The Scientific Status of the Labour Theory of Value

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Contents

In this paper we wish to argue that the labour theory of value is a scientific theory in the strongest sense of the empirical sciences. We first elaborate upon what we take to be criteria of scientificity, and then show that these are in practice met by the labour theory of value.

1 General criteria of scientificity

Criterion of testability

Scientific theories tell us something about the material world. They are means by which we can both explain and predict aspects of reality. They are not the only form of explanation: myth, story telling and religion also explain things, but with more limited predictive power.

A theory which makes no predictions is never scientific, whilst one whose predictions have now been invalidated has forfeited any prior claims to science. A scientific theory makes testable predictions. Note that by "prediction" we don't just mean forecasting the future, though this can be part of it. An historical science can formulate *temporal* "postdictions" as *logical* predictions. Scientific predictions make statements about the world that are not available as prior data. For instance, the australopithecine long predated Darwin, but its existence—as the "missing link"—was only subsequently deduced on the basis of the theory of evolution. Such predictions involve applying some general law to pre-given data to produce derived data whose validity can then be tested. The derived data need not be in the future, or even unknown, provided that they are not made available as input data.

Elegance or simplicity

A second criterion is elegance, captured in William of Occam's dictum that entities should not be multiplied without cause. Given two theories, predicting available data equally well, science opts for the simpler. Ptolemy plus epicycles might run Newton a close race, had not simplicity favored the latter.

This favoring of the simple echoes the demands of prediction. The better prediction extends our knowledge furthest on the basis of the least pre-given information. A theory with added epicycles, special cases and fudge factors may predict observation well… since the observations are woven into its very weft.

Information gain

A scientific law compresses many, even a potential infinity of, observations into a simple formula. It is a machine for gaining information. In this guise we revisit prediction and simplicity. The information gained from a law is given by the information yielded from the law's application less the information put in. We can put in information either in the data-set to which the law is applied, or in the formula in which the law is encoded.[1] Although the encoding of the formula should, in principle, be included in any measure of the information cost of a

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[1] Strictly the formula and input data should be expressed in a form suitable for interpretation by the Universal Turing Machine. A good exposition of the concept of the Universal Turing Machine is provided by Penrose (1989).

theory, for the value theories that we will consider the formula lengths are essentially the same, though the input data lengths are not.

Let us refer to the application of a law as the function application $p = L(d)$, where L stands for the law, d for the data to which it is applied, and p the predictions produced. For a law to be valid the information content of p must exceed the sum of the information content in L and in d. The first criterion said that the predictions must not be included in the input data; they must be new information, p must not just be a repetition of d. The theory may predict the input data but it must predict more besides. Our second criterion, simplicity, ensures that the law itself does not simply tabulate its predictions. The information gain criterion incorporates both criteria in a stronger form: the sum of the information in the input data and the encoding of the law must be less than the predictions produced. Only then is there real information gain (Solomonoff, 1964).

Randomness

Random processes exhibit no lawful behavior, and thus cannot be predicted. Information theory states that a sequence of numbers is random if there exists no formula shorter than the sequence itself, capable of generating the sequence. A non-random sequence, by contrast, has a shorter generator. 1, 1, 2, 3, 5, 8 is arguably random while 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, 233, 377, 510, 887, 1397 is not, since the latter can be generated by the Fibonacci formula

$$f(n) = f(n-1) + f(n-2); \quad f(0) = 1; \quad f(1) = 1$$

of shorter length. A scientific law captures the non-random behavior of reality. If we view the law plus its input data as a formula, the formula must be shorter than the data its application produces.

Our object in this paper is to use this general perspective to assess the relative merits of three variant formulae for predicting observed prices, namely "standard" Marxian values (or vertically integrated labour coefficients), Sraffian prices of production, and prices of production as interpreted by the "Temporal Single System" (TSS) school (e.g. McGlone and Kliman, 1996). We are aware that these theories may be conceived as serving discursive purposes other than the prediction of actual prices, but we treat them here as predictive formulae.

2 Three formulae

This section deals with the size of the formula needed to construct three variant predictors of prices.

