Material intensity, productivity and economic growth

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Many models of economic growth exclude materials from the production function. Growing environmental pressures and resource prices suggest that this may be increasingly inappropriate. This paper explores the relationship between material intensity, productivity and national accounts using a panel data set of manufacturing subsectors in the United States over 47 years. The first contribution is to identify sectoral production functions that explicitly incorporate material inputs while allowing for heterogeneity in both technology and productivity. The second contribution is that the paper finds a negative correlation between material intensity and total factor productivity (TFP) — sectors that are less material-intensive have higher rates of productivity. This finding is replicated at the firm level. We propose tentative hypotheses to explain this association, but testing is left for further work. Depending upon the nature of the mechanism linking a reduction in material intensity to an increase in TFP, the implications could be significant: policies that reduce material intensity, such as shifting taxation from labour to natural resources, would increase productivity and economic growth. A third contribution is to suggest that an empirical bias in productivity, as measured in national accounts, may arise due to the exclusion of material inputs. Current conventions of measuring productivity in national accounts may overstate the productivity of resource-intensive sectors relative to other sectors.

Keywords: Material intensity, material efficiency, productivity, total factor productivity, economic growth

We are grateful to Julian Allwood, Alex Bowen, Eric Beinhocker, Nicola Brandt, John Daley, Markus Eberhardt, Simon Dietz, Ross Garnaut, Elizabeth Garnsey, Eric Neumayer, Carl Obst and Alan Seatter, among others, for useful discussions about the issues addressed in this paper. We are extremely grateful to Hyunjin Kim for outstandingly diligent and helpful research assistance. Hepburn is grateful to the Grattan Institute in Melbourne, Australia, for hospitality during the final stages of the paper.

1. Introduction

Since the industrial revolution, energy and material costs have fallen dramatically and economic development has proceeded rapidly along an energy- and materials-intensive growth path. Over the 20th century, despite a quadrupling of the population and a 20-fold increase in economic output, material resources became more and more plentiful relative to manufactured capital and labour, and technological advances continued to drive down the price of natural resources. Economists usually omitted natural and environmental resources from production functions altogether, as capital and labour were more important determinants of output, and measurement issues meant that data on material inputs was challenging to analyse.

This material-intensive economic model has generated increases in gross domestic product (GDP) and has largely been extremely beneficial for humans. GDP does not directly measure welfare or happiness; it is an approximate measure of real economic output, measured in terms of its *value* to humans (in units of dollars or other currency, rather than tonnes). Nevertheless, GDP is important. The financial crisis and so-called 'great contraction' of 2008 onwards demonstrates the extremely damaging consequences of a drop in GDP and stagnant economic growth. In rich countries, recessions imply unemployment, increases in crime and mental illness, and increased poverty. In poor countries, sustained growth is absolutely vital to lift billions out of poverty. Economic growth is clearly good.

However, economic growth has also substantially increased pressure on (i) environmental resources such as climate, fisheries and biodiversity and (ii) natural resources and commodities. In a variety of domains, so-called 'planetary boundaries' are being exceeded [47]. Commodity prices have increased by almost 150% in real terms over the last 10 years, after falling for much of the 20th century [24], and 44 million people fell into poverty due to rising food prices in the second half of 2010 [35].

Current environmental and resource pressures seem likely to increase as the human population swells from 7 billion to 9-10 billion and, critically, as the number of middle class consumers grows from 1 billion to 4 billion people [37].† If increases in living standards are to occur without social and environmental dislocation, major improvements in the efficiency and productivity with which we use materials will be required.

Given these pressures, omitting material inputs from economic production functions, as is common in macroeconomic modeling, appears increasingly unwise. Production functions with capital and labour as the sole 'factors of production' may have been justified a century ago; it was a sensible modeling strategy to ignore materials, given their relative abundance and the absence of useful data. However, our results indicate that it is likely that omitting material inputs may lead to biased estimates of productivity.‡ Generating sustained economic growth while preserving natural resources will require a careful analytical focus on the role of materials and energy in generating output and welfare, rather than assuming they are so abundant as to be irrelevant.

This paper explores the important relationship between 'material intensity', economic growth and productivity. In the dataset we use, material inputs are defined as the sum of physical intermediate inputs, energy and purchased services.¶ We

† Middle class consumers are defined as those with daily per capita spending of between $10 and $100 in purchasing power parity terms [37].

‡ Perhaps as importantly, omitting materials reflects an inaccurate assumption about scarcity and value. For instance, this type of assumption has led to the adoption of national accounts which do not include genuine balance sheets measuring wealth and other stocks; the focus is almost entirely on flows. One consequence is that many nations, such as Australia, effectively account for the extraction of natural resources as a form of income, rather than as a partial asset sale.

¶ While intermediate inputs are not disaggregated further in our dataset, the US Annual Survey of Manufactures indicates that material inputs (as defined in this paper) comprise around 61 per employ data from two different sources. The primary analysis of the paper uses data on industrial subsectors from the United States over the 47 years from 1958 to 2005. Material cots largely declined over this period until just after 2000, at which point they increased rapidly, driven by the onset of the 'Platinum Age' [29]. Firm-level data from South Korea is used to demonstrate that the results are not an artifact of sectoral aggregation. In both cases, we estimate or use production functions that explicitly account for the role of material inputs, and then explore the association between the material intensity of production and total factor productivity (TFP). Productivity is commonly defined as a ratio of a volume (not value) measure of output to a volume measure of input use [42], while TFP accounts for impacts on total output that are not explained by the (measured) inputs, as discussed in section 2 below.

The analysis in this paper indicates that lower material intensity is positively associated with higher total factor productivity, both across the U.S. subsectors and across the South Korean firms. In other words, firms and industries that employ modes of production that use more labour and fewer material inputs appear to have overall higher total factor productivity. If a causal relationship were to be established between material intensity and productivity within a sector, which is left for further research, it would follow that annual improvements in material efficiency would increase economic growth rates, and at the same time attenuate resource pressures. Even if no causal relationship exists, the results in this paper suggest that policies which encourage the growth of less material-intensive sectors will lead to increases in average productivity. Policies to promote material efficiency (or more general reductions in material intensity) should thus be explored, given the potential microeconomic and macroeconomic benefits. In particular, the results in this paper provide support for considering policies to reduce labour taxation and to increase taxes on natural resources.

The paper proceeds as follows. Section 2 sets out the theoretical economics of material efficiency, reviewing research that has employed production functions incorporating 'materials', and exploring the relationship with productivity and economic growth. This section also provides the theoretical basis for the empirical part of the paper, presented in section 3. Section 3 describes the data, methodology and results of our analysis of U.S. manufacturing subsectors and South Korean firms. Section 4 explores the policy implications of our analysis and section 5 concludes.

