USAGE-ITC:
Data and Parameters

By Peter B. Dixon, Maureen Rimmer, and Daina McDonald
Centre of Policy Studies, Monash University

Christine A. McDaniel, Edward J. Balistreri, and Kyle Johnson
United States International Trade Commission

and
Eina V. Wong, University of Colorado

USAGE:
Data and Parameters

By Peter B. Dixon, Maureen Rimmer, Daina McDonald,
Christine A. McDaniel, Edward J. Balistreri, and Kyle Johnson
Eina V. Wong*

Key words: General equilibrium modeling, input-output data, substitution elasticities

Abstract: The USAGE-ITC model contains both cross-sectional detail and dynamic capabilities. This paper describes the data supporting the USAGE-ITC model. Principal data components include a highly detailed input-output matrix derived from U.S. Commerce Department data, a time series of somewhat more aggregated input-output data from the U.S. Department of Labor, and trade and macro-economic data from various sources. These include a benchmark input-output table for the United States at a highly detailed level, with 483 commodities produced by 498 industries, as well as annual input-output tables at a more aggregated (192 sector) level. Supporting the data are compilations and re-estimations of underlying elasticities.

* Dixon, Rimmer, and McDonald are at the Centre of Policy Studies, Monash University, Clayton, Victoria, Australia 3800. Balistreri, McDaniel, and Johnson are at the Office of Economics, U.S. International Trade Commission, Washington, DC 20436. Wong is at the Department of Economics, University of Colorado, Boulder, Colorado 80309. Please address comments to Kyle Johnson (kjohnson@usitc.gov). This paper is the result of ongoing research by the authors and does not represent the views of their respective institutions.

USAGE: Data and Parameters

I. Introduction

This paper is a digest of pieces that the various authors have put together over the past year and a half, in laying the groundwork for the USAGE model of the United States economy. The USAGE (U.S. Applied General Equilibrium) model has been described in the other papers presented at this session. It is a single-country model, which seeks (eventually) to cover a great deal of detail about that single country. To do so it demands a great deal of data, and some possibly heroic assumptions about the economy supported by the data.

In the details of its construction, the USAGE model is driven by the data available. Although there are never enough good data to satisfy modelers, it sometimes has seemed that a greater lack has been in the time and ingenuity needed to make good and effective use of the data available. This presentation starts by considering the foundation data, the information needed to establish the benchmark for the model. It then extends the single-period benchmark through time, looking at the data and parameters that make the model richly and empirically dynamic. These sections were principally written by Dixon, Rimmer, and McDonald. The final section of the paper is taken from work by Balistreri, McDaniel, and Wong on the foundations of estimating production function substitution elasticities.

II. The Base Year

In building a CGE model the first step is to set up an input-output data base for a given year. For the USAGE model the selection of the base year was largely dictated by the availability of the highly disaggregated benchmark input-output table produced for 1992 by the U.S. Commerce Department's Bureau of Economic Analysis. The next such benchmark table, for the year 1997, is scheduled to be released later in 2002.

The starting point for our USAGE database is thus the 1992 input-output data published by the BEA. This can be represented as five matrices identifying C commodities and *I* industries. These data are often referred to as a 498-order input-output table. As explained below, not all of the 498 industry and commodity identifiers used in the BEA data refer to genuine commodities and industries. The edited BEA tables contain data for 483 commodities and 493 industries (C= 483 and *I* = 493).

The five edited matrices making up the BEA input-output data are as follows:

(1) intermediate-input flows of C commodities to *I* industries.

(2) flows of C commodities to 40 categories of final demand. The final demand categories consist of personal consumption, gross private fixed investment, change in business inventories, exports, imports and 35 Federal and State and local government activities.

(3) usage of eight types of margins (rail, truck, water, air, oil pipeline, gas pipeline, wholesale and retail) associated with each commodity flow in data sets (1) and (2).

