IT Productivity and Aggregation using Income Accounting

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Introduction We examine the relationship between the Cobb-Douglas production function that is frequently used in information technology (IT) productivity studies and the income accounting identity. In doing so we evaluate the impact of this relationship on the question about aggregation from firm-level data to industry-level data when estimating IT productivity, that is, whether industry-level estimates are meaningful. In addition we examine whether the income accounting identity can help explain elements of total factor productivity (TFP) – information that is not contained in the output elasticities of the inputs after estimating a production function.

Aggregation The issue of aggregation has been studied for more than a half century in economics, and it has focused on whether macro-level production functions such as those at the economy or sector-level represent the aggregation of micro-level decisions such as those made by a manager or entrepreneur. The initial goal was to specify conditions under which aggregation was internally consistent – that is, whether mathematical forms of production functions at the firm or product-level could be aggregated into a parsimonious and interpretable production function such as a Cobb-Douglas at the economy or sector-level.

There are two levels of aggregation problems. The first is at the level of inputs and whether we can aggregate different kinds of inputs into a single input measure – for example, aggregating lathes and extrusion machines together into a common capital input. Leontief (1947a, 1947b) dealt with aggregation of variables into homogenous groups and showed that if the marginal rate of substitution (MRS) of the individual inputs in the aggregated group of inputs is independent of inputs that are not in that group, then it is possible to aggregate that group of inputs. For example, different kinds of capital can be aggregated into a single input if the MRS of the different kinds of capital is independent of labor. This condition is strong and implies pairwise independence of the substitution possibilities of all groups of inputs. However, if the underlying production function for a firm has a Cobb-Douglas form, then because the Cobb-Douglas satisfies these independence conditions between all pairs of IT capital, non-IT capital, and labor, then we can aggregate within input groups.

The second is whether a sector or economy-level production function can be aggregated from a set of firms, each having potentially different production functions. Nataf (1948) proved that such an aggregation is valid if the individual firm production functions are *additively separable in inputs*. This condition holds for the log-linear Cobb-Douglas form. Nonetheless, some argue additive separability is a highly restrictive condition unlikely to be true across the economy. Fisher (1971) conducted simulation studies of aggregation of firm level data, and estimated aggregate production functions. He concluded that the requirements "*. . . under which the production possibilities of a technically diverse economy can be represented by an aggregate production function are far too stringent to be believable*

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(p306)."

Even though the aggregation conditions limit the choice of production functions to those that are related to the Cobb-Douglas, there is evidence that the Cobb-Douglas form is empirically robust. Gurbaxani, Melville and Kraemer (2000) found that a Cobb-Douglas used to predict IT spending as a function of personnel and hardware was independent of scale and time, meaning that a similar form with similar input proportions holds for different size firms across time. This homotheticity of IT spending supports the aggregation of hardware and of personnel each into single measures. Van Garderen, Lee and Pesaran (2003) found that least squares estimates of some aggregated of log-linear models like the Cobb-Douglas can yield consistent estimates of the output elasticities with some restrictions on the distribution of aggregate shocks. Indeed, they suggest that the Cobb-Douglas provides a very reasonable representation of output movements, regardless of level. This is consistent with other research that suggests that the basic requirements for sensible aggregation may be met for firms in the same industry or for narrow sectors of the economy (Walters, 1963).

TFP As TFP represents the (unspecified) ways that inputs combine to produce output outside of the mathematical representation of the inputs in the production function, the result of aggregation of these effects from, say, firm-level to industry-level make it hard to interpret what level of effects are contained in TFP. Isolating the role of IT in TFP is even more challenging.

Several studies have used variants of the Cobb-Douglas to explain the influence of IT on TFP. Hitt and Tambe (2006) examined within-industry productivity spillovers of IT from an industry knowledge pool. They used firm-level data from 1987-1993, where the spillovers modeled an element of TFP. They found significant within-industry IT spillovers, although lower than those previously estimated. Using industry-level data from 1987-1999, Cheng and Nault (2007) studied between-industry productivity spillovers of IT that occur from a mis-measurement of the value of intermediate inputs. Specifying a Cobb-Douglas that included the mis-measurement of intermediate inputs modeled as an element of TFP, they found significant IT spillovers from IT-induced quality improvements in intermediate inputs.

Brynjolffson and Hitt (2003) hypothesized the existence of unmeasured inputs such as organizational capital in making up TFP, and related this to growth in computer capital. Using firm-level data from 1987-1994 and Cobb-Douglas related forms, they found that the long-run contribution of computerization is significantly higher than short-run (annual) returns to computer capital, and thus computer capital together with unmeasured inputs in the long run contribute to TFP. Mittal and Nault (2009) modeled labor and non-IT capital as an exponential function of IT capital to capture indirect effects of IT on the productive efficiency of the other inputs. The exponential function allowed the indirect effects to be captured as an additional term in the Cobb-Douglas, hence directly explaining part of TFP. Using industry-level data from 1953-2000 they found that indirect effects of IT on the productive efficiency of labor and non-IT capital were significant across manufacturing in the U.S., and were more significant in IT-intensive industries.