Vertically integrated labour coefficients

These are obtained (in principle—but see section 3 for a discussion of practical issues) as the n-vector v that solves

$$v = Av + \lambda$$

where A is an $n \times n$ matrix of technical coefficients and λ is an n-vector of direct labour-hours per physical unit of output. The required data are then the n^2 technical coefficients and the n direct-labour coefficients. The solution vector is typically obtained using an iteration

$$\begin{aligned} v(0) &= \lambda \\ v(n+1) &= Av(n) + \lambda \end{aligned}$$

which terminates when the largest element of the difference vector $v(n+1) - v(n)$ shrinks below some set tolerance.

Sraffian prices of production

These are obtained as the n-vector p that solves[2]

$$p = (1 + r)Ap + w$$

where the scalar r represents the general rate of profit and w is an n-vector of (direct) wages paid per unit of output in each industry. The data requirements here are essentially the same as for the vertically integrated labour coefficients, although one more piece of information is required, namely the profit rate (or the real wage, from which the profit rate can be inferred). The calculation proceeds in a similar manner, for instance via the iteration

$$\begin{aligned} p(0) &= w \\ p(n+1) &= (1 + r)[Ap(n)] + w \end{aligned}$$

[2]If wages are taken to be paid in advance then the following equation is respecified as $p = (1 + r)(Ap + w)$.

TSS prices of production

TSS prices of production are obtained as the sum of the (predetermined) price of the inputs plus an aliquot share of the aggregate profit. Writing u for such prices we have

$$u = (1 + r)[Ap(-1) + w]$$

where $p(-1)$ denotes the given vector of input prices as of the beginning of the period and the other symbols are as defined above. The data-requirement for calculating this vector is clearly greater than that for the vertically integrated labour coefficients and Sraffian prices, since in addition to the A matrix and the wage vector we also require a vector of given input prices.

3 Some practical concerns

Section 2 skated over some issues that have to be faced when the above-mentioned formulae are actually put to use. This section raises two such issues. The first, which can be dealt with quite briefly, concerns the distinction between fixed and circulating capital. The "textbook" presentation of the calculation of prices of production (whether in the Sraffian or the TSS variant) in effect assumes a pure circulating capital system, which suppresses the distinction between capital stocks (on which, presumably, the rate of profit "ought" to be equalized) and the flow consumption of capital (as measured in the "A" matrix of an input–output table). When this simplifying assumption is dropped, it becomes apparent that the price of production calculation requires additional data—namely the stocks of capital in each industry—while the vertically integrated labour coefficients emerge as distinctly the most parsimonious predictor.

The second question demands a fuller discussion since it goes to the heart of the project of predicting prices using empirical labour values. In the standard presentation of the principle of calculation of Marxian values one starts from data on (a) intersectoral flows of product *in natura* and (b) direct labour-hours performed in each sector of the economy. Given the statistics that are available for capitalist economies, however, one has no choice but to use data that are expressed in monetary terms. Instead of in-kind figures for, say, the quantity of coal used by the steel industry or the quantity of aluminium used by the aircraft industry, we have figures for the *money value* of the purchases of each industry from each other industry. And instead of a vector of hours of direct labour performed in each industry we have a vector of wage bills.

This raises a concern: if prices are written into the data we are using to calculate labour values in the first place, is there not something circular about turning around and claiming to predict or explain prices on the basis of these values? In fact this objection is mistaken, but since it has some force *prima facie* we shall address it in detail. It will be useful to distinguish two points: the use of a wage-bill vector as a proxy for a labour-hours vector, and the use of monetary intersectoral flows (and output figures) in place of in-kind flows. The first of these issues does create a real problem (but not a very serious one, in our view), while the second does not.

Wage bills versus labour hours

By using wage-bill data as a proxy for labour hours one is in effect computing a vector, not of vertically integrated *labour* coefficients as such, but of vertically integrated wage-cost coefficients. If the wage were uniform across industries this would not matter at all, but the existence of inter-industry wage differentials creates a complication. The question is, what is the relationship between such wage differentials on the one hand, and intersectoral differences in the "value-creating" power of labour on the other? Here are two polar possibilities:

1. Intersectoral wage differentials have nothing to do with differential value-creation: they are an arbitrary outcome of market or other social forces. In this case, clearly, the "values" calculated using the wage-bill proxy will be inaccurate as a representation of "true" values. Further, it is likely that the figures thus obtained will be better correlated with market prices than the unknown "true" values—since wage-cost is presumably relatively closely related to actual capitalist pricing practice—leading to an over-statement of the predictive power of the labour theory of value.

