital stock data calculated in this way constitutes the beginning-of-period capital stock for the first year in which we observe each firm. We allow capital stock to depreciate at 6 percent rate in each period, and each period's total net capital expenditure in real price is added to the net-of-depreciation capital stock for that period to calculate the end-of-period capital stock.

Deflators:

The implicit price index for capital services has been obtained from the VICS at the two-digit sector level. For all other input and output measures, nominal values are converted to constant prices using ONS deflators for the most disaggregated SIC sector available:

Gross output:

Output deflators have been extracted from the producer price index (PPI) series by the ONS for sectors at the four digit level (UK SIC2007). When the index for the relevant four digit sector is not available, the corresponding three digit sector's output price index has been used. When the PPI for neither four, nor three digit sectors are available, then the two digit sector deflators are used. If a mapping between the sector in the data set and the ONS PPI series cannot be found, the overall manufacturing sector PPI for outputs produced in the UK (JVZ7) is used. The exact series codes for each sector are available in the ONS PPI release MM22 (reference to the relevant series are available in Table 2).

Materials:

In the same PPI release where we obtained the output price indices, information on the prices of materials and fuel input is available. A similar procedure to that for the output price deflators has been used to map the reporting units in the ARD dataset with their corresponding deflator series. The sector mapping is available in the ONS PPI MM22 Reference Tables, which is summarised in Table 2.

Wages:

For production workers, labour input deflators have been constructed using the Annual Survey of Hours and Earnings data from the ONS, which is available for the period 1997-2013 (ASHE Tables 4.1a). Mean and median weekly earnings for each two-digit sector category are available for all years, while mean and median annual earnings are available from 1999 onwards. We therefore use the median weekly earnings averaged over the year as the index for labour input. The earnings information uses SIC 1992 for the period 1997-2001, SIC 2003 for the period 2002-2007, and SIC 2007 for the period 2008-2009. The conversion for two-digit sectors between the different classifications can be obtained in a rather straightforward manner, whereas this is not possible for four-digit sectors. For this reason, a two-digit sector index has been created and used to deflate the labour input.

Research and Development:

The R&D input amount (total expenditure) is deflated using a weighted index composed of an R&D salaries index (50 percent) and a GDP deflator series (50 percent). As the deflator for the salaries of R&D personnel, we use an index based on the annual average pay for Science and Technology Professionals reported in ASHE, taking 1997 values as the base year. We use the information for SOC Code 21 in Table 2.7a of the ONS ASHE releases. The GDP deflator is the **pgdp** series from the OECD Economic Outlook No 90, December 2011.

Table S. 2.a. Sectoral composition of full sample and long-form BERD sub-sample

Two digit sector	Description	All observations	Share of total value added	Long-form BERD observations	Share of total value added
A	Agriculture, forestry, fishing	75	0.1%		
B	Extractive industries	657	2.5%		
C	Food, beverages, tobacco	2,280	19.2%	46	2.6%
D	Textiles and clothes	1,183	1.6%		
E	Wood, paper, publishing	2,358	10.9%		
F	Refined petroleum	49	0.9%	15	0.8%
G	Chemicals	899	12.8%	141 (G and H combined)	4.6% (G and H combined)
H	Pharmaceuticals	65	0.6%		
I	Rubber and plastics	594	2.6%		
J	Nonmetallic minerals	829	2.4%		
K	Basic iron ore, ferro alloys	608	2.9%		
L	Nonferrous metals	249	1.0%		
M	Fabricated metal products	902	1.7%		
N	Machinery and equipment	849	4.8%	115	2.9%
O	Office machinery, computers	146	1.9%	13	0.7%
P	Electrical machinery	272	0.9%		
Q	Radio, TV, communication	253	2.7%	55	1.0%
R	Precision instruments	206	1.0%	87	0.7%
S	Motor vehicles	463	16.9%	29	5.1%
T	Railway, rolling stock	173	0.4%		
U	Shipbuilding	96	0.6%		
V	Aircraft, spacecraft	204	6.2%	59	3.7%
W	Furniture	608	1.5%	12	0.1%
X	Recycling	86	0.2%		
Y	Utilities	138	4.0%		
Other[a]	n/a	n/a	n/a	31	1.4%
Total		14,242	100%	603	23.7%