(4) flows to *I* industries of three categories of value added: compensation of employees; indirect taxes; and all other, e.g. gross profits.

(5) a C commodity by *I* industry make matrix.

The data from which we formed these five matrices are described on page M-3 of BEA (1998) and were obtained on diskette (BEA product NDN-0179).

After some straightforward adjustments databases (1) to (5) were constructed in the form shown in Figure 1 where: PV1 to PV6 represent direct uses of commodities (not identified by import/domestic source) valued in producer prices; MAR1 to MAR6 represent margins on the flows in PV1 to PV6; PVM represents imports; LAB, TAX0 and OVA are components of value added; and MAKE represents commodity outputs by industries. Data set (1) formed the basis for PV1; data set (2) formed the basis for PV2, PV3, …, PV6, -PVM; data set (3) formed the basis for MAR1, MAR2, …, MAR6;

data set (4) formed the basis for LAB, TAX0 and OVA; and data set (5) formed the basis for MAKE. The column sums of PV1, MAR1, LAB, TAX0 and OVA match the column sums of MAKE. For non-margin commodities the row sums of PV1, PV2, …, PV6 and –PVM match the corresponding row sums of MAKE. Finally, for any commodity n which is a margin, the sum across the n-row of PV1, …, -PVM plus all the n-entries in MAR1, …, MAR6 matches the commodity n-row sum in MAKE.

The remainder of this section explains why, in forming Figure 1, the 498-order BEA data were reduced to 483 commodities and 493 industries. Then, we consider conventions in the BEA data concerning: (a) valuation of flows and the recording of indirect taxes; (b) imports; (c) secondary production; (d) public-sector demands particularly the use of negative entries; and (e) value added.

Reducing the BEA data to genuine commodities and industries

The BEA input-output data includes 498 industry identifiers and 498 identical commodity identifiers. Of these identifiers, 480 refer to industries which are the principal producer of the commodity sharing the same identifier. In Figure 2, this is the set $COM \cap IND$.

Thirteen industry identifiers refer to industries that are not the principal producer of any commodity. Thus, there is no commodity named for any of these thirteen industries. The thirteen industries without corresponding commodities are listed in the left panel of Table 3.1. The right panel shows the main commodity produced by each of these industries, or equivalently it shows the industry which is the principal producer of the main product of the thirteen industries.[1]

Three commodity identifiers refer to commodities for which there is either no producing industry or no industry for which the commodity is the principal output. These three commodities are:

800000 Noncomparable imports. This commodity consists of goods and services purchased by US households and businesses in foreign countries. Examples include tourism expenditures and purchases of services provided to US airlines and ships. Noncomparable imports are represented in row 800000 of the BEA data by positive entries. These are offset by a negative entry in the BEA import column, giving a row total of zero. In column 800000 of the BEA data, all entries are zero. As can be confirmed from data set (5) no industry produces commodity 800000.

810002 Used and secondhand goods. These are sold by one industry and final users and bought by other industries and final users. Sales are represented in row 810002 of the BEA data as negative items and purchases as positive items. The row total is zero. In column 810002 all entries are zero. As can be confirmed from data set (5) no industry produces commodity 810002.

810001 Scrap. Row 810001 in the BEA data indicates many users of domestically produced and imported scrap. It also reveals that households demand a negative quantity of scrap. We interpret this as meaning that households are net sellers of scrap. Column 810001 consists entirely of zeros. While scrap is not produced by a scrap industry, data set (5) shows that scrap is produced as a secondary product by several industries

Two identifiers refer to neither commodities nor industries. They are labels on rows and columns used to introduce accounting adjustments. The two identifiers are:

---

[1] One curious feature of data set (1) is that it includes rows for the last three identifiers (381200, 381300, 180203) listed in the left panel of Table 3.1 but not for the other ten. The rows for 381200, 381300 and 180203 are entirely made up of zeros.