2. Intersectoral wage differentials are an accurate reflection of differential value-creating power. Wage differentials reflect the cost of training, while relatively highly trained labour creates more value per clock hour—or more precisely, transfers to the product the labour-content of the training alongside the actual creation of new value. In this case the industry wage-bill figures are actually a better approximation to

what one is trying, theoretically, to measure than simple direct clock hours would be.

As we have said elsewhere (e.g. Cockshott, Cottrell and Michaelson, 1995), surely the truth lies somewhere between these poles. Intersectoral wage differentials will in part reflect "genuine" differences in value productivity, and partly reflect extraneous factors. In any case, if the input–output structure of the economy exhibits fairly strong interdependence then the vertically integrated wage-cost coefficients for any given sector will comprise a broad mix of labour from different sectors so that the effects of the extraneous factors will tend to cancel out.

Product flows: Quantities versus monetary magnitudes

The necessity of working with monetary magnitudes rather than in-kind product flows is in part a result of the degree of aggregation of the actually available input–output tables for capitalist economies. That is, in order to construct a meaningful input-output table *in natura* it is necessary that the data be fully disaggregated by product, but many of the industries as defined in the actual tables produce a wide range of different products. There can be no meaningful number for the *quantity* of output of "Aircraft and Parts" or "Electronic Components and Accessories", or for the in-kind flow of the product of the latter industry into the former. The practical solution is to present the aggregate monetary values of flows of this sort.

But this does not create a problem, if one is interested in comparing the aggregate monetary value of the output of the industries with the aggregate labour-value of those same outputs. The point is this: *The vector of aggregate sectoral labour values calculated from a monetary table will agree with the vector calculated from a physical table, up to a scalar, regardless of the price vector and the (common) wage rate used in constructing the monetary table.* Or in other words, the vector of sectoral labour values obtained is independent of the price vector used. One might just as well (if it were practically possible) use an arbitrary vector of accounting prices or weights to construct the "monetary" table. The fact that actual prices are used in the published data does not in any way "contaminate" the value figures one obtains; no spurious goodness of fit between values and prices is induced.

Proof

Consider an economy characterized by the following arrays:

- U — An $n \times n$ matrix of intersectoral product flows in kind, such that u_{ij} represents the amount of industry j's output used as input in industry i.
- q — An $n \times 1$ vector of gross outputs of the industries, in their natural units.
- l — An $n \times 1$ vector of direct labour-hours performed in each industry.

It will be useful also to define an $n \times n$ diagonal matrix Q such that

$$Q_{ij} = \begin{cases} q_i & \text{for } i = j \\ 0 & \text{for } i \neq j \end{cases}$$

The standard calculation of labour-values proceeds as follows. First calculate the $n \times n$ matrix of technical coefficients as $A = Q^{-1}U$ and the n-vector of direct labour input per unit of physical output as $\lambda = Q^{-1}l$. The n-vector of unit values (vertically integrated labour coefficients) is then given by

$$v = (I - Q^{-1}U)^{-1}Q^{-1}l = (I - A)^{-1}\lambda$$

and the n-vector of *aggregate* values of the sectoral outputs is

$$V = Qv = Q(I - A)^{-1}\lambda \tag{1}$$

We now construct the monetary counterpart to the above arrays. Let the n-vector p represent the prices of the commodities and the scalar w denote the (common) money wage rate.[3] Let us also define an $n \times n$ diagonal matrix P such that

$$P_{ij} = \begin{cases} p_i & \text{for } i = j \\ 0 & \text{for } i \neq j \end{cases}$$

Corresponding to each of the initial "real" arrays above there is a monetary version as follows:

- $\hat{U} = UP$ — Matrix of money-values of intersectoral product flows
- $\hat{q} = Pq$ — Vector of money-values of gross outputs
- $\hat{l} = wl$ — Vector of industry wage-bills

[3] Having addressed the issue of intersectoral wage differentials above, we abstract from it here.