[a] Sectors with fewer than 10 long form BERD observations cannot be separately identified

Table S. 2.b PPI deflator series, references to the ONS MM22 Tables

Table 1: Price Indices of Materials & Fuel purchased: All Manufacturing & Selected Industries (SIC07) - 6207000050 to 6107219000
Table 1a: Price Indices of Materials & Fuel purchased: All Manufacturing & Selected Industries (SIC07) - 6107120000 to 6107236000
Table 2: Price Indices of UK Output: All Manufacturing & Selected Industries (SIC07) - 7200700000 to 7112270000
Table 2a: Price Indices of UK Output: All Manufacturing & Selected Industries (SIC07) - 7112280000 to 7112330000
Table 3: Price Indices of Materials & Fuels purchased by Group (SIC07) - 6107206070 to 6107217000
Table 3a: Price Indices of Materials & Fuels purchased by Group (SIC07) - 6107218000 to 6107325400
Table 3b: Price Indices of Materials & Fuels purchased by Group (SIC07) - 6107226000 to 6107433990
Table 4: Price Indices of Products Manufactured in the UK (SIC07) - 0811000000 to 1031140000
Table 4a: Price Indices of Products Manufactured in the UK (SIC07) - 1032000000 to 1082230000
Table 4b: Price Indices of Products Manufactured in the UK (SIC07) - 1083000000 to 1107190000
Table 4c: Price Indices of Products Manufactured in the UK (SIC07) - 1310000000 to 1629000000
Table 4d: Price Indices of Products Manufactured in the UK (SIC07) 1712350000 to 1920268000
Table 4e: Price Indices of Products Manufactured in the UK (SIC07) - 2012000000 to 2120130000
Table 4f: Price Indices of Products Manufactured in the UK (SIC07) - 2211000000 to 2332110000
Table 4g: Price Indices of Products Manufactured in the UK (SIC07) - 2341000000 to 2453000000
Table 4h: Price Indices of Products Manufactured in the UK (SIC07) - 2511000000 to 2620130000
Table 4i: Price Indices of Products Manufactured in the UK (SIC07) - 2620300000 to 2814130000
Table 4j: Price Indices of Products Manufactured in the UK (SIC07) - 2815000000 to 2899000000
Table 4k: Price Indices of Products Manufactured in the UK (SIC07) - 2910000000 to 3220000000
Table 4l: Price Indices of Products Manufactured in the UK (SIC07) - 3230000000 to 3320600000

Table S. 3.a. Descriptive statistics

a) Full sample (14,242 observations).

Variable	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
Gross output	72,780	269,660	5,927	17,926	48,410
No of employees	420	876	71	176	429
Average wage	20	16	14	19	24
Capital stock	68,354	349,190	4,304	12,958	34,848
Material inputs	46,767	189,259	3,279	10,759	30,261

b) Long-form BERD sub-sample (603 observations).

Variable	Mean	Std Dev	Lower Quartile	Median	Upper Quartile
Gross output	406,747	818,719	82,407	164,159	537,011
No of employees	1,612	2,066	558	891	1,683
Average wage	31	39	23	28	33
Capital stock	324,620	652,439	50,600	104,319	359,654
Material inputs	261,784	576,240	39,630	100,253	292,074
R&D spending	24,312	59,214	4,695	8,528	18,487

Note: All variables (except number of employees) are measured in thousands of 1997 pounds.

For the long-form BERD sub-sample, the measures of employment, average wage and material inputs are corrected for double-counting of R&D.

Data cleaning steps:

Starting with the raw BERD data, we followed the data cleaning steps summarised in Table S. 3.b. In the rightmost three columns of the table, we dropped firm-year observations according to the following filters: in Step 1, we removed observations with materials and labour cost share either greater than unity, or that fall in the lowest percentile. We also dropped observations with capital cost share negative or greater than unity. In Step 2, we removed all observations on a firm if in any year, one of labour cost, capital stock, output or materials expenditure experienced an “absolute growth rate” (negative or positive) of more than twice the prior year’s level. Finally, in Step 3, we required firms to have at least four consecutive observations with long form R&D data.