830001 Rest of the world adjustment to final users[2]. The 830001 column in the BEA data consists entirely of zeros. The row adds to zero. It has a large negative entry (-$66,481 million) in the private consumption column. This is almost exactly offset by a positive entry in the export column ($67,325 million). The aim of these two entries is to recognize that some private consumption expenditure is undertaken by foreigners (e.g. students and tourists) while visiting the United States. In the national accounts these expenditures are classified as exports, not consumption. By including the adjustment in the input-output tables, the BEA ensures that the column sums for private consumption and for exports are compatible with private consumption and exports in the national accounts.

850000 Inventory valuation adjustment. Column 850000 has one nonzero entry (-$7,982 million) which occurs in the other value-added row. There is a matching sale of -$7,982 million in the inventory column of row 850000. The column and row are included in the input-output tables to aid compatibility with the national accounts. In the input-output tables, the change in inventory column shows positive entries if there is genuine accumulation of inventories but also if there is an increase in the price of inventories (valuation effect). The negative entry in row 850000 of the inventory column eliminates the valuation effect. This must be matched with a reduction in value added which is achieved by the negative entry in the other value-added row of column 850000.

In summary, as can be seen in Figure 2, our study of the commodity and industry identifiers in the BEA data indicates that 483 identifiers refer to genuine commodities and 493 refer to genuine industries. Thus in our edited version of the BEA data used to form Figure 1, C is 483 and *I* is 493.

In editing the BEA data into a 483 by 493 format we have omitted various blank rows and columns from the original BEA data. However, we have also omitted two genuine sets of data entries: those concerned with transferring foreign-visitor expenditures out of consumption and those concerned with inventory valuation adjustment. The first omission means that total private consumption expenditure in Figure 1 is greater than that in the BEA tables and that total exports is lower than that in the BEA tables. In creating USAGE we will return to this issue when we model tourist and other foreign-visitor expenditures. The second omission means that total inventory accumulation and total value added in Figure 3.1 are both greater than in the BEA tables. In creating USAGE we plan to ignore this discrepancy.

---

[2] The code used in data set (1) is 830001. In BEA (1998) page M-36 there is a code 830000 and no code 830001. We assume that codes 830001 and 830000 refer to the same thing.

III. Historical Data.

Introduction

The United States Bureau of Labor Statistics (BLS) provides input-output tables for each year from 1983 to 1998. These tables identify 192 industries and commodities.

The BLS tables will play an important role in the construction and application of USAGE. In using the BLS tables we need to be familiar with the statistical conventions that underlie them. We also want to know what the BLS tables say about each industry. This will be critical background material in interpreting and presenting USAGE forecasts.

In the rest of this section we describe the format of the BLS tables. In the next section we present a table showing growth in US output for each commodity, together with contributions to growth from changes in intermediate usage, private investment, private consumption, exports, government demand, inventories and imports. The table is useful in giving a quick indication of the relative growth performances of different commodities and the patterns of their sales.

In the final section of this part we use the BLS data for each industry and commodity to produce descriptions and charts showing movements in output, employment and other variables of interest. A sample of one such description is included, although the supporting documentation for the USAGE model will include descriptions of all 192 BLS industries.

Description of BLS input-output tables

The nature of these data is summarized in table 2. It is also illustrated schematically in figure 31. In this figure, PV1T, PV2T, … , PV6T refer to direct and margin flows of 192 commodities (not disaggregated between domestic and imported) to 192 industries and to final users. Margin use of commodity n in delivering inputs to industry j is aggregated with industry j's direct use of commodity n and entered in the (n,j) position of PV1T. Value added in the BLS tables appears as a single row.

The industries and commodities appearing in the BLS data are mainly simple aggregations of those in the 498-order input-output table for 1992 published by the United States Bureau of Economic Analysis (BEA). By aggregating the BEA tables we can obtain components of the BLS data for 1992. The BLS data for other years are updated or backdated tables estimated mainly from National Income and Product Accounts (NIPA) data for final demands and value added.