From these we can construct counterparts to the derived "real" arrays. First the $n \times n$ diagonal matrix $\hat{Q}$, whose diagonal elements are $p_i q_i$, is given by

$$\hat{Q}_{ij} = \begin{cases} \hat{q}_i & \text{for } i = j \\ 0 & \text{for } i \neq j \end{cases} = QP \tag{2}$$

The counterpart to the matrix of technical coefficients is

$$\begin{aligned} \hat{A} &= \hat{Q}^{-1}\hat{U} = (QP)^{-1}UP \\ &= P^{-1}Q^{-1}UP = P^{-1}AP \end{aligned} \tag{3}$$

The elements of $\hat{A}$ represent the dollars' worth of input from sector j required to produce a dollar's worth of output in sector i. Finally, the counterpart to λ is the n-vector $\hat{\lambda}$

$$\begin{aligned} \hat{\lambda} &= \hat{Q}^{-1}\hat{l} = (QP)^{-1}wl \\ &= wP^{-1}Q^{-1}l = P^{-1}w\lambda \end{aligned} \tag{4}$$

whose elements represent the direct labour cost per dollar's worth of output in each sector.

Now here is the issue: suppose we are not privy to the information on product flows in kind and labour-hours, and have at our disposal only the information given in the monetary tables. On this basis we can calculate a vector $\hat{v}$,

$$\hat{v} = (I - \hat{A})^{-1}\hat{\lambda}$$

While v_i represented the vertically integrated labour hours per physical unit of output of commodity i, the $\hat{v}_i$ that we are able to obtain from the monetary tables represents the vertically integrated labour cost per dollar's worth of output of commodity i. If we then multiply up by the money-value of the gross outputs of the industries we obtain the vector of vertically integrated labour costs for the industries.

$$\hat{V} = \hat{Q}\hat{v} = \hat{Q}(I - \hat{A})^{-1}\hat{\lambda} \tag{5}$$

We are interested in the relationship between (1), the aggregate sectoral values that could be obtained in principle from the data *in natura*, and (5), the corresponding figures obtained by using the monetary data.

On the basis of the correspondences (2), (3) and (4) we can rewrite (5) as

$$\hat{V} = QP(I - P^{-1}AP)^{-1}P^{-1}w\lambda \tag{6}$$

Recall that (1) specified $V = Q(I - A)^{-1}\lambda$. Comparing these two equations we see that $\hat{V} = wV$ on condition that

$$(I - A)^{-1} = P(I - P^{-1}AP)^{-1}P^{-1} \tag{7}$$

That this condition is indeed satisfied may be seen by taking inverses on both sides of (7). On the left, we simply get $(I - A)$; on the right we get

$$\begin{aligned} &[P(I - P^{-1}AP)^{-1}P^{-1}]^{-1} \\ &= P(I - P^{-1}AP)P^{-1} \\ &= (P - AP)P^{-1} = I - A \end{aligned}$$

This means we have proved that $\hat{V} = wV$, which is to say that the aggregate sectoral values obtained from the monetary data agree—up to a scalar, namely w, the common money wage rate—with those that would be obtained from the data *in natura*, if these were available. The aggregate value vector is independent of the price vector used in forming the monetary tables.

4 Comparison of information gain

We can now return to our main theme, the assessment of the three versions of value theory in terms of predictive power or information gain. As we have shown, the labour theory of value has the simplest formula, the Sraffian price of production formulation has a slightly more complex formula, and the TSS price of production theory has the most complex formula (counting only the data input). A more complex formula can be justified if the increase in prediction gained exceeds the additional formulaic complexity.

The general equation for the information content or entropy of a sequence of symbols is

$$H = -\sum_i \pi_i \log_2(\pi_i)$$

where H is the entropy of the sequence in bits, π_i is the probability of the i^{th} symbol occuring, and we sum over the whole sequence of symbols.[4] Let us identify our symbols as being the ratio p/e where p is a market price and e is an estimator of market price, either a labour value or some form of price of production. Defining our symbols in this way we

[4] For discussion of information and entropy see for instance Reza (1961), Chaitin (1987).

obtain the conditional entropy of the market price vector P given the estimator vector E. Thus

$$H(P|E) = -\sum_i \pi_i \log_2(\pi_i)$$

where $\pi_i = \Pr(p/e \in x_i)$, the probability that a randomly selected unit of output has a p/e ratio that falls within the i^{th} small interval (the width of these intervals being determined by the precision of measurement).