Table S. 3.b. Data cleaning

Period	Cell count in BERD (aggregated to unique reporting unit-years) (I)	Cell count in ARD production sector, sampled, raw data (II)	Cell count for observations which are matched between the production ARD and BERD at the RU level* (III)	Cell count in (III) with positive R&D*	Number of long forms (all sectors)	Cell count for the long form recipients rep.units, with ARD prod. sector matches	Removing the obs. with no capital stock at the end of t-1	Step 1	Step 2	Step 3
1997	8,191	12,083	5,990	1,516	352	147				
1998	9,198	12,593	7,851	2,254	349	141	126	112	109	41
1999	8,544	12,450	8,464	1,951	359	152	133	114	106	47
2000	9,481	12,265	8,237	2,114	359	149	121	98	87	58
2001	9,447	12,879	8,424	1,905	610	159	143	124	114	64
2002	11,825	11,899	7,998	2,433	643	158	135	111	101	71
2003	10,356	11,585	7,571	1,921	588	131	116	102	94	68
2004	12,780	11,228	7,182	2,223	627	134	110	96	88	65
2005	13,117	10,671	6,579	2,212	629	141	126	107	98	56
2006	17,475	9,705	5,939	2,361	648	153	128	108	98	56
2007	19,588	10,558	5,424	2,666	762	154	133	112	100	44
2008	17,961	7,024	3,181	1,647	785	146	125	106	95	33

*includes ARD-BERD matched observations, including BERD observations with imputed values.

Table S. 3.c. Sample characteristics for the combined set of R&D and production units

Period	Mean age	Median age	Mean no of employees	Median no of employees	Share of foreign owned companies	Number of obs
1998	17.9	19.0	473	254	17%	1167
1999	18.8	20.0	447	228	18%	1446
2000	19.6	20.0	430	200	20%	1705
2001	20.5	22.0	413	183	23%	1651
2002	20.8	21.0	382	157	24%	1663
2003	22.0	22.5	384	156	25%	1608
2004	23.2	24.0	404	144	25%	1499
2005	24.1	25.5	430	143	27%	1258
2006	25.3	28.0	493	161	30%	1000
2007	26.5	30.0	512	182	..	773
2008	28.4	32.0	559	283	41%	472

Table S. 4. Static production functions

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
β_L: labour	0.247 (.008)	0.331 (.009)	0.328 (.009)	0.328 (.009)	0.328 (.009)	0.328 (.009)	0.328 (0.009)
β_W: wage		0.338 (.031)	0.331 (.031)	0.331 (.031)	0.331 (.031)	0.331 (.031)	0.331 (0.031)
β_K: capital	0.114 (.013)	0.079 (.010)	0.075 (.010)	0.075 (.010)	0.075 (.010)	0.075 (.010)	0.075 (0.010)
β_M: materials	0.655 (.013)	0.595 (.015)	0.597 (.015)	0.597 (.015)	0.597 (.015)	0.597 (.015)	0.598 (0.015)
β_R: R&D dummy			0.144 (.024)		0.072 (.170)		
β_R: R&D spending				0.014 (.002)	0.007 (.017)		-0.009 (0.043)
β_R: R&D Q1						0.107 (.033)	0.190 (0.383)
β_R: R&D Q2						0.142 (.031)	0.230 (0.405)
β_R: R&D Q3						0.187 (.050)	0.282 (0.447)
β_R: R&D Q4						0.139 (.037)	0.246 (0.488)
p-value: equal β_R					0.000	0.5253	0.000
R squared	0.968	0.972	0.972	0.972	0.972	0.972	0.972
Observations	14,242	14,242	14,242	14,242	14,242	14,242	14,242
Obs with R&D	603	603	603	603	603	603	603

This is a detailed version of Table 4 in the original paper, with Column (vii) added.

OLS estimates.

Standard errors reported in brackets are asymptotically robust to heteroskedasticity and serial correlation (cluster-robust at the reporting unit level).

All specifications include year dummies and two-digit sector dummies.

For column (v), a Wald test reject the hypothesis that the two coefficients on the two R&D variables are both zero, with a p-value of 0.000.

For column (vi), a Wald test cannot reject the hypothesis that the four coefficients on the four R&D quartile dummy variables are jointly different from zero, with a p-value of 0.699.

For column (vii), a Wald test cannot reject the hypothesis that the four coefficients on the four R&D quartile dummy variables are jointly different from zero, with a p-value of 0.700.