2. The theoretical economics of material efficiency

Material efficiency is often defined as the provision of more goods and services with fewer materials [2], although it should be emphasised that the definition of materials within the engineering literature is usually narrower than in economics, focusing on physical natural resources, such as steel, rather than all intermediate inputs. Conditional on input factor prices, material use per unit of output will be lower in sectors or firms where the output elasticity of materials is lower. Within economics, material efficiency is rarely examined; the most closely-related research examines natural resources as a broad theoretical concept [23; 30; 50; 52] or focuses specifically on energy. In this paper, we define a material-intensive sector as being

cent of expenditures on inputs, and that this is in turn comprised of, on average, around 3 per cent energy inputs, 14 per cent services and 44 per cent physical intermediate inputs.

one in which the cost share of materials in total cost is relatively high; using a Cobb-Douglas production function, this is equivalent to the output elasticity of materials being high.

This section reviews the relevant economic literature. Subsection (a) examines attempts to incorporate materials in economic production functions, subsection (b) sets out the theoretical links between material use and TFP, and subsection (c) establishes the basis for the empirical section of the paper.

(*a*) *Materials in the production function*

Materials have occasionally been included in economic growth models exploring the sustainability of economic growth. For instance, theory indicates that sustainable growth is possible, even with exhaustible natural resources, provided that other human-made capital and other replacement resources substitute for depleted resources [50]. Technological advances and capital accumulation are also able to offset declining natural resources, provided the rate of technological advance is high enough [52].† Empirically, however, it appears that current investments in human and manufactured capital by several countries are insufficient to offset the depletion of natural capital [3].

The increases in energy prices in the 1970s stimulated much research into energy consumption and its relationship with gross output [14; 48]. This led to an interest in directly accounting for so-called 'intermediate inputs' — energy goods, materials, and services — in the production function. Since then, many studies have estimated KLEM (capital, labor, energy, and materials) and KLEMS (capital, labor, energy, materials, and services) production functions, for data as early as 1947 [12].‡ These various research efforts provide a useful starting point for this paper. However, this area of research does not extend to examining material intensity and its relationship with productivity.

(*b*) *Total factor productivity*

Productivity has a number of definitions in different contexts. It is typically measured in national accounts as the ratio of outputs, measured by mass or volume (not value), to inputs, measured by mass or volume [42]. In the economic growth literature, productivity has been defined in a number of ways, including as value-added per worker and as the constant term in the production function (loosely, that part of output which cannot be explained after accounting for the application of defined inputs including capital and labour). Measures of productivity were initially developed as part of early research into economic growth [49; 53]. TFP is not directly measured, but emerges as the residual in the regression of total output on measured inputs. So, for instance, if important inputs are omitted, measured TFP

† The specific requirement is that the rate of technical change divided by the discount rate is greater than the output elasticity of resources [52].

‡ It is long been argued that energy is an additional and significant input in the production function, that cannot simply be substituted for by other inputs [18; 21; 22; 30; 51]. Ayres argues that 'exergy services' — energy inputs multiplied by an overall conversion efficiency — are a key driver of economic growth, and that incorporating exergy as a factor of production increases the explanatory power of traditional production functions [4–6]. This literature is relevant here, as it demonstrates that omitting relevant inputs reduces the value of aggregate production functions.

may be biased upwards. Measures of TFP from the economic growth literature were subsequently used as the basis for analysis of productivity growth across firms, industries, and countries [17; 38–40]. Early studies tended to estimate TFP by representing the production process using a value-added function [10], in which 'value added', V, is related to gross output, Y, and intermediate inputs, M, as:

$$V = Y - M \tag{2.1}$$

A value-added estimation approach is commonly employed to determine productivity, because of a lack of data available to base the analysis on gross output. However, the value-added approach has several limitations [42]. It does not take into account inputs other than capital and labor, and therefore neglects all intermediate inputs. It therefore assumes that technical change only operates on capital and labor inputs and that all other inputs are used in fixed proportions. Generally, the hypothesis that technology affects only primary inputs has not held up to empirical verification, and technical change has been observed to be a complex factor, with some changes affecting all factors of production simultaneously, while other types of change affect individual factors of production separately [27]. Furthermore, the value-added approach does not correspond directly to a specific model of production [15]. When data allow, the gross-output approach is likely to be preferred [9].

The relationship between TFP and 'technology choice' (represented formally by the coefficients of the production function; that is, the choice of the mix of labour, capital, material and energy inputs) has not, to our knowledge, been explored in the literature. Yet understanding if there is a relationship between the input intensity of different production techniques and total productivity is surely important. This paper attempts to conduct such an analysis using empirical methods, examining the relationship between TFP and the material intensity of production, as measured by the output elasticity of material inputs. The next section explains our methodological strategy.

(*c*) *Theoretical basis for the empirical analysis*

We define the gross-output and the value-added production functions and set out explicitly the measure of productivity adopted. Let Y represent real gross output, K be the value of the real capital stock, L a measure of real labour input, M the real value of intermediate inputs (what is referred to in this paper as material inputs).† Let t and i be indices representing time and individuals (such as firms, sectors or countries) respectively. Taking the Cobb-Douglas functional form [19] as a first-order logarithmic Taylor series approximation of the production function, the value-added specification is given by:

$$\ln V_{it} = \ln a_{it} + b_{K_i} \ln K_{it} + b_{L_i} \ln L_{it}, \tag{2.2}$$

$$V_{it} = Y_{it} - M_{it}. \tag{2.3}$$

† It would be ideal to further disaggregate intermediate inputs, in particular to separate out purchased services and account for the impact of different rates of outsourcing between sectors. Some data sets include sub-categories of intermediate inputs, but did not have sufficient observations for our analysis. We proceed with the analysis based upon the intermediate inputs aggregate, however, because services, the component least related to physical raw materials, represents less than one quarter of the intermediate inputs on average in US manufacturing.

The gross output specification is given by:

$$\ln Y_{it} = \alpha_{it} + \beta_{K_i} \ln K_{it} + \beta_{L_i} \ln L_{it} + \beta_{M_i} \ln M_{it}. \tag{2.4}$$

The production function is said to have constant returns to scale if $\beta_K + \beta_L + \beta_M = 1$; this is equivalent to the function being linearly homogenous. When this condition holds there is a proportionate relationship between inputs and output; for example, if an industry has 10 per cent more of each input it will produce 10 per cent more output. If the sum of the coefficients is less than (greater than) unity, the industry is said to have decreasing (increasing) returns to scale and the industry would consequently be more profitable by becoming smaller (larger). Constant returns to scale are sometimes imposed when sectoral or economy-wide production functions are estimated for two reasons: firstly, economic theory suggests that this condition should hold where markets are competitive and, secondly, the estimated output elasticity of capital is often insignificant or even negative in the absence of the constant returns assumption. The null hypothesis of constant returns to scale is rejected in some, but not all, of the sectors we consider. Results are presented both with and without this restriction, and the findings of the paper hold in either case.

The estimates β in the logarithmic specification of equation 2.4 are equivalent to the output elasticity of each input; for example, the material coefficient can be interpreted as saying that a one per cent increase in the amount of material inputs will increase output by β_M per cent. Note that there is a distinction between the material intensity of production, as defined by the coefficients of the production function, and the physical volume of materials which a firm or sector uses. The production function determines the output which would be expected to be generated from a certain set of inputs; but the exact choice of factor ratios will be determined by the reactions of a profit-maximising firm subject to the fixed constraints of factor prices and the production function. The ratio of materials to other inputs (e.g. materials per worker) will vary with factor prices even if the production function is fixed (i.e. lower prices will mean more material use but not a different material intensity using our measure).