In general the best estimator will be that which gives the lowest conditional entropy of the market price vector, since this means that most of the information content of the latter vector is already encoded in the estimator. Given the total information content of the market price vector $H(P)$, we can calculate the mutual information or "transinformation" (Reza, 1961) as $I(P; E) = H(P) - H(P|E)$. This figure represents the reduction in uncertainty regarding P that is achieved by conditioning on the predictor E; other things equal we would like this to be as large as possible, but we also have to factor into our assessment the required information input. In this light the marginal predictive efficiency of a theory is given by

$$\frac{\Delta I(P; E)}{\Delta I(\text{input})},$$

the ratio of incremental transinformation to incremental information input, relative to a simpler theory. This marginal predictive efficiency gives a measure of the elegance of the theory.

To perform these calculations we thus require (1) a figure for the total information content of the market price vector, and (2) the probability distribution for the ratio p/e. We estimate the information content of the market price vector by making an assumption about the accuracy of the source data, namely that figures are given to 3 digits or 9.96 bits of accuracy. The information content of the market price vector would then be 47 industries each contributing 9.96 bits, or about 470 bits. The exact number of digits assumed is relatively unimportant, since a higher $H(P)$ will "benefit" (i.e. raise the value of $H(P; E)$ for) all the methods of estimation equally.

The data

Our data were drawn from the 1987 US input–output table along with BEA capital stocks figures for the same year.[5] The BEA give figures for plant and equipment at a higher level of aggregation than that employed in the i/o table. We therefore had to merge some rows and columns of the i/o table to ensure that each industry had a distinct figure provided for the value of plant and equipment. The resulting table has 47 columns and 61 rows. The columns—which constitute a square submatrix along with the first 47 rows—represent the aggregated industry groups. The remaining rows consist of:

- Inputs for which there is no corresponding industry output listed such as "Educational and social services, and membership organizations" or "Noncomparable imports" (a total of 9 rows).
- "Compensation of employees", which we treat as equivalent to variable capital.
- "Other value added", which we treat as being profit;
- "Finance"—we treat this as corresponding to interest and include it in our measure of profit;
- "Real estate and royalties"; and
- "Indirect business tax and nontax liability".

The last two items create some analytical problems. At the aggregate level they are arguably part of surplus value, yet both indirect taxes and rents appear as costs from the point of view of the firms paying them, and insofar as there is any tendency for equalization of the rate of profit, we would expect this to be net rather than gross of indirect taxes and rent payments. Pending a more satisfactory solution, we have in the present study simply netted these out of all our calculations (i.e. excluded them from our measures of both costs and profits).

The BEA figures are for fixed capital; we assumed that in addition industries held stocks of working capital amounting to one month's prime costs (where prime costs included wages in the TSS case but not in the Sraffian case).

It should be noted that modeling capital stocks is the logical dual of modeling turnover times. We are assuming that for the aggregate capital, turnover of circulating capital is one month. This assumption is

[5] Specifically, the stock data came from files wealth14–wealth17 on diskette 4 of the BEA's series of diskettes for Fixed Reproducible Tangible Wealth in the United States, 1925–1989.

based upon the heroic simplification that there exist 12 production periods per year corresponding to monthly salary payments, and that the total stocks of goods held in the production, wholesale and retail chain amount to one month's sales. That is to say, we assume that the turnover time of variable capital is one month with wages paid in advance, and that circulating constant capital is purchased simultaneously with labour. (In the calculation of Sraffian prices we assume wages are paid at the end of the month.) A more sophisticated study would look at company accounts for firms in each sector to build up a model of the actual stocks of working capital. Industries operating just-in-time production will have considerably lower stocks and thus faster turnover; for other industries one month's stocks may be an underestimate.

Correlations

The iterative procedures described earlier were used to compute the total value of output, industry by industry, using the labour value and Sraffian models. The TSS estimate of total values was derived in one pass without transforming the inputs. This gave three estimates for the aggregate price vector; the correlations between these estimates and observed prices are shown in Table 1.