Table S. 5. Choice between natural logarithm and inverse hyperbolic sine transform

	(i)	(ii)	(iii)	(iv)
β_L: labour ($\sinh^{-1}$)	0.247 (0.008)	0.331 (0.009)		
β_W: wage (sinh-1)		0.338 (0.031)		
β_K: capital ($\sinh^{-1}$)	0.114 (0.013)	0.079 (0.010)		
β_M: materials ($\sinh^{-1}$)	0.655 (0.013)	0.595 (0.015)		
β_L: labour (log)			0.247 (0.008)	0.331 (0.009)
β_W: wage (log)				0.333 (0.029)
β_K: capital (log)			0.114 (0.013)	0.080 (0.010)
β_M: materials (log)			0.654 (0.012)	0.594 (0.015)
R squared	0.968	0.972	0.970	0.974
Observations	14242	14242	14242	14242
Obs with R&D	603	603	603	603

OLS estimates.

Standard errors reported in brackets are asymptotically robust to heteroskedasticity and serial correlation (cluster-robust at the reporting unit level).

All specifications include year dummies and two-digit sector dummies.

Construction of the R&D stock values:

The initial values for the R&D stock variable follow Equation (7) in Bond and Guceri (2016):

$$R_{i,t-1} = \left(\frac{g+\delta}{1+g}\right) G_{it}$$

Depreciation rate δ is assumed to be 0.15 and the steady state growth rate g of R&D is assumed to be 0.05. We then construct the initial stock of R&D, using the information that we have on R&D flow from the previous period ($R_{i,t-1}$) and the assumptions on the steady state growth rate and depreciation rate of the R&D stock. We then use the perpetual inventory method following Equation (6) in Bond and Guceri (2016):

$$G_{it} = (1-\delta)G_{i,t-1} + R_{i,t-1}$$

Table S. 6. Choice between stock and flow measures for R&D

	(i)	(ii)	(iii)	(iv)
β_L: labour	0.328 (0.009)	0.315 (0.010)	0.328 (0.009)	0.315 (0.010)
β_W: wage	0.331 (0.031)	0.331 (0.031)	0.331 (0.031)	0.331 (0.031)
β_K: capital	0.075 (0.010)	0.072 (0.010)	0.075 (0.010)	0.072 (0.010)
β_M: materials	0.597 (0.015)	0.597 (0.015)	0.597 (0.015)	0.597 (0.015)
β_R: R&D spending	0.014 (0.002)	0.014 (0.002)		
β_R: R&D stock			0.012 (0.002)	0.012 (0.002)
β_A: Age Q2		0.003 (0.010)		0.003 (0.010)
β_A: Age Q3		-0.021 (0.010)		-0.021 (0.010)
β_A: Age Q4		-0.038 (0.012)		-0.038 (0.012)
β_S: Size band 250-399		0.034 (0.012)		0.034 (0.012)
β_S: Size band 400-999		0.051 (0.015)		0.051 (0.015)

β_S: Size band 1000+		0.062 (0.021)		0.062 (0.021)
β_F: Foreign		0.040 (0.009)		0.040 (0.009)
R squared	0.972	0.973	0.972	0.973
Observations	14242	14242	14242	14242
Obs with R&D	603	603	603	603

Assumptions in calculating the R&D capital stock: steady state growth rate of 5%, depreciation of R&D capital of 15%.

Table S. 7. Age quartiles upper bound threshold age levels

Quartile 1	Quartile 2	Quartile 3	Quartile 4
14	23	29	36

Table S. 8. Number of observations in each of the size bands

Cell counts	250-400 emp	400-1000 emp	1000+ emp
No R&D	2000	2398	913
R&D rep.unit	31	252	318

Table S. 9. Number of observations in each of the domestic and foreign-owned firm groups

	No R&D frequency	R&D rep.unit frequency
Domestic/Unknown	10,673	361
Foreign	2,966	242
Total	13,639	603

Double counting corrected non-R&D total labour cost is constructed by subtracting the researcher salaries (**slries)** variable in BERD from ARD's total labour cost (**totlabcost)** variable. The nominal values are used, and then the net-of-R&D labour cost is deflated using the appropriate two-digit SIC employment deflators constructed using the ASHE. Similarly, from the ARD materials variable (**totpurch**), we obtained the double counting corrected non-R&D materials cost by subtracting the R&D current spending other than salaries and wages (**curr_oth**). Again, the nominal annual values are used, then the net-of R&D materials cost is deflated using the appropriate PPI input indices as described earlier.