The value-added production function is valid if materials are separable from other inputs, there is perfect competition, no changes in the rate of outsourcing and homogeneous technology. Biases from value-added production functions can arise if any of these conditions is not met, which is why employing the gross-output production function to derive econometric estimates of total factor productivity is preferred for our analysis. Furthermore, we show that there is a systematic divergence between measures of total factor productivity based upon the gross output and value-added production functions, and that the size of this divergence is a function of the material intensity of production. Value added is an important concept not only because it is the dominant specification for accounting for cross- and within-country income differences, but also because it forms the analytical underpinning for national accounting of GDP. Value-added measures also capture the extent to which an industry generates national income (rather than output). It is therefore of great interest to understand the nature and extent of any impact on productivity measurements from the exclusion of material inputs.

Consider the bias if the true model is given by equation 2.4 but we estimate equation 2.2. The first order conditions for profit maximisation can be derived by taking the marginal product of each factor, i.e. the derivatives of the 3-factor gross output production function in equation 2.4, and setting these equal to factor prices and solving the three resulting simultaneous equations for the input quantities of K, L and M. Letting p_F represent the price of factor F and letting $A = e^{\alpha}$ we have:

$$M = \left[\frac{Y}{A} \left(\frac{p_K}{\beta_K} \right)^{\beta_K} \left(\frac{p_L}{\beta_L} \right)^{\beta_L} \left(\frac{\beta_M}{p_M} \right)^{\beta_K + \beta_L} \right]^{1/(\beta_K + \beta_L + \beta_M)} . \tag{2.5}$$

Without loss of generality, we assume constant returns to scale for simplicity and write equation 2.5 as $M = \gamma \frac{Y}{A}$ (note that prices and the output elasticities are taken to be fixed so γ is a constant). In order to understand the bias in the coefficients in equation 2.2 we want to express the true model of production (firms physically produce gross output, e.g. tonnes of steel, rather than value-added which is rather an accounting construct derived from gross output) in a form that corresponds to the incorrect model and then compare coefficients. Repeated substitution of equation 2.4 into equation 2.2, using equations 2.3 and 2.5, and suppressing subscripts for notational clarity, gives:

$$\begin{aligned} \ln V &= \ln Y + \ln(1 - \frac{M}{Y}) \qquad (2.6) \\ &= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M \ln M + \ln(1 - \frac{\gamma}{A}) \\ &= \ln A + \beta_K \ln K + \beta_L \ln L + \beta_M [\ln Y - \ln A + \ln \gamma] + \ln(1 - \frac{\gamma}{A}) \\ &= \ln A + \frac{\beta_M}{1 - \beta_M} \ln \gamma + \ln(1 - \frac{\gamma}{A}) + \frac{\beta_K}{1 - \beta_M} \ln K + \frac{\beta_L}{1 - \beta_M} \ln L. \end{aligned}$$

In our 3-factor model with constant returns to scale, the bias in the value-added coefficients is therefore:

$$\ln a = \ln A + \frac{\beta_M}{1 - \beta_M} \ln \gamma + \ln(1 - \frac{\gamma}{A}), \; b_K = \frac{\beta_K}{\beta_K + \beta_L}, \; b_L = \frac{\beta_L}{\beta_K + \beta_L}. \tag{2.7}$$

Equation 2.7 shows that estimates of TFP from a value-added production function will be biased estimates of gross output total factor productivity and the size of this bias will be increasing in β_M. While value-added is a useful summary statistic for discussing the distribution of income, its omission of materials and the resultant bias in measures of TFP means that underlying productivity from a production perspective is better measured using the gross-output production function.

In the empirical work which follows in section 3, we investigate the observed pattern between underlying productivity and material intensity using the gross-output specification.

3. Empirical analysis

In this section we investigate the hypothesis that a higher material intensity is associated with lower underlying TFP and, furthermore, show that estimates of value-added total factor productivity are indeed biased in the manner derived in equation 2.7.

NAICS code	Sector description
311	Food Manufacturing
312	Beverage and Tobacco Product Manufacturing
313	Textile Mills
314	Textile Product Mills
315	Apparel Manufacturing
316	Leather and Allied Product Manufacturing
321	Wood Products
322	Paper Products
323	Printing and Related Support Activities
324	Petroleum and Coal Products
325	Chemical Products
326	Plastics and Rubber Products
327	Non-metallic Mineral Products
331	Primary Metal Products
332	Fabricated Metal Products
333	Machinery
335	Electrical Equipment, Appliances and Components
336	Transportation Equipment
337	Furniture and Related Products
339	Miscellaneous Manufacturing

Table 1. *NAICS industry definitions.*

(*a*) *Data*

We investigate our hypothesis using the NBER-CES manufacturing industry database, and full details of variable definitions and database construction are available from the website of the NBER [11]. The dataset is a panel of 473 manufacturing industries defined to the six-digit level (based upon NAICS codes) from 1958 to 2005. The data are unbalanced in that some industries enter or leave manufacturing due to a change in the industry coding structure in 1996, but all data have been coded so that they are consistent with the current sectoral definitions.

The dataset contains annual industry level data on employment and hours, nominal value of shipments, value-added, capital stock and material inputs, along with price indices for sales, capital stock, and material inputs. Firm output is constructed as the value of shipments plus the change in inventories using the price index for shipments to deflate into real values. Hours worked are calculated by multiplying total employment by the average hours worked by production workers: the hours of non-production workers are not available and so we assume that non-production workers in a sector put in the same number of hours as production workers. Real value-added is calculated by using the price indices for shipments and materials, with the price index for shipments being used as a deflator for inventories. Two NAICS industries — 334111 (computers) and 334413 (semiconductors) — are excluded from the analysis due to difficulties in constructing accurate price deflators. We do not have data on human capital, such as average education of workers, at the subsectoral level but, in the context of models with heterogenous technology, human capital can be controlled for by the inclusion of intercept and time trend terms under plausible conditions [26].

(*b*) *Specification of material intensity and parameter heterogeneity*

In this analysis, 'technology' is used to refer to the set of coefficients $\beta_K, \beta_L, \beta_M$, while TFP is defined as the constant term α, and is allowed to vary over time and across sectors through the inclusion of binary dummy variables. The least restrictive assumption we could make on technology in this context would be to allow each six-digit industry to have its own set of production function coefficients, possibly varying over time. However, this would have the disadvantage of reducing the sample size available for each estimated production function, would not allow for the exploitation of the panel dimension of the dataset and, most importantly, would not allow unrestricted TFP evolution as there would be insufficient observations to include year dummies. We therefore allow for technological heterogeneity at the three-digit level (i.e. the industries defined in Table 1), and assume that every six-digit subsector of a three-digit industry has common technology. Technology is also held to be fixed within a three-digit industry over time.† This is, of course, more restrictive than allowing technology to differ by six-digit subsector, but less restrictive than estimating a production function at the level of aggregate manufacturing or of the aggregate economy. It has recently been argued that the focus in the literature on cross-country and cross-sectoral production functions on matters of endogeneity and specification has neglected the important possible role of parameter heterogeneity [26]. This paper presents evidence that one critical element of this heterogeneity is in the role of material inputs in production.