Table 1: Correlations between sectoral prices and predictors, for 47 sectors of US industry

	Observed price
Labour values	0.983
TSS prices	0.989
Sraffian prices	0.983

As can be seen, all the estimates are highly correlated with market prices, with the TSS estimates performing marginally better than the other two. The reported correlations are unweighted; each industrial sector is simply counted as one observation. We also calculated the correlations between the logs of the variables—in line with Shaikh's argument (1984) for a multiplicative error term in the price–value relationship. The ranking of the correlations remained unchanged (labour values 0.980, TSS prices 0.986, Sraffian prices 0.980). And we calculated weighted correlations, the weights supplied by the predictor variable (e.g. the proportion of social labour time accounted for by each sector in the case of labour values): in this case the TSS prices are still ahead at a correlation of 0.989, but labour values (0.987) did better than Sraffian prices (0.985).

Conditional entropies

For each industry we then computed the ratios of the market price of output to each of the estimators, giving the ratio vectors market price/value, market price/TSS price and market price/Sraffian price. The entropies of these vectors were computed as follows.

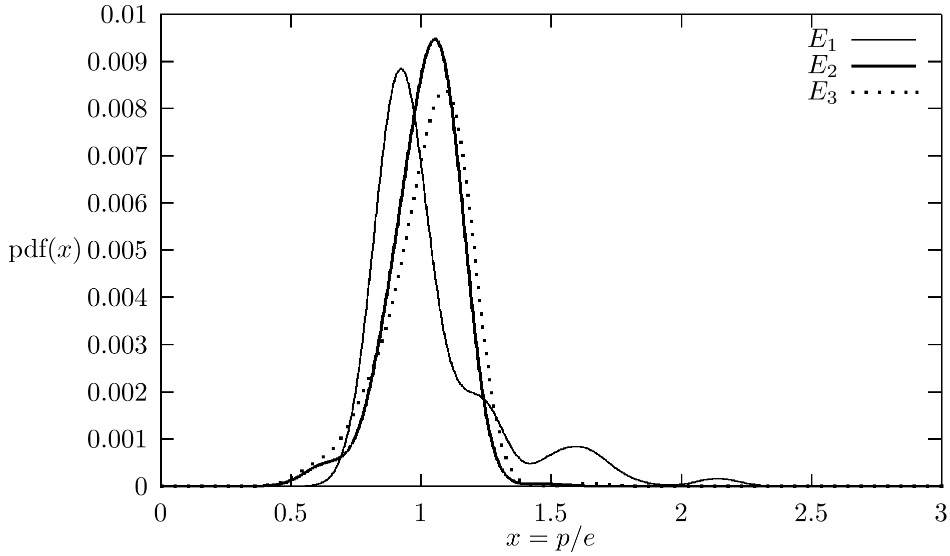
1. A Gaussian convolution (with standard deviation 0.08) was run over the observations, with each observation weighted by the total money output of the industry in question. This resulted in a tabulation of the probability density function relating prices to the various estimates. The theoretical basis for the convolution is that each discrete observation is in fact the mean figure for an entire industry: we assume that the different producers in the industry exhibit a normal distribution of their price–value ratios around this mean. A Gaussian convolution substitutes for each individual observation a normal distribution having the same mean and the same integral. The density functions are shown in Figure 1.

2. The entropy function $H = -\pi_i \log_2 \pi_i$ was integrated over the range 0 to 3 with 1000 integration steps. Taking 1000 integration steps corresponds to a maximum possible value of the integral of $\log_2 1000 = 9.96$, the assumed accuracy of the data in the tables. The interval [0,3] was chosen for integration as the probability densities for all estimators fall to zero outside this range.

The resulting conditional entropies of market prices, with respect to each of the estimators, are shown in Table 2. The fourth row of the table shows the total amount of information about prices for the 47 industries that each of the theories is able to produce. In terms of information output the TSS model outranks the Sraffa model which outranks the labour value model.

In terms of information *input* the ranking is the other way round, as the Sraffa model requires an additional 47-element vector of capital stocks, and the TSS model requires a further 47-element vector

Figure 1: Probability density functions for observed price/estimator (E_1 = labour values, E_2 = TSS prices, E_3 = Sraffian prices)



of input prices. What is the additional information contained in each of these vectors? If we assume them to be accurate to 3 figures, then each of these vectors contains 468 bits. But it is probably unreasonable to require that figures for prices and capital stocks be provided with this degree of accuracy. Since the motivation of the TSS model, at least, is to reproduce the Marxian technique for transforming values into prices of production, we will assume that the capital stock figures need only be as accurate as the output prices generated by labour values alone—roughly 1.9 bits per figure or 90 bits per vector. The efficiency with which this additional information is used in the Sraffian theory is low: for every one bit added to the input data about 0.15 bits of information is added to the output data.