The R&D input amount is then deflated using an index composed of 50 percent R&D salaries and 50 percent GDP deflator constructed using the ASHE series for the Occupation Class for Science and Technology Professionals and 50 percent GDP deflator as described earlier.

Table S. 10. Double counting correction of inputs

	(i)	(ii)	(iii)	(iv)
β_L: labour	0.245 (0.008)	0.328 (0.009)		
β_W: wage		0.331 (0.031)		
β_K: capital	0.108 (0.013)	0.075 (0.010)	0.103 (0.013)	0.071 (0.010)
β_M: materials	0.656 (0.012)	0.597 (0.015)		
β_L: labour (uncorrected)			0.247 (0.008)	0.328 (0.009)
β_W: wage (uncorrected)				0.329 (0.031)
β_M: materials (uncorrected)			0.661 (0.012)	0.602 (0.015)
β_R: R&D dummy	0.189 (0.026)	0.144 (0.024)	0.082 (0.024)	0.026 (0.023)
R squared	0.968	0.972	0.969	0.972
Observations	14242	14242	14242	14242
Obs with R&D	603	603	603	603

Table S. 11. Dynamic production functions

	(i)	(ii)
β_L: labour	0.381 (.058)	0.366 (.053)
β_W: wage	0.378 (.135)	0.362 (.113)
β_K: capital	0.061 (.050)	0.049 (.052)
β_L: materials	0.625 (.044)	0.634 (.042)
β_R: R&D spending		0.037 (.021)
Observations	11,288	11,288
Obs with R&D	492	492
1st order autocorrelation	-12.37	-12.69
2nd order autocorrelation	1.34	1.46
Hansen (p): all instruments	0.169	0.269
Hansen (p): levels instruments	0.025	0.060

System GMM estimates, using the instruments described in the text, implemented in Stata using Roodman's (2009) xtabond2 command.

Standard errors reported in brackets are asymptotically robust to heteroskedasticity and serial correlation (cluster-robust at the reporting unit level).

All specifications include year dummies and two-digit sector dummies.

Test statistics for no 1st/2nd order serial correlation in the first-differenced residuals are Arellano-Bond (1991) tests, asymptotically standard normal under the hypothesis of no serial correlation.

p-values are reported for the Hansen tests of overidentifying restrictions.

Table S. 12. Unrestricted model

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\beta_{L.Y}$: lagged output	0.859 (0.081)	0.192 (0.082)	0.482 (0.181)	0.858 (0.082)	0.187 (0.081)	0.478 (0.180)
β_L: labour	0.357 (0.031)	0.344 (0.026)	0.498 (0.175)	0.357 (0.031)	0.346 (0.026)	0.434 (0.162)
$\beta_{L.L}$: lagged labour	-0.313 (0.024)	-0.064 (0.029)	-0.361 (0.111)	-0.313 (0.024)	-0.059 (0.028)	-0.303 (0.098)
β_W: wage	0.340 (0.033)	0.320 (0.023)	0.469 (0.194)	0.339 (0.033)	0.322 (0.023)	0.432 (0.170)
$\beta_{L.W}$: lagged wage	-0.288 (0.021)	-0.045 (0.028)	-0.274 (0.113)	-0.288 (0.021)	-0.04 (0.027)	-0.237 (0.099)
β_K: capital	0.008 (0.015)	0.002 (0.013)	0.167 (0.088)	0.008 (0.014)	0.001 (0.013)	0.172 (0.090)
$\beta_{L.K}$: lagged capital	-0.003 (0.014)	0.023 (0.013)	-0.1 (0.076)	-0.003 (0.014)	0.022 (0.013)	-0.121 (0.075)
β_L: materials	0.428 (0.012)	0.436 (0.014)	0.531 (0.122)	0.428 (0.012)	0.437 (0.014)	0.555 (0.115)
$\beta_{L.M}$: lagged mater.	-0.335 (0.044)	-0.030 (0.038)	-0.201 (0.053)	-0.334 (0.045)	-0.028 (0.037)	-0.214 (0.048)
β_R: R&D spending				0.005 (0.006)	0.012 (0.008)	-0.020 (0.042)
$\beta_{L.R}$: lagged R&D				-0.003 (0.005)	0.007 (0.007)	0.043 (0.044)
R squared	0.991	0.604		0.991	0.605	
Observations	11288	11288	11288	11288	11288	11288
Obs with R&D	492	492	492	492	492	492
1st order autocorr.			-13.092			-11.144
2nd order autocorr.			0.111			0.087
Hansen (p): all instruments			0.632			0.688
Hansen (p): levels instruments			0.091			0.330
B_L: long-run labour	0.311 (0.028)	0.347 (0.027	0.264 (0.071)	0.308 (0.027)	0.353 (0.027)	0.251 (0.073)