Our Results We show that with a mild condition that is likely to hold in the medium term the income accounting identity can be expressed as a variant of the Cobb-Douglas production function. The income accounting identity is a true ex post relationship that holds at all levels of aggregation, which means that the Cobb-Douglas has an income accounting basis regardless of the level of aggregation. In addition, we find that the variant of the Cobb-

Douglas that is derived from the income accounting identity, which we call the AI-based Cobb-Douglas, has additional terms – terms that relate to average returns to each of the inputs. This means that TFP is in part explained by average returns to the inputs.

We then estimate the Cobb-Douglas and the AI-based Cobb-Douglas on a limited set of industry-level data. The set of data is limited because of the additional terms requiring average returns, and the U.S. data sources only maintain data required to compute these returns for a small set of industries. In the estimation we find that the Cobb-Douglas and the AI-based Cobb-Douglas fit the data very well, and the AI-based Cobb-Douglas estimates are closer to historical estimates for output elasticities of the inputs. More importantly, the estimates from the AI-based Cobb-Douglas are internally consistent and significant beyond the Cobb-Douglas, meaning that in our estimation the additional terms relating to average returns to the inputs explains part of TFP. Finally, we find that our estimates using capital stocks are more internally consistent than those using capital inputs (flows), indicating that error is introduced in the derivation of capital inputs from capital stocks.

Estimation Forms In our analysis we estimate both two-input and three-input versions of the Cobb-Douglas and AI-based Cobb-Douglas. The two-input versions combine non-IT capital and IT capital into a single capital. The Cobb-Douglas estimation form is

$$y_t = a + \alpha l_t + \beta k_t + \gamma z_t + \epsilon_t^{cd}, \tag{1}$$

where y_t, l_t, k_t and z_t are the natural log of value added, labor, non-IT capital, and IT capital, respectively. a is TFP and ϵ_t^{cd} is a random disturbance. The AI-based Cobb-Douglas estimation form is

$$y_t = \lambda + a_1 ln(\omega_t) + b_1 ln(u_t) + c_1 ln(v_t) + a_2 l_t + b_2 k_t + c_2 z_t + \epsilon_t^{ai}, \tag{2}$$

where ω_t, u_t and v_t are the wage rate, the rate of return on non-IT capital, and the rate of return on IT capital, respectively. ϵ_t^{ai} is a random disturbance. We expect that the coefficients of the inputs are equal to their rates of return: $a_1 = a_2$, $b_1 = b_2$ and $c_1 = c_2$.

Data and Econometric Adjustments As a basis for our calculations, we use times-series data from 1995-2006 for 14 three-digit NAICS manufacturing industries. Our industries differ in what they produce and in size, and are subjected to common economy level shocks and smoothing procedures. Using the Wooldridge test for autocorrelation in panel data, we found that AR1 is present in our data. Consequently, we control for panel-specific AR1 in our estimations, which in effect acts as an industry-level control. In addition, as we expect heteroskedasticity, we also control for it at the industry-level.

Results from the Cobb-Douglas Our estimates of output elasticities from the Cobb-Douglas form in (1) are in Table 1 (two inputs) and Table 2 (three inputs). In each table we provide results using a stock measure of capital and a flow measure of capital: average real productive capital stock and real capital input, respectively. In addition, we provide results over our complete period 1995-2006, and for two sub-periods centered on 2000, 1995-2000 and 2000-2006, noting that 2000 is the base year. Examining the odd-numbered (CD) rows in Table 1 we find roughly a 60-40 split between labor and capital across our measures of capital and across our different time periods, and all the elasticities are significant at

			Elasticity/coefficient estimates for				
			Labor hours l	Wage rate $ln(\omega)$	Capital c	Return to Capital $ln(r)$	Sum of O.E.
Capital as Avg. Real Productive Capital Stock							
1995-2006	1.	CD	0.596*	-	0.436*	-	1.032
Obs: 168	2.	AI	0.722*	0.718*	0.299*	0.305*	
1995-2000	3.	CD	0.689*	-	0.415*	-	1.004
Obs: 84	4.	AI	0.761*	0.744*	0.271*	0.283*	
2000-2006	5.	CD	0.558*	-	0.408*	-	0.996
Obs: 98	6.	AI	0.656*	0.732*	0.326*	0.348*	
Capital as Real Capital Input							
1995-2006	7.	CD	0.611*	-	0.422*	-	1.033
Obs: 168	8.	AI	0.712*	0.730*	0.297*	0.305*	
1995-2000	9.	CD	0.715*	-	0.397*	-	1.012
Obs: 84	10.	AI	0.749*	0.744*	0.274*	0.283*	
2000-2006	11.	CD	0.588*	-	0.410*	-	0.998
Obs: 98	12.	AI	0.657*	0.735*	0.325*	0.348*	

Table 1: Estimation results for 2 Input Factors

$p < .01$. These estimates reflect both the output elasticities of labor and capital, and their input shares as their sum is close to 1.0 – also implying constant returns to scale.