It should be noted that there is a significant difference between the additional information in the two cases. In the TSS case, the extra information required is about the variable being predicted by the model, namely price. Ideally we should supply the prices lagged by one production period as inputs to the calculation. Using input–output table data this is not possible so we in fact used current relative market prices. Given that the price data in the tables reflect the average prices prevailing over a year—considerably longer than any plausible estimate of the "production period"—the distinction between the current and previous period becomes blurred. The figures used cover the months January to December 1987. Assuming a one-month advance of variable and circulating capital, the period for which the input price data should, ideally, have been obtained is December 1986 to November 1987. Since these two periods are substantially overlapping, the actual price data used must be a very good approximation to the price data that we should have used. Taking this into account, the TSS theory appears to have negative predictive efficiency. What we get out is an estimate of this price vector that is less accurate than the one we start out with. The information gain (actually, loss) here is thus $H(P_t|P_{t-1}) - H(E_t) \geq -354$ bits. The construction of a predictor using untransformed input prices produces a net information gain only if the correlation between the price vector for 1.xii.86 to 30.xi.87 and that for 1.i.87 to 31.xii.87 is less than the correlation between the TSS estimator and the latter.

5 Non-equalization of profit rates

Most accounts of the theory of value entail the expectation that Sraffian prices of production should

Table 2: Entropy calculations (P = observed price, E_1 = labour values, E_2 = TSS prices, E_3 = Sraffian prices)

	$(P\|E_1)$	$(P\|E_2)$	$(P\|E_3)$
Conditional entropy	8.028	7.538	7.734
Potential entropy	9.966	9.966	9.966
Transinformation, $I(P;E)$			
– per prediction	1.938	2.428	2.232
– for all 47 industries	91.09	114.12	104.90
Subtract what is already known about prices	0	−468	0
Net prediction	91.09	−354	104.90
Additional information input	0	90	90
Information gain per additional bit input	–	−3.93	0.153

Table 3: Profit rates and organic composition, BEA fixed capital plus one month's circulating constant capital as estimate of capital stock (C). Summary statistics weighted by denominator in each case.

	s/C	c/v	s/v
Mean	0.292	1.948	0.569
Standard deviation	0.221	3.042	0.500
Coefficient of variation	0.756	1.562	0.878
	s/C and c/v (weighted by C)	s/C and v/c (weighted by C)	
Correlation coefficient	−0.454	0.780	

predict actual prices substantially better than the simple labour theory of value (LTV).[6] We find this is not so. The Sraffian predictor performs about the same as the LTV under the correlation metric, and only slightly better under the entropy metric.[7] This finding demands some explanation. The fact that the Sraffian predictor is not clearly ahead of the LTV is comprehensible in terms of the fact that profit rates, counter to Sraffian theory, tend to be lower in industries with a high organic composition of capital.

This is shown in both Table 3 and Figure 2. The table displays the correlation coefficient between the rate of profit and organic composition, and also between the profit rate and the inverse of organic composition, across the 47 sectors. The former coefficient—at −.454—is statistically significant at the 1% level. If, however, prices corresponded to the simple LTV we would expect to find a positive linear relationship between profit rate and the inverse of organic composition (in other words, the relationship between profit rate and organic composition would be inverse, rather than negative linear), so the second coefficient is perhaps more telling: at 0.780 it has a p-value or marginal significance level < 0.0001.

Figure 2 shows three sets of points:

1. the observed rate of profit, measured as s/C (where C denotes capital stock);
2. the rate of profit that would be predicted on the basis of Volume I of *Capital*, i.e. $s'v/C$, where s' is the mean rate of exploitation in the economy; and
3. the rate of profit that would be predicted on the basis of prices of production (mean s/C).

It can be seen that the observed rates of profit fall close to the rates that would be predicted by the Volume I theory. The exception is for a few industries with unusually high organic compositions > 10.