Private consumption

The 80 consumption columns in Figure 1.1 are NIPA categories. The 192 by 80 consumption matrix provides a mapping between the 192 BLS input-output categories and NIPA consumption categories. Macro models used by the BLS generate forecasts for NIPA categories. This explains why the BLS has retained this matrix. For analyzing the BLS input-output tables we have aggregated the 192 by 80 consumption matrices for each year into single columns (192 by 1).

Private investment

The 38 investment columns in Figure 1.1 are NIPA categories. The 192 by 38 investment matrix provides a mapping between the 192 BLS input-output commodity categories and NIPA investment commodity categories (eg mobile homes). Again, macro models used by the BLS generate forecasts for NIPA investment categories, explaining why the BLS has retained this matrix. For analyzing the BLS input-output tables we have aggregated the 192 by 38 investment matrices into single columns (192 by 1).

Government demands

The eight categories of government expenditure in the BLS tables are: Federal expenditure by defense/non-defense and by consumption/investment; and State and local expenditure by education/non-education and by consumption/investment. The BLS government data exhibit the same problem as the BEA data, namely negative entries for State and local government use of some commodities (eg education and health). As explained by Dixon and Rimmer[3], these negative entries represent sales of commodities by government rather than purchases. For analyzing the BLS input-output tables, we have left the negative entries unchanged and aggregated the 192 by 8 government matrices into single columns (192 by 1).

Exports

The BLS data for exports show separate columns for goods and for services. Most commodities are either exported predominantly as goods or predominantly as services. However, exports of some goods are split between these two categories. For example, 76 per cent of Ship and boat building and repairing is exported as a good and 24 per cent as a service. We suspect that the 24 per cent is the repairing component.

Margins services used in facilitating flows of goods to ports of exit are recorded in the margin commodity rows of the goods column. Direct exports of services are recorded in the service column.

For analyzing the BLS input-output tables, we have aggregated the 192 by 2 export matrices into single columns (192 by 1).

Imports

The BLS data for imports show separate columns for goods and for services. As in the BEA data, most imports in the BLS data are recorded as negative items. However, there are three positive items in the goods column: in the rows for Wholesale trade, Air transport and Water transport. As discussed in Dixon and Rimmer (see footnote 1), the Wholesale trade entry is duty on imports, and the Air transport and Water transport entries refer to the use of US transport in facilitating the flow of imports from foreign countries to the US. The Air transport and Water transport entries in the service import column are negative. These entries refer to passenger transportation purchases by US residents from foreign carriers.

---

[3] Dixon, P.B. and M.T. Rimmer, “MONASH-USA: Creating a 1992 Benchmark Input-Output Database”, working paper available from the Centre of Policy Studies, May 2001.

For analyzing the BLS input-output tables, we have left the import entries unchanged but aggregated the 192 by 2 import matrices into single columns (192 by 1).

Additional data

The BLS input-output tables show only one row for value added. However, the BLS supplies considerable additional data on employment. Among other things, these data will be used to disaggregate value added. So far we have located BLS data for each year from 1983 to 1998 and for each industry for:

- total jobs, thousands;
- total hours of all persons, millions;
- wage and salary jobs, thousands;
- wage and salary hours, millions;
- production worker jobs, thousands;
- production worker hours, millions;
- self-employed and unpaid family worker jobs, thousands; and
- self-employed and unpaid family worker hours, millions.

In this paper, the only employment data that we use is for total jobs.

Output growth for US commodities: 1983 to 1998

Table 3 below is an extract of a much longer table detailing all of the industry sectors in the BLS tables. The starting point for table 3 is the equation

$$Z_i(t) = D_{1i}(t) + D_{2i}(t) + D_{3i}(t) + D_{4i}(t) + D_{5i}(t) + D_{6i}(t) - M_i(t) \qquad (2.1)$$

where

$Z_i(t)$ is output of commodity i in year t;

$D_{qi}(t)$ is demand for commodity i (both domestic and imported) in year t of type q (intermediate, q=1; investment, q=2; private consumption, q=3; export, q=4; government, q=5; and inventories q=6); and

$M_i(t)$ is imports of commodity i in year t.