If prices of inputs and technology are taken to be exogenous and there is perfect competition and constant returns to scale then the first-order conditions of profit maximisation in equation 2.4 imply that the share of material inputs in total cost will be equal to β_M, and an augmented condition holds if the restrictions do not apply. While only the exogeneity restrictions are imposed in our modelling, we use this result as a motivation for our empirical definition of material intensity: a sector is said to be more material-intensive if the coefficient β_M is higher, and this paper aims to investigate the relationship between total factor productivity and material intensity by estimating production functions for different subsectors of US manufacturing.†

(*c*) *Estimation strategy*

We employ econometric methods to estimates the parameters of an aggregate production function and express productivity in terms of the estimated parameters. Among various approaches, the primary method used to estimate TFP has been the growth accounting method [27; 36]. The growth accounting approach is a non-parametric technique that weights different types or qualities of factors by income shares [33; 41]. While the growth accounting approach has been the generally preferred standard approach due to its less stringent data requirements, it requires five key assumptions to hold in order to be valid. Firstly, it assumes a sta-

† This, along with the inclusion of time dummies, means that secular trends in productivity and the share of materials are not the cause of our results; rather, they are driven by the cross-section variation between sectors.

† Equation 2.4 shows why material per unit of output is not an appropriate measure to investigate our hypotheses, as an increase in TFP (i.e. α) will trivially decrease material per unit of output.

ble relationship between inputs and outputs at various levels of the economy, with marginal products that are measurable by observed factor prices [8]. Secondly, the production function used must exhibit constant returns to scale [41]. Thirdly, the approach assumes that producers behave efficiently, minimizing costs and maximizing profits [41]. The approach also requires perfectly competitive markets within which participants are price takers who can only adjust quantities [41]. Lastly, a particular form of technical change must be assumed. The econometric method does not require these a priori assumptions of the growth accounting method, and rather, enables the testing of these assumptions [13].

Equations 2.2 and 2.4 are estimated in this paper using a range of econometric techniques. The literature on estimating production functions, particularly in the context of panel data with a long time series dimension is rapidly evolving. One of the key difficulties in this literature has been finding a specification and an estimation method which achieve both economic and econometric regularity [27]. A recent survey of the state of production function estimation is given by [26], and we direct readers there to obtain a full discussion of the different estimation techniques available and the conditions required for each of them to produce unbiased and efficient estimates of the true underlying parameters.

We employ four different econometric techniques: ordinary least squares (OLS), the standard panel data fixed effects estimator (FE), the mean groups estimator (MG) [45] and the common correlated effects mean group estimator (CCEMG) [44]. These latter two estimators allow for more general forms of cross-section and time series dependence, as well as forms of heterogeneity in the error structure. Briefly, the OLS estimator will be valid if statistical error for each observation is independently and normally distributed. A fixed effects estimator relaxes this assumption by allowing for common time-invariant factors within a subsector. The mean groups estimator will yield consistent estimates so long as there is not heterogeneity in unobserved variables and errors are stationary. The CCEMG estimator allow for heterogeneity in the unobservables and allows for cross-section dependence resulting from unobserved factors common between sectors (e.g. common shocks affecting more than one subsector). These issues would require a fuller treatment in order to precisely identify the production function parameters and to make possible statements about a causal impact of material intensity on total factor productivity, and so that claim is not made in this paper. Rather, we seek to demonstrate that material intensity is related to total factor productivity and that the relationship is robust to a number of different econometric approaches.

The key results of this paper — that sectors with higher material intensity tend to have lower levels of TFP and that value-added estimates of TFP have a bias which is increasing in material intensity — are robust to these choices of estimation technique. We present the results from all four estimation methods graphically, in each case with and without the constant returns to scale restriction. For the sake of brevity, only the OLS results are presented in table form in the main body of the paper, but the results from the other estimators in table form are available from the authors upon request.

(*d*) *Results and Discussion*

The results from the OLS regression for each of the twenty industries considered are presented in table 2. The production function coefficients are generally plausible: the coefficients on labour and materials are all positive, as are the majority of those on capital. Due to difficulties in the valuation of capital stock it is not uncommon for some estimates of β_K to be negative or poorly identified, and constant returns to scale are often imposed to achieve regularity given that the condition should be satisfied in an industry in equilibrium.† For example, Burnside [16] concludes that constant returns to scale is probably an appropriate restriction for US sectoral-level production functions. Both the restricted and unrestricted results are presented here, and the conclusions follow regardless.

While our primary interest is in the pattern between the sets of coefficients α, β_K, β_L and β_M, we first describe their absolute estimates to give a feel for the results. The highest material intensity (as measured by β_M) is observed in the apparel (315) and leather (316) sectors, where materials account for around 90 per cent of total inputs; the lowest is found in electrical equipment (335) and furniture (337) manufacturing, where the share is under 50 per cent. Total factor productivity, defined relative to that in the food manufacturing sector (311), is highest in fabricated metal products (332) and machinery (333) and lowest in leather products (316) and plastics and rubber (326).

The relationship between the material intensity of an industry and its total factor productivity is shown in figure 1. There is a clear relationship in the pattern of coefficients across industries: those sectors with a higher material intensity tend to have lower total factor productivity. This pattern is repeated for the fixed effects estimator, shown in figure 2, and the MG and CCEMG estimators, shown in figure 3.

The β coefficients of the production function sum to a quantity close to unity for all industries where the estimation is unrestricted. Therefore, a negative pattern between β_M and TFP implies that there is likely a positive pattern between TFP and at least one of the other coefficients. Figure 4 depicts the observed pattern between the labour output elasticity and TFP using the results from table 2. There is a strong positive relationship: sectors which are more intensive in their use of labour inputs tend to have higher TFP. There is no clear pattern in relation to capital intensity, not shown for brevity. The fact that labour-intensive sectors have higher TFP and material-intensive sectors have lower TFP is reminiscent of the 'double dividend' hypothesis that replacing labour taxes with environmental taxes might reduce the costs imposed by the tax system [31].

Because TFP is, by its very nature, capturing unobserved elements of the production process, it is not possible to infer from this analysis the precise nature of the relationship between the two. It may be the case that reducing material intensity causes changes in unobserved factors which lead to increase TFP directly, or it may be that changes in an associated unobservable factor result both in a lower share of materials and higher TFP. In the former case policies to reduce materials intensity would have a direct TFP benefit; in the latter case it would depend upon

† Recall that because α is defined as the constant term in a logarithmic equation, negative values simply refer to levels of TFP of between zero and one and are not cause for concern.