B_W: long-run wage	0.365 (0.048)	0.341 (0.026)	0.377 (0.09)	0.359 (0.048)	0.346 (0.024)	0.375 (0.08)
B_K: long-run capital	0.036 (0.055)	0.03 (0.016)	0.129 (0.046)	0.033 (0.054)	0.028 (0.015)	0.097 (0.051)
B_M: long-run materials	0.655 (0.071)	0.503 (0.021)	0.637 (0.058)	0.656 (0.07)	0.504 (0.021)	0.655 (0.059)
B_R: long-run R&D	. .	. .	. .	0.013 (0.005)	0.023 (0.018)	0.045 (0.025)
COMFAC (p)	0.003	0.000	0.000	0.003	0.000	0.001
CF (labour)	0.322	0.853	0.24	0.307	0.632	0.269
CF (wage)	0.635	0.288	0.613	0.722	0.177	0.726
CF (capital)	0.662	0.049	0.595	0.684	0.055	0.285
CF (materials)	0.001	0.000	0.355	0.001	0.000	0.391
CF (R&D)	.	.	.	0.261	0.264	0.181

System GMM estimates, using the instruments described in the text, implemented in Stata using Roodman's (2009) xtabond2 command.

Standard errors reported in brackets are asymptotically robust to heteroskedasticity and serial correlation (cluster-robust at the reporting unit level).

All specifications include year dummies and two-digit sector dummies.

Test statistics for no 1st/2nd order serial correlation in the first-differenced residuals are Arellano-Bond (1991) tests, asymptotically standard normal under the hypothesis of no serial correlation.

p-values are reported for the Hansen tests of overidentifying restrictions.

Long run coefficients indicated with a capital B, with standard errors in brackets underneath the coefficients (computed using the delta method).

p-values are reported for the tests of common factor restrictions. The row titled COMFAC (p) presents the results from a joint test of all input coefficients satisfying the restriction, and the individual rows titled CF ("input") present the p-values of the tests for individual inputs.

Table S. 13. Static production functions with R&D of affiliated establishments

	(i)	(ii)	(iii)	(iv)
β_L: labour	0.327 (.009)	0.327 (.009)	0.327 (.009)	0.326 (.009)
β_W: wage	0.328 (.031)	0.328 (.031)	0.328 (.031)	0.328 (.031)
β_K: capital	0.072 (.010)	0.072 (.010)	0.072 (.010)	0.072 (.010)
β_L: materials	0.599 (.015)	0.600 (.015)	0.599 (.015)	0.600 (.015)
β_R: own R&D dummy	0.157 (.025)	0.159 (.025)		
β_R: group R&D dummy	0.066 (.016)			
β_R: group R&D dummy: same sector		0.088 (.020)		
β_R: group R&D dummy: other sectors		0.007 (.020)		
β_R: own R&D			0.016 (.003)	0.016 (.003)
β_R: group R&D			0.007 (.002)	
β_R: group R&D: same sector				0.009 (.002)
β_R: group R&D: other sectors				-0.001 (.002)
R squared	0.972	0.972	0.972	0.972
Observations	14,242	14,242	14,242	14,242
Obs with own R&D	603	603	603	603
Obs with group R&D	3,631	3,631	3,631	3,631

OLS estimates.

Standard errors reported in brackets are asymptotically robust to heteroskedasticity and serial correlation (cluster-robust at the reporting unit level).

All specifications include year dummies and two-digit sector dummies.