From (2.1) we obtain

$$z_i(83{,}98) = \sum_{q=1}^{6} S_{qi}(83) * d_{qi}(83{,}98) - S_{mi}(83) * m_i(83{,}98) \quad (2.2)$$

where

$z_i(83,98)$ is the percentage change in the output of commodity i from 1983 to 1998;

$d_{qi}(83,98)$ is the percentage change in the demand of type q for commodity i from 1983 to 1998;

$m_i(83,98)$ is the percentage change in the imports of commodity i from 1983 to 1998; and

$S_{qi}(83)$ and $S_{mi}(83)$ are the ratios of the demand of type q and imports of i to output in 1983.

The first column of Table 3 gives values for $z_i(83,98)$. Columns (2) to (8) decompose this, setting out the terms on the RHS of (2.2). They show the contribution to growth in US output of commodity i from growth in demand of type q as $S_{qi}(83) * d_{qi}(83,98)$. Thus, for example, if the share of q in total

US usage of commodity i is 10 per cent and growth in q's demand between 1983 and 1998 for i is 50 per cent, then we say that the contribution of q to growth in US output of i is 5 percentage points. If US imports in 1983 were 10 per cent of the size of US output, then we say that a 50 per cent growth in imports makes a negative contribution to US output of 5 percentage points. As well as growth contributions, columns (2) to (8) show in italics percentage growths, $d_{qi}(83,98)$ and $m_i(83,98)$.

In computing the final row of table 3 we aggregated the terms in (2.1) over all i. Thus, the entries in this final row mean that output of all commodities grew by 60.2 per cent between 1983 and 1998, intermediate demand grew by 61.3 per cent contributing 25.8 percentage points to the growth in total output, etc.

Table 3 should be thought of merely as a convenient method of presenting a large amount of data. It shows growth rates for commodities and indicates sales patterns. The table should not be thought of as a mechanism for explaining developments in the US economy. For example, we should not think of rapid import growth as the *cause* of the sharp decline in the output of Footwear (commodity 108). Via USAGE we may be able to show that the cause of Footwear decline in the US was slow technological progress in the US Footwear industry relative to that in other US industries. We may find that fast technological progress in the rest of the economy supported strong wage growth, leaving US Footwear producers in an uncompetitive position relative to foreign suppliers. Similarly, we should not think of rapid growth in investment demand as the main cause of rapid growth in the output of Computer and office equipment (commodity 45). Using USAGE we expect to be able to explain growth in investment demand for Computer and office equipment in terms of technological breakthroughs leading to dramatic reductions in its price. It is these technological breakthroughs that then become the explanation of growth in the output of Computer and office equipment.

Descriptions of output growth for BLS input-output commodities and industries

In the BLS input-output tables the 192 industries have the same names as the 192 commodities. Over 90 per cent of the production of most commodities takes place in their like-named industry, and over 90 per cent of the production of most industries is accounted for by their like-named commodity. For these commodities/industries we can discuss commodity and industry growth rates simultaneously, making little distinction between them. For example, we can have a single discussion covering both the Landscape and horticultural services commodity and industry, commodity and industry 3, because 97 per cent of the commodity is produced by the industry, and 98 per cent of the output of the industry is accounted for by the commodity.

The BLS data shows for a few commodities several major producing industries and for a few industries several major commodities. For example, significant quantities of the Advertising commodity (commodity 143) are produced by 5 industries, and the output of each of these 5 industries includes significant quantities of other commodities. Thus, for Advertising and other multi-industry commodities and multi-commodity industries, our discussion needs to encompass several industries and commodities simultaneously.