NAICS code	α (TFP)	β_K	β_L	β_M	α (CRS)	β_K(CRS)	β_M(CRS)
311		0.22*	0.23*	0.53*		0.14*	0.62*
		0.01	0.01	0.01		0.01	0.01
312	0.28*	-0.05*	0.13*	0.83*	0.00	0.09*	0.71*
	(0.09)	(-0.02)	(0.02)	(0.02)	(0.06)	(0.02)	(0.01)
313	-0.51*	0.18*	0.16*	0.62*	-0.34*	0.18*	0.58*
	(-0.09)	(0.03)	(0.02)	(0.03)	(-0.06)	(0.03)	(0.03)
314	-0.19	-0.07*	0.17*	0.81*	0.15*	0.01	0.61*
	(-0.10)	(-0.03)	(0.03)	(0.04)	(0.07)	(0.03)	(0.04)
315	-0.58*	-0.01	0.05*	0.90*	-0.47*	-0.01	0.83*
	(-0.07)	(-0.01)	(0.01)	(0.01)	(-0.04)	(-0.01)	(0.01)
316	-1.19*	0.06*	0.08*	0.91*	-0.63*	0.01	0.88*
	(-0.12)	(0.03)	(0.03)	(0.04)	(-0.07)	(0.02)	(0.03)
321	-0.56*	-0.05*	0.29*	0.79*	-0.39*	-0.05*	0.83*
	(-0.09)	(-0.02)	(0.02)	(0.02)	(-0.07)	(-0.02)	(0.02)
322	-0.16*	0.12*	0.17*	0.66*	-0.10	0.07*	0.68*
	(-0.08)	(0.01)	(0.02)	(0.02)	(-0.06)	(0.01)	(0.02)
323[a]	0.28*	0.05*	0.37*	0.57*	0.51*	0.00	0.58*
	(0.06)	(0.02)	(0.02)	(0.02)	(0.06)	(0.02)	(0.02)
324[a]	-0.53*	0.08	0.15*	0.76*	-0.34*	0.01	0.81*
	(-0.09)	(0.05)	(0.05)	(0.06)	(-0.08)	(0.03)	(0.03)
325	-0.30*	0.03*	0.47*	0.64*	0.05	0.05*	0.70*
	(-0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
326[a]	-0.67*	0.02	0.16*	0.82*	-0.41*	0.07*	0.74*
	(-0.08)	(0.02)	(0.02)	(0.03)	(-0.07)	(0.02)	(0.03)
327[a]	-0.08	0.16*	0.27*	0.56*	-0.06	0.11*	0.64*
	(-0.07)	(0.02)	(0.02)	(0.02)	(-0.05)	(0.01)	(0.02)
331	0.09	0.01	0.31*	0.66*	0.15*	0.07*	0.62*
	(0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
332	0.59*	0.07*	0.39*	0.50*	0.60*	0.08*	0.47*
	(0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
333	0.32*	0.05*	0.43*	0.54*	0.58*	0.02	0.56*
	(0.06)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
335	0.17*	0.29*	0.44*	0.31*	0.43*	0.27*	0.35*
	(0.09)	(0.02)	(0.01)	(0.02)	(0.05)	(0.02)	(0.02)
336	-0.35*	0.00	0.42*	0.67*	0.09*	0.10*	0.62*
	(-0.05)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.01)
337	0.13	0.21*	0.30*	0.47*	0.09	0.05*	0.62*
	(0.10)	(0.02)	(0.02)	(0.04)	(0.08)	(0.02)	(0.04)
339	-0.56*	0.14*	0.28*	0.65*	0.18*	0.11*	0.58*
	(-0.07)	(0.01)	(0.02)	(0.02)	(0.05)	(0.01)	(0.02)

Table 2. *The dependent variable is log of real output in 1987 $US. Observations have been weighted according to employment in the sector. Constant returns to scale in K, L and M have been imposed in columns denoted (CRS), although the null hypothesis of CRS was rejected in all industries other than those denoted with an a. Note that in the CRS estimates* $\beta_K + \beta_L + \beta_M = 1$ *and hence* β_L *is not reported. Year dummies were included but have not been reported. Standard errors in parenthesis and * indicates significance at* $p < 0.05$*. Industry 311 is the omitted category and so* α *in that industry is implicitly defined as zero. The null hypothesis of common technology across these industries is easily rejected. The* R^2 *of this regression is 0.9996 and the residual standard error is 1.05 on 20339 degrees of freedom.*

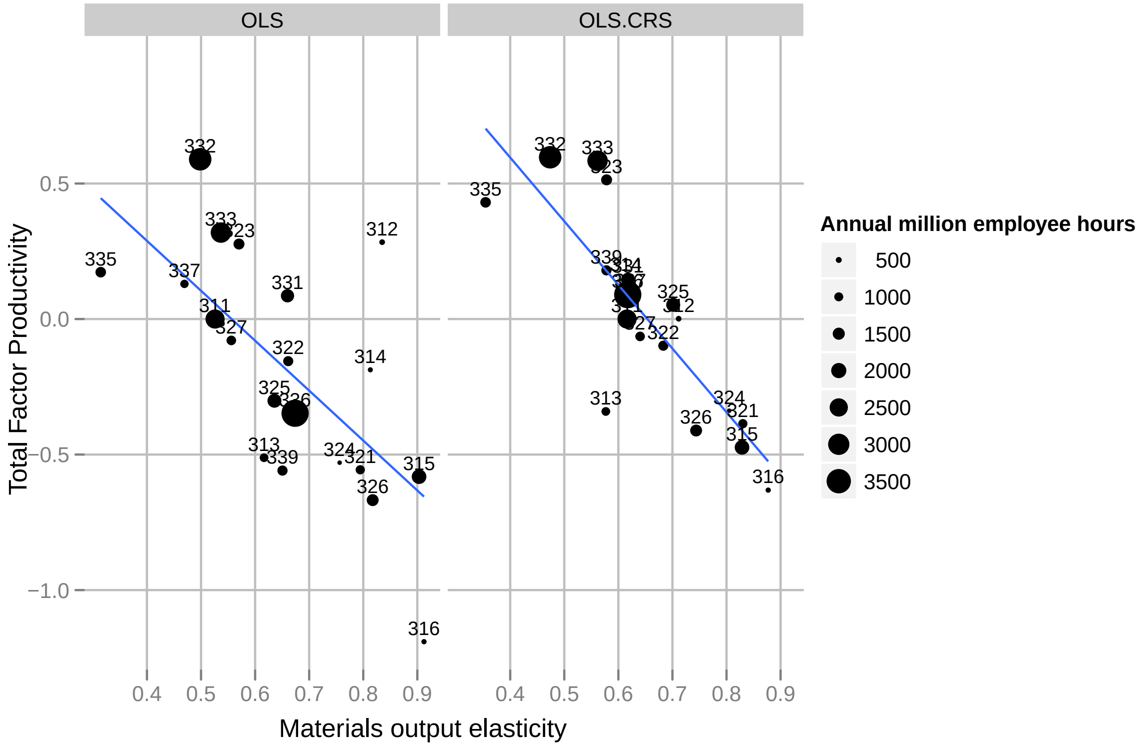

Figure 1. Material intensity and TFP in US manufacturing sectors estimated from an OLS production function. The line represents a simple employment-weighted OLS regression line for illustrative purposes only. The CRS suffix applies where constant returns to scale have been imposed.