Table 2 shows our results from separating IT capital from non-IT capital. Again, the odd numbered rows report the Cobb-Douglas results, and all but two of the elasticities are significant at $p < .01$. The output elasticity of labor is consistent at between .623-.661 across the six Cobb-Douglas regressions. The output elasticity of IT capital is substantially higher than in prior studies, and is twice as large in the 2000-2006 period as in the 1995-2000 period. In contrast, the output elasticity of non-IT capital is smaller than in most of the prior studies, and is not significantly different from zero in the 2000-2006 period. The results are fairly consistent across our different measures of capital, suggesting that whether we measure capital as a stock or as a flow is not critical to the results. The sum of the output elasticities is close to 1.0, again implying constant returns to scale.

Results from the AI-Based Cobb-Douglas Our estimates of output elasticities and rate of return coefficients from the AI-based Cobb-Douglas form in (2) are also in Tables 1 and 2. As with the Cobb-Douglas we described above, we provide results for two different measures of capital – a stock and a flow, and for three different time periods – 1995-2000 and two sub-periods.

To begin, because the Cobb-Douglas in (1) is nested in the AI-based Cobb-Douglas in (2),

			Elasticity/coefficient estimates for						Sum of O.E
			Labor hours l	Wage rate $ln(\omega)$	Non-IT capital k	Return Non-IT Capital $ln(u)$	IT Capital z	Return IT Capital $ln(v)$	
Capital as Avg. Real Productive Capital Stock									
1995-2006	1.	CD	0.660*	-	0.167*	-	0.205*	-	1.032
Obs: 168	2.	AI	0.726*	0.713*	0.272*	0.243*	0.034*	0.073*	
1995-2000	3.	CD	0.630*	-	0.219*	-	0.156*	-	1.005
Obs: 84	4.	AI	0.780*	0.731*	0.243*	0.229*	0.029*	0.055*	
2000-2006	5.	CD	0.656*	-	0.020	-	0.335*	-	1.011
Obs: 98	6.	AI	0.663*	0.671*	0.272*	0.287*	0.070*	0.057*	
Capital as Real Capital Input									
1995-2006	7.	CD	0.639*	-	0.253*	-	0.137*	-	1.029
Obs: 168	8.	AI	0.726*	0.709*	0.272*	0.238*	0.034*	0.082*	
1995-2000	9.	CD	0.623*	-	0.274*	-	0.108*	-	1.054
Obs: 84	10.	AI	0.753*	0.743*	0.245*	0.205*	0.032*	0.107*	
2000-2006	11.	CD	0.661*	-	0.014	-	0.342*	-	1.017
Obs: 98	12.	AI	0.665*	0.668*	0.270*	0.288*	0.073*	0.055*	

Table 2: Estimation results for 3 Input Factors

we ran Wald tests with the null hypothesis that $a_1, b_1, c_1 = 0$. This hypothesis tests whether the additional terms in the AI-based Cobb-Douglas add significant explanatory power. In all twelve cases (two versus three inputs, two measures of capital, three time periods) the hypothesis is rejected at $p < .0001$, so that in each case the additional terms add significant explanatory power.

Next, with the two-input AI-based Cobb-Douglas in Table 1 we find that the output elasticities of labor increase as compared to the Cobb-Douglas, and those of capital decrease. These results are consistent across measures of capital and time periods. More importantly, the coefficients of the wage rate are close to the output elasticity of labor, as are the coefficients on returns to capital to the output elasticities of capital, consistent with what the accounting identity predicts. The inclusion of the rates of return on labor (wage rate) and on capital appear to calibrate the output elasticities.

Examining Table 2 that contains our results for the three-input AI-based Cobb-Douglas, we find that again the labor output elasticity increases slightly as compared with the Cobb-Douglas, and is very close to the coefficient of the wage rate. More striking is the effect of the inclusion of the rates of return coefficients on the output elasticities of non-IT capital and of IT capital. Across both measures of capital and across the different time periods, the output elasticities of non-IT capital and IT capital are much closer to their levels in prior studies. Moreover, their magnitudes are very close to those of their rate of return coefficients, again consistent with the accounting identity.

The results reported above can be summarized as follows. First, the Wald tests show the additional explanatory power of the AI-based Cobb-Douglas. Second, the consistency in the estimates of output elasticities and rates of return demonstrate the empirical regularity of the accounting identity. Third, especially in the case of non-IT capital and IT capital, the inclusion of the rates of return in the specification calibrates the estimates of the output elasticities and explains contributions from TFP. Finally, the calibration appears to be superior when using productive capital stock rather than capital input, suggesting errors are introduced when deriving capital flows from capital stocks.

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