Information such as that in table 3 is being augmented by other sources of industry data to help formulate brief historical descriptions of the 192 industry sectors. A description of the computer and office equipment industry, which appears below after the other tables, serves as an example. These descriptions serve to provide a reality check to use of the model.

III. An Estimation of U.S. Industry-Level Capital-Labor Substitution Elasticities[4]

In addition to the underlying data describing the status of the U.S. economy at the baseline year and at each year from 1963 to 1998, the model also includes a database of parameters describing the responsiveness of the economy to changes in policy or other economic conditions. Among these parameters are elasticities of demand by households for commodities, substitution elasticities between imported and domestically produced goods, and elasticities of substitution in production between capital and labor. Many of these parameters are being freshly re-estimated by members of the project team. The remainder of this final section of our presentation describes some work we have done on the elasticities of substitution in production between capital and labor.

A key parameter that determines the distributional impacts of a policy shift in general equilibrium simulations is the elasticity of substitution between capital and labor. In this paper we provide the most comprehensive and up-to-date set of capital-labor substitution elasticity estimates for the U.S. economy. We exploit a rich data source recently released by the Bureau of Economic Analysis (BEA) and estimate both the long- and short-run elasticities for 28 industries using established time series techniques.

Given the structure of most growth models, we posit that the true relationship between capital and labor is likely to be close to Cobb-Douglas. We cannot reject the Cobb-Douglas specification in 20 of the 28 industries, and for seven of those industries we fail to reject the Leontief specification. We cannot reject Cobb-Douglas for aggregate manufacturing. Also, a comparison of econometric estimates and value-added weighted averages for several aggregations brings into question the common practice of averaging estimates for use in flexible aggregation models.

Our objective is to consistently estimate a comprehensive set of capital-labor substitution elasticities for the U.S. economy. The current data only enable estimations at the two-digit level (28 sectors). Using appropriate time-series techniques we distinguish between short-run and relatively higher long-run elasticities. We also estimate elasticities for a few aggregations. We test our prior of a Cobb-Douglas relationship. In addition, we examine the implications of weighted average aggregations of industry level elasticities, because this is a conventional practice relied upon by many modelers. Our estimates provide support for using the Cobb-Douglas specification as a transparent starting point in parameterizing applied CGE models and should be useful for researchers working on simulation and sensitivity analysis.

In the next subsection we discuss general issues surrounding parameterization, measurement and calibration, and the problems inherent in elasticity estimation. In the full version of this paper we present the argument for Cobb-Douglas in the growth literature; that subsection is omitted here for brevity. In subsection three we discuss the empirical model, including the specification and the data. In subsection four we outline the estimation results, which are presented in an appendix to the full version of this paper. In the last subsection we provide concluding remarks.

ISSUES SURROUNDING THE PARAMETERIZATION OF THE CAPITAL-LABOR RELATIONSHIP

---

[4] This section is taken from Balistreri, McDaniel, and Wong, *An Estimation of U.S. Industry-Level Capital-Labor Substitution Elasticities: Cobb-Douglas as a Reasonable Starting Point?* USITC Office of Economics Working Paper No. 2001-12-A, December 2001.

The elasticity of substitution between capital and labor is a key parameter in quantifying distributional impacts of policy. Measurement of this parameter is, however, problematic and controversial. From a structural perspective the problem is that capital accumulation is inherently a complex dynamic problem. Once investments are made they may be specific to a given process making reallocation costly. In the historic data it is impossible to identify the portion of capital return that is normal versus that which is due to a productivity realization away from its expected mean. Furthermore, it is impossible to directly identify the misallocation of physical capital due to adjustment costs in the time series. Given these realities, it is futile to expect estimations based on our static notion of capital input demand (like those presented below) not to suffer from misspecification. Transparent estimations of the capital-labor relationship based on a static equilibrium include the seminal work on CES functions by Arrow, Chenery, Minhas, and Solow (1961).[5]

Another way to think about the problem is that information sets, about shocks and uncertainty over time, are themselves time dependent. This indicates that forward-looking investments, based on rational expectations at the time they were made, are likely to realize a non-zero economic profit in the historical record. Macro-economists have struggled with these issues for some time, and real business cycle models are a promising area of research.[6] However, for our purpose these models provide little, if any, sectoral detail and are actually partially calibrated relying on assumed elasticities. For example, Kydland and Prescott (1982) and much of the literature that follows assume a Cobb-Douglas relationship between capital and labor in aggregate production.