whether the policy to reduce material intensity acted via the relevant unobservable factor.†

Some readers may be concerned that the relationship at the sectoral level is an artifact of the aggregation of firms, and that any variation can be solely accounted for by sectoral composition alone rather than by material intensity. Observing the same relationship at the firm level would go some way to assuaging this fear. Figure 5 presents some indicative evidence at the firm level that this relationship between material intensity and total factor productivity is not purely a sectoral one. The data set used are a panel of 863 medium-sized manufacturing firms† from South

† This could be addressed by allowing the production function parameters to vary over time, but we do not have sufficient data to robustly estimate production functions for a single industry over time without imposing restrictions on the nature of technology evolution. The data requirements to do so are relatively strenuous as a large data set is required to generate an estimate of a production function which then provides only a single observation for the analysis of the TFP-technology nexus. One possible method would be to obtain a panel data set with a large number of firms from each of a number of industries each followed for a sufficiently long time dimension so that a production function could be estimated separately for a number of time periods and the evolution of material intensity and total factor productivity observed (of course, one would need to address the usual econometric issues such as endogeneity to establish a causal relationship even with such a data set).

† From the textile, garments, machinery, electronics and wood products sectors.

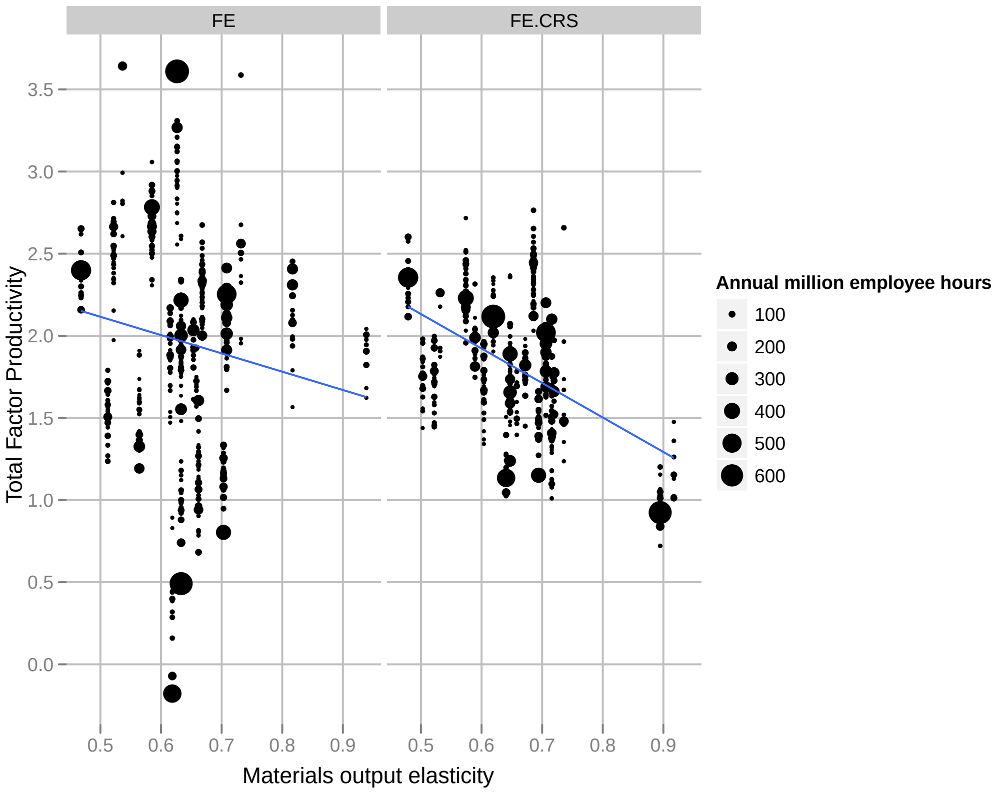

Figure 2. Material intensity and TFP in US manufacturing sectors estimated using the fixed effects estimator. The line represents a simple OLS regression line for illustrative purposes only. Note that all subsectors of each three-digit sector have the same material intensity coefficient by construction. The CRS suffix applies where constant returns to scale have been imposed.

Korea observed for three years from 1996 to 1998 from a survey conducted by the World Bank, see [32] for a full description of the data set (the ideal comparison, a panel of US firms from the sectors and years of the sectoral data was not accessible). Total factor productivity is calculated using a production function previously estimated using this data [7], and material intensity is calculated as material inputs per unit of labour input. Note that because a single production function was estimated for this dataset, that β_M is the same for all firms and so an alternative measure of factor intensity was required. Using material inputs per unit of output cannot be used as this may generate a spurious relationship: a hypothetical exogenous increase in total factor productivity would increase output per material input even if there was no change in the manner in which materials were used in the production process.

Finally, we return to the value-added specification and the hypothesis derived in equation 2.7 that value-added estimates of total factor productivity are biased estimates of underlying total factor productivity, and that the size of this bias is increasing in material intensity. Value-added TFP is calculated by estimating equation 2.2 using OLS with constant returns to scale imposed (because income