But what are these industries? It transpires that they fall into two categories, each arguably "exceptional". First there are the regulated utilities, electricity supply and gas supply. Electricity supply has an organic composition of 23.15, and displays a rate of profit half way between that predicted by the simple labour theory of value and that predicted by the price of production theory. The gas utilities have a rate of profit of 20% on an organic composition of 10.4; the labour theory of value would predict a profit rate of 7% and the production price theory 32%. In each case the industry is regulated, and of course the regulatory system builds in the assumption that the utilities should earn an average rate of profit. Second, there are industries of high organic composition in which rent plays a major role. At an organic composition of 16.4, the crude petroleum and natural gas industry has a rate of profit substantially in excess of that predicted by the labour theory of value, and approximating more closely that predicted by an equalization of the rate of profit. But an industry like this would, on the basis of the Ricardian theory of differential rent, be expected to sell its product above its mean value, and hence report above average profits. In a similar position we find the oil refining industry with an organic composition of 9.4. Oil production and oil refining have similar rates of profit, at 31% and 32%. Since the industry is vertically integrated, this would indicate that the oil monopolies chose to report their super profits as earned pro-rata on capital employed in primary and secondary production. In both cases, however, the super profit can be explained by differential rent.

[6] The exception being Farjoun and Machover (1983).

[7] Correlation, which depends upon squared errors, lays more emphasis on a few big errors whereas entropy, which depends upon log errors, lays more emphasis on a large number of small errors—hence the possibility of a difference in assessment according to the two metrics.

Sensitivity to turnover time

As mentioned above, we do not currently have independent data on turnover times across the sectors, hence our figures for sectoral capital stocks are not entirely satisfactory. The most we can do in the present paper is examine the sensitivity of the results to the (common) assumption about turnover time. Table 4 replicates Table 3 under the alternative assumption that industry capital stocks are composed of BEA fixed capital plus 2 months' worth of wages plus 3 months' worth of circulating constant capital. The correlations indicative of a negative or inverse association between profit rate and organic composition are still statistically significant, and apparently robust with respect to this sort of change.

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Figure 2: Relationship between profit rates and organic composition, BEA fixed capital plus one month's circulating constant capital as estimate of capital stock (log scales)

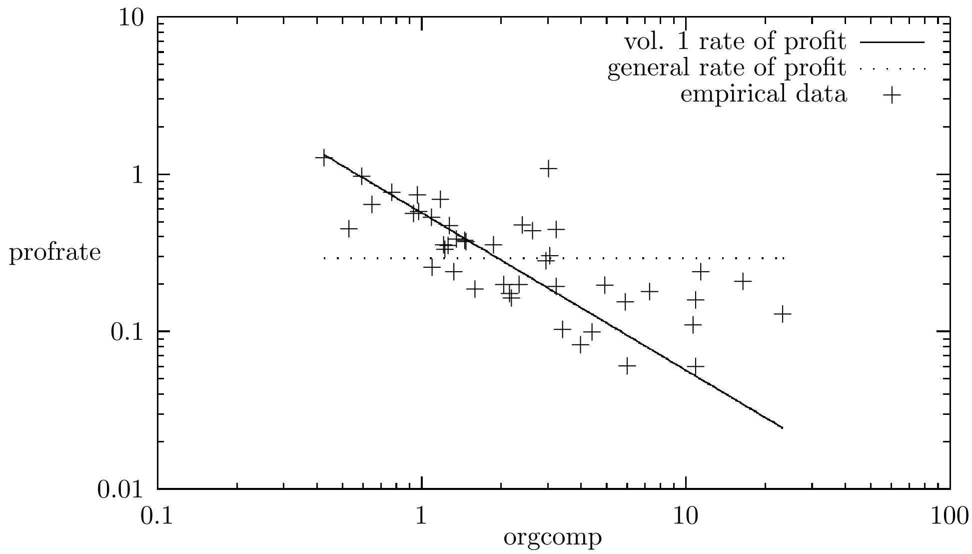

Table 4: Profit rates and organic composition, BEA fixed capital plus 3 months' circulating constant capital and 2 months' wages as estimate of capital stock (C)

	s/C	c/v
Mean	0.239	2.218
Standard deviation	0.133	3.146
Coefficient of variation	0.558	1.418
	s/C and c/v (weighted by C)	s/C and v/c (weighted by C)
Correlation coefficient	−0.457	0.650

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