Like those macro-economists who find calibrated business cycle models appealing for their structural integrity, micro-economists interested in comparative policy analysis face a monumental data shortage relative to the parameter requirements. There is a necessity to build a model that includes enough structural detail to capture important features of the economy. At the same time, we require a quantitative context that is not so abstract as to leave the question completely uninformed.

For example, fundamental questions of competing tax policy are arguably best informed from a general equilibrium perspective (Harberger (1962) and Shoven and Whalley (1972)). There are few micro-consistent observations relative to the number of parameters that support such a model, if it is to produce anything but trivial quantitative results. Even fewer observations exist across relevant variations in exogenous instruments (alternative tax policies). Thus, reduced-form models are not likely to be accurate in revealing the effects of structural policy shifts especially when most questions concern new untested alternative policy initiatives. The data shortage, in the context of comparative policy studies, has precipitated a movement toward calibrated microeconomic models. Dawkins, Srinivasan, and Whalley (2001) offer a complete perspective on calibration and its role in economics.

Calibration usually follows a method that includes the interaction of a strict theoretic structure with two distinct types of data. The first type of data represents the benchmark equilibrium. In the context of constant-elasticity-of-substitution (CES) forms, the first type of data identify exactly the distribution (or share) and efficiency parameters (Uzawa (1962), Rutherford (1995)). The data that determine these parameters are inherently local to the reference solution. So, although they establish a quantitative base for initiating policy experiments, they do little to inform the global properties of the model.

[5] Arrow, Chenery, Minhas and Solow (1961) find strong evidence that the capital-labor substitution elasticity is between zero and unity.

[6] See Gregory and Smith (1991) for a survey.

The second type of data indicates the degree of response and is often independent of the local equilibrium.[7] These are data that indicate the elasticity or slope parameters. In most applications we compile a database that includes a point estimate on each of the required parameters. The key question is the source of the estimates. The estimates seldom come from an independent source, and they rarely are estimated in a way that is consistent with the model structure. The problematic nature of this practice is outlined by the critiques of Jorgenson (1984) and McKitrick (1995).

Examples of models that integrate some elements of consistent econometric estimation include Jorgenson (1984), Jorgenson, Selesnick and Wilcoxen (1992), McKitrick (1995), and McKibbin, Shackleton, and Wilcoxen (1998). Wilcoxen (1988) explains the method used to construct the necessary data for his time series estimation. He constructs consistent annual input-output tables for the years 1947 through 1985. This might appear to be a rich data source, but in fact his primary data only consists of 6 benchmark tables (1947, 1958, 1963, 1967, 1972, and 1977) that often used evolving industry definition. The complete data set was only arrived at after filling the holes (often with square pegs). It is interesting to note that McKibbin, Shackleton, and Wilcoxen explicitly reject some of their estimates and impose arbitrarily lower production elasticities (on energy sectors in this case). Their explanation for imposing these lower elasticities was to "help the model more accurately track the physical quantities of energy inputs and outputs to the sector" (p.7). We interpret this as their rejection of the econometric point estimates, not because the statistical model failed, but on practical grounds; the estimates imply unrealistic responses when used in the model.