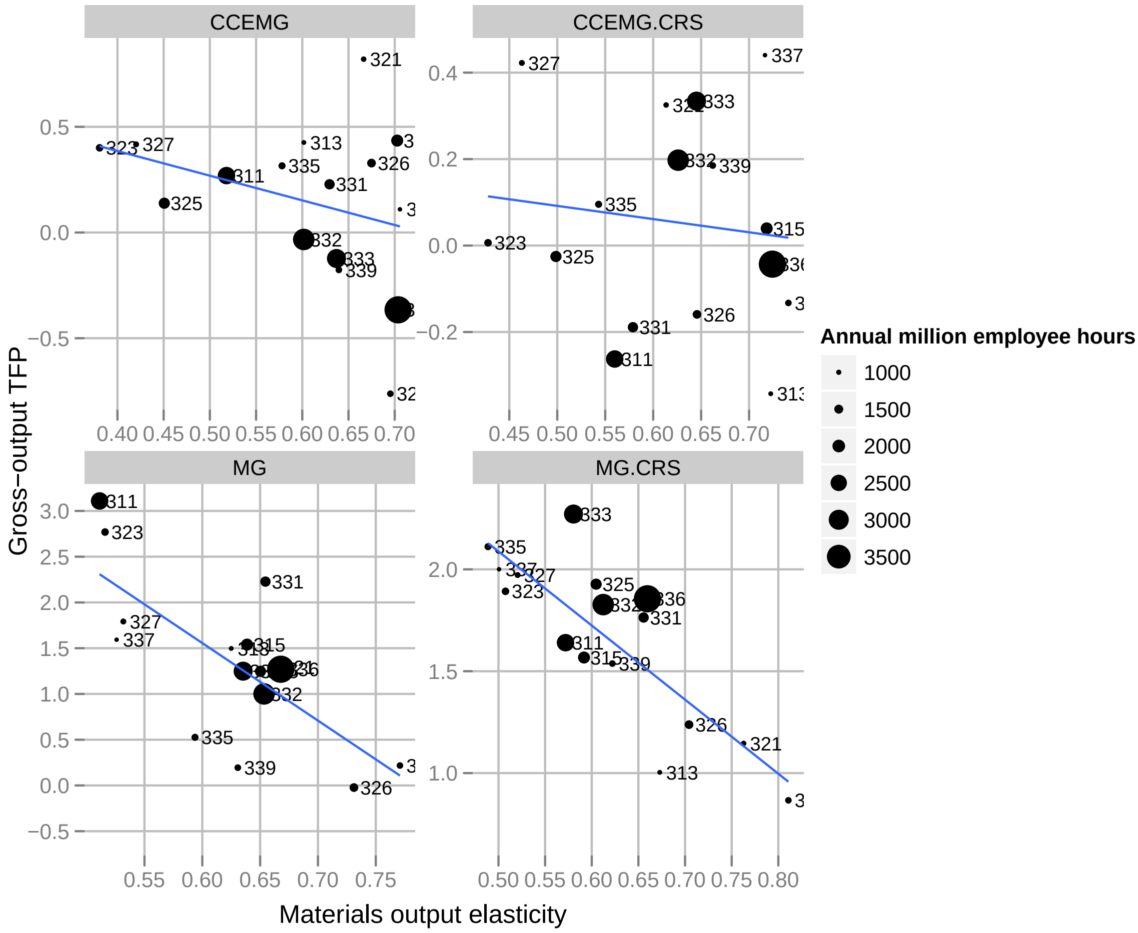

Figure 3. Material intensity and TFP in US manufacturing sectors estimated using the MG and CCEMG techniques. The line represents a simple OLS regression line for illustrative purposes only. Sectors with 10 or fewer groups have been excluded as these estimators perform poorly in such situations. The CRS suffix applies where constant returns to scale have been imposed.

shares must necessarily sum to one in the value-added framework). The relationship between value-added TFP, gross-output TFP and material intensity can then be obtained from a suitable regression. Table 3 presents the results from an OLS estimation with value-added TFP and the dependent variable and gross output total factor productivity α and material intensity β_M as independent variables. As predicted by equation 2.7 the coefficient on α is equal to one, and the coefficient on β_M is positive.

This empirical evidence backs up the theoretical conclusion that value-added measures of productivity — which account for almost all estimates of productivity based upon macroeconomic data — are biased upwards for material-intensive sectors. Under the form of productivity accounting used in the national accounts of most countries, sectors which are more material-intensive are counted as having

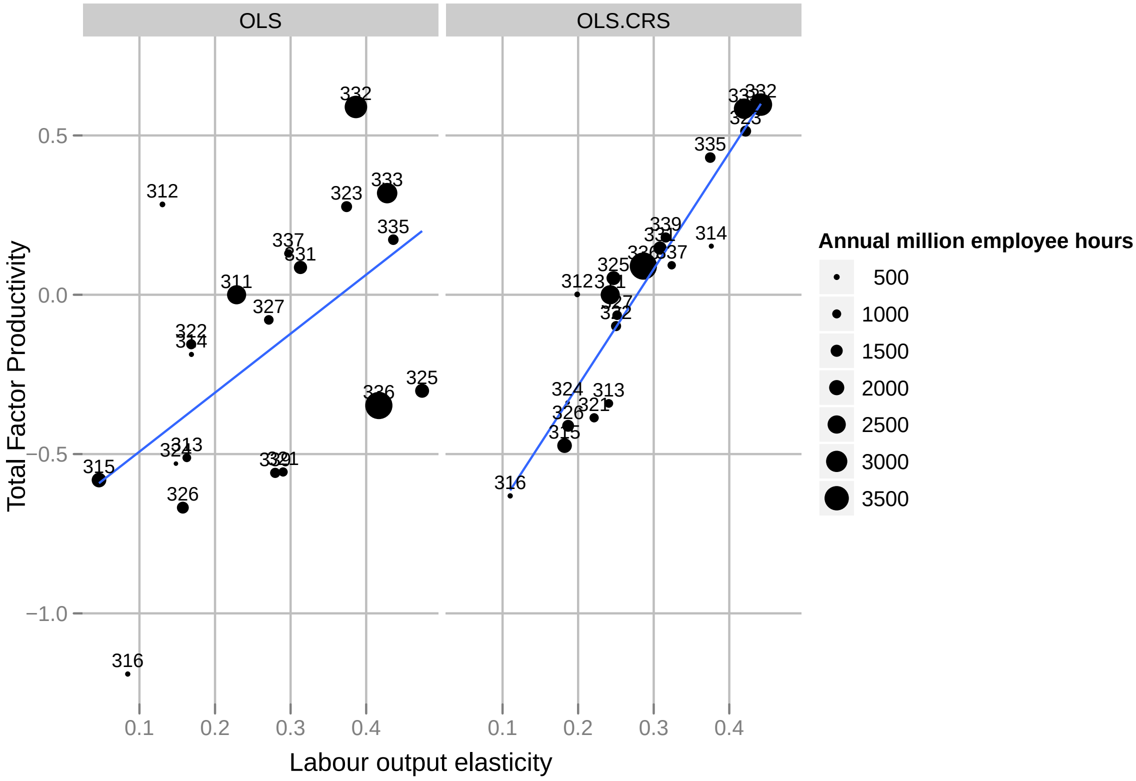

Figure 4. Labour intensity and TFP in US manufacturing sectors estimated from an OLS production function. The line represents a simple employment-weighted OLS regression line for illustrative purposes only.

systematically higher TFP than they should do in practice. This has implications for the measurement of wealth and suggests that the share of material-intensive sectors in the economy may be sub-optimal.

4. Policy implications

Some of the policy implications from our empirical results depend upon the conceptual basis for the relationship discovered between material intensity and TFP; that is, the precise nature of the unobserved factors driving TFF which are associated with material intensity. While we do not test them here, we find at least two possibilities plausible. First, because TFP captures all unobservables, if there are more positive spillovers from one factor of production than others, a higher intensity in that factor of production will be associated with higher TFP. For instance, it may be that there are positive externalities from human capital accumulation in the workforce [1]. This would explain why TFP is higher in industries that are more labour-intense. If capital also provides some degree of positive externalities, then it would follow that material-intensive industries, with a lower cost share of capital and labour, will be associated with lower TFP. Whether policies to reduce material