'Group' R&D measures refer to R&D of affiliated establishments for the production units which themselves have no R&D.

Table S. 14. Static production functions with R&D of affiliated establishments – Additional specifications

	(i).a	(i).b	(ii).a	(ii).b	(iii).a	(iii).b	(iv).a	(iv).b
β_L: labour	0.327 (.009)	0.327 (.009)	0.327 (.009)	0.327 (.009)	0.327 (.009)	0.327 (.009)	0.326 (.009)	0.326 (.009)
β_W: wage	0.328 (.031)	0.329 (.031)	0.328 (.031)	0.328 (.031)	0.328 (.031)	0.328 (.031)	0.328 (.031)	0.328 (.031)
β_K: capital	0.072 (.010)	0.073 (.010)	0.072 (.010)	0.072 (.010)	0.072 (.010)	0.072 (.010)	0.071 (.010)	0.072 (.010)
β_L: materials	0.599 (.015)	0.599 (.015)	0.600 (.015)	0.599 (.015)	0.599 (.015)	0.599 (.015)	0.600 (.015)	0.599 (.015)
β_R: own R&D dummy	0.157 (.025)	0.178 (.029)	0.159 (.025)	0.181 (0.029)				
β_R: group R&D dummy for RU with no R&D itself	0.066 (.016)	0.066 (.016)						
β_R: rest of group R&D dummy for RU with R&D		-0.065 (0.036)						
β_R: group R&D dummy for RU with no R&D itself: same sector			0.088 (.019)	0.088 (.019)				
β_R: rest of group R&D dummy for RU for RU with R&D: same sector				-0.079 (.034)				
β_R: own R&D					0.016 (0.003)	0.019 (0.003)	0.016 (0.003)	0.019 (0.003)
β_R: group R&D for RU with no R&D itself					0.007 (0.002)	0.007 (0.002)		
β_R: rest of group R&D for RU for RU with R&D						-0.007 (0.003)		
β_R: group R&D for RU with no R&D itself: same sector							0.009 (0.002)	0.009 (0.002)
β_R: rest of group R&D for RU with R&D: same sector								-0.011 (0.003)
R squared	0.972	0.972	0.972	0.972	0.972	0.972	0.972	0.972
Observations	14,242	14,242	14,242	14,242	14,242	14,242	14,242	14,242
Obs with own R&D	603	603	603	603	603	603	603	603
Obs with group R&D	3,631	3,631	3,631	3,631	3,631	3,631	3,631	3,631

Table S. 15. Static production functions with R&D of affiliated establishments – Additional controls

	(i)	(ii)	(iii)	(iv)
β_L: labour	0.327 (.009)	0.315 (.009)	0.326 (.009)	0.315 (.009)
β_W: wage	0.328 (.031)	0.328 (.031)	0.328 (.031)	0.328 (.031)
β_K: capital	0.072 (.010)	0.072 (.010)	0.072 (.010)	0.068 (.010)
β_L: materials	0.600 (.015)	0.599 (.015)	0.600 (.015)	0.599 (.015)
β_R: own R&D dummy	0.159 (.025)	0.154 (.025)		
β_R: group R&D dummy: same sector	0.088 (.020)	0.086 (.020)		
β_R: group R&D dummy: other sectors	0.007 (.020)	0.007 (.019)		
β_R: own R&D			0.016 (.003)	0.016 (.003)
β_R: group R&D: same sector			0.009 (.002)	0.009 (.002)
β_R: group R&D: other sectors			-0.001 (.002)	-0.001 (.002)
β_S: Size band 250-399		0.033 (0.012)		0.034 (0.012)
β_S: Size band 400-999		0.047 (0.014)		0.049 (0.014)
β_S: Size band 1000+		0.05 (0.021)		0.053 (0.021)
β_A: Age Q2		0.002 (0.010)		0.002 (0.010)
β_A: Age Q3		-0.023 (0.010)		-0.022 (0.010)
β_A: Age Q4		-0.038		-0.038

		(0.012)		(0.012)
β_F: Foreign		0.038 (0.009)		0.038 (0.008)
R squared	0.972	0.972	0.972	0.973
Observations	14,242	14,242	14,242	14,242
Obs with own R&D	603	603	603	603
Obs with group R&D	3,631	3,631	3,631	3,631

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