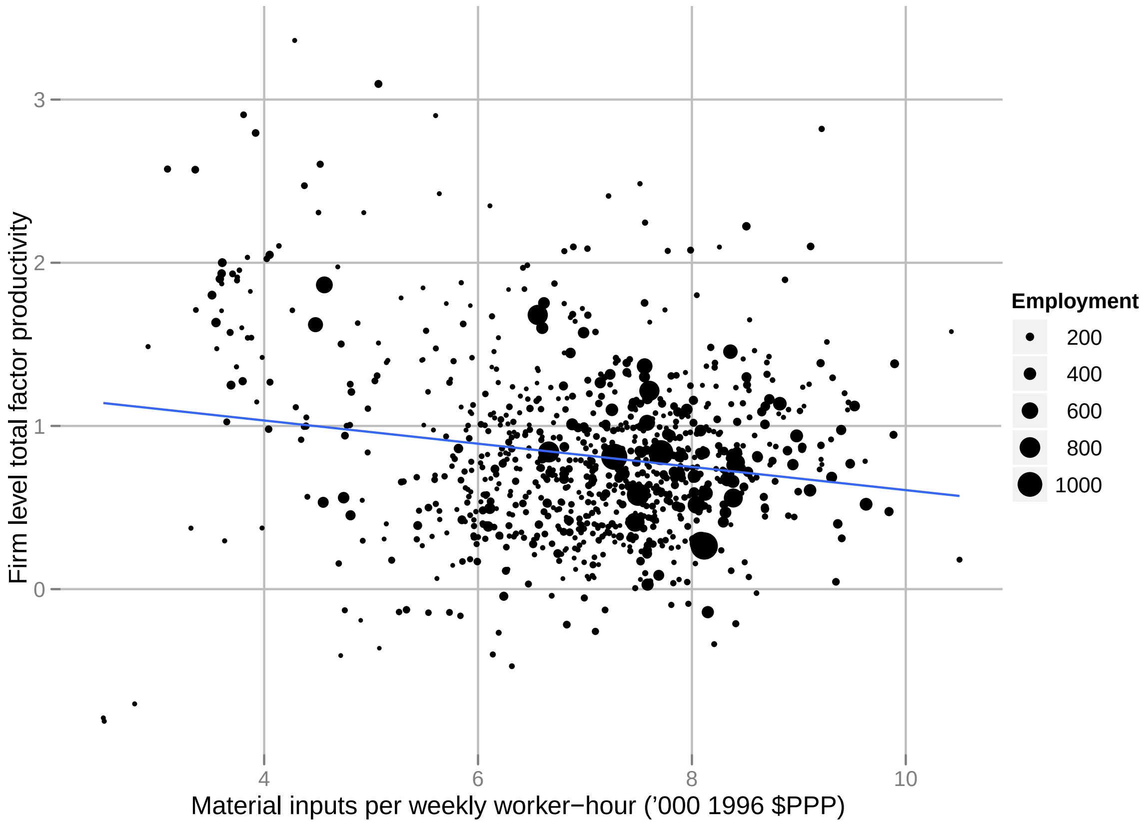

Figure 5. Material input per worker and TFP in South Korean manufacturing firms based upon a production function estimated using system GMM. The line represents a simple employment-weighted OLS regression line for illustrative purposes only.

	OLS
(Intercept)	-0.41
	(0.88)
Gross output TFP	1.00
	(0.51)
β_M	3.47*
	(1.41)
N	20
R^2	0.27
adj. R^2	0.18
Resid. sd	0.72

Table 3. *The dependent variable is value-added TFP. Standard errors in parenthesis and * indicates significance at* $p < 0.05$.

use directly would themselves lead to increased TFP would depend upon the nature of the externalities. Second, by analogy to Porter & van der Linde [46], it may be that firms that search for ways of lowering their material intensity also have with higher TFP, either because the quest for innovation on material use creates other opportunities that are captured by the firms or, perhaps more likely, firms that are well-managed are able to both reduce their material intensity and also deliver greater TFP as a result of superior management practices.

The broad observation that reduced material intensity is associated with higher TFP potentially points towards three major policy implications.

First, irrespective of causality underpinning our results, it seems likely that productivity could be improved, and environmental and resource pressure reduced, by a reduction in the subsidies spent annually on materials and resource use. Such subsidies provide incentives for firms to increase material intensity which, as we have seen, is associated with lower TFP. Perhaps US $1 trillion is spent every year on directly subsidizing the consumption of resources [25]. This includes subsidies of approximately $400 billion on energy [34], around $2-300 billion of equivalent support on agriculture [43], approximately US $200-300 on water [25], and approximately US $15-35 billion on fisheries [55]. To take one particularly perverse example, subsidies worth 0.5% of EU GDP are spent annually on providing tax relief for company cars, which increases greenhouse gas emissions by between 4-8% [20].

While these direct subsidies are vast, they pale in comparison with the indirect subsidies in the form of natural assets that governments have failed to properly price. There is another US $1 trillion, very approximately, in the form of subsidy for the use of the atmosphere as a sink for greenhouse gas emissions [25]. The indirect subsidy associated with lack of payments for biodiversity loss and other environmental costs is estimated at perhaps as much as $6.6 trillion [54].† By comparison, global GDP is around US $60 trillion at 2010 prices. Various countries, including Norway, Brazil and Australia have imposed explicit resource taxes, but taxes in one area do not undo the problems created by subsidies in another.

Second, productivity might be increased by other policies focussed on reducing material intensity, beyond reducing perverse subsidies. One obvious example of this would be shifting the tax base away from labour, the factor input that correlates with higher TFP, and towards resources, the factor correlated with lower TFP. This is true regardless of whether the results in this paper are driven by sectoral composition effects, or whether the relevant unobservables are directly related to material use within sectors. Taxing environmental externalities is obviously economically rational, as is taxing mineral rents [28] irrespective of other considerations. For instance, in contrast to the very substantial tax rates on labour, only a very small proportion of tax revenues are raised globally from taxation of resource use. For instance, only 6% of public budgets are raised from environmental taxes in the European Union. It is not impossible for this figure to be increased: the corresponding figure is roughly 10% in Denmark.

Third, our results suggest that value-added measures of productivity, as commonly embodied in national accounting frameworks, may overstate the underlying productivity of material-intensive sectors. As data from national accounts inform

† This estimate should be viewed with high methodological scepticism and are vast underestimates of infinity. Nevertheless, it can be taken as an indication that the scale of the 'subsidy' is extremely large.

economic policy, it is possible that this bias has led to policies which have sub-optimally increased the size of material-intensive sectors in the economy. National accounts should also endeavor to measure gross output and material use as well as value-added. If possible, material use should be further decomposed to separate energy and services from other natural resources.

5. Conclusion

This paper investigated the relationship between material intensity and economic productivity. This was achieved through the estimation of value-added and gross output production functions for US industrial subsectors allowing for subsectoral heterogeneity in both of the key variables of interest: total factor productivity and material intensity.

There are three key results from our empirical analysis. First, there is a negative relationship between material intensity and total factor productivity in the data examined. Second, there is a positive relationship between labour intensity and total factor productivity. Those sectors which are more intensive in their use of humans, rather than raw materials, have higher levels of total factor productivity, which means that a greater level of output is achieved from any given level of inputs. Firm-level evidence indicates that this relationship may not just be a result of sectoral composition. However, the determination of a causal impact within a sector of a reduction in material intensity increasing total factor productivity is left to future research. Third, value-added measures of productivity, inherent in the national accounts of almost all countries, systematically overstate the productivity of material-intensive sectors. Changing national accounting frameworks to include material inputs, and improving the scope and quality of their measurement, should be a priority if natural resources are to be used efficiently and productivity maximised.

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