Although we utilize a new data source containing a full annual time series from 1947 to 1998, the benchmark tables that form the foundation for these are identical to those used by Wilcoxen (1988), except for the extensions to include recent benchmark tables. We can claim some independence given that the BEA completed the gaps in the data set, but this does not necessarily improve the data. The documentation provides an indication of how the BEA actually constructed the data (Lum, Moyer, and Yuskavage (2000), and *Survey of Current Business* (2001)).

Another problematic aspect of our exercise is its lack of specificity. Finding a set of elasticities that can be applied to an arbitrarily aggregated multi-sector model requires multiple applications of a given specification. Focus on the intricacies of each industry is difficult in this context and is outside the scope of this paper. Better estimates might be obtained by sector-specific studies less interested in a general method.

Following the lead of the real business cycle literature and a philosophical acceptance of calibration as a method of estimation (Dawkins, Srinivasan, and Whalley (2001)), there is a new direction in the literature to combine aspects of stochastic estimation in structural general equilibrium models (Liu, Arndt, and Hertel (2001), and Francois (2001)). These ideas are in there infancy but appear promising.

---

[7] In some cases the benchmark equilibrium and response data are not separable in the calibration process. Rich response data on higher order curvatures (cross elasticities of substitution) require flexible functional forms (Perroni and Rutherford (1996)). In these forms the benchmark equilibrium is explicitly tied to the response data. Even with convenient functions, however, there are cases where elasticities and shares must be considered simultaneously. For example, any number of leisure value shares are consistent with a given uncompensated labor supply elasticity in a benchmark equilibrium. This is true even when a CES is specified between separable-leisure and other consumption, because the choice of labor supply effects income. Balard (1999) makes an important argument that it is prudent to consider the interactions between substitution elasticities and value-shares when calibrating labor supply because welfare analysis is sensitive to the implied income elasticity of leisure. Other cases of calibration that blur the line between benchmark equilibrium data and response parameters include merger simulation models (Frobe and Werden (1996)). These procedure combines the market data and elasticities to imply the firms' marginal costs.

In contrast this study offers a set of elasticities using standard econometric techniques that might be useful in the traditional calibrated computational model. Again, we offer these as a starting point for analysis. Our estimates have the advantage that they update earlier work using the latest data, cover a number of sectors, and provide an indication of the long-run versus short-run elasticities.

EMPIRICAL MODEL

The value added nest of the production function is assumed to take on a constant elasticity of substitution form. Inputs of capital and labor enter in the following fashion:

$$Y = [\alpha \cdot K^{(\sigma-1)/\sigma} + (1-\alpha) \cdot L^{(\sigma-1)/\sigma}]^{\frac{\sigma}{\sigma-1}} \quad (5)$$

where σ is the constant elasticity of substitution between the factor inputs, and α is the distribution parameter. Constrained optimization of (5) yields the following log linear specification:

$$\ln\frac{K}{L} = \sigma \cdot \ln\frac{\alpha}{1-\alpha} + \sigma \cdot \ln\frac{w}{r} \quad (6)$$

where *w* and *r* are the wage and rental rates, respectively. This equation may be stylized to fit the linear regression equation:

$$\ln y = \beta_o + \beta_1 \ln x + \varepsilon \quad (7)$$

where *y* is the capital-labor ratio, *x* is the wage-rental ratio, and ϵ is the independent and identically distributed (iid) error. The elasticity of substitution between capital and labor is represented by β_1, the coefficient of interest.

Data

The four data series that are required to operationalize equation (7) are labor inputs, capital inputs, payments to labor, and payments to capital. A newly released data set by the BEA includes these series, specifically, full-time equivalent employees, compensation of employees, and property type income. Compensation of employees is defined as the sum of wages, salary, and supplements to wages and salaries. Property type income includes corporate profits, proprietor's income, rental income, net interest, private capital consumption allowances, business transfer payments, and government consumption of fixed capital.[8] The BEA data include new estimates of gross product by industry over 1947-1998, and represent significant improvements over previous data, namely, a comprehensive revision of the national income and product accounts (NIPA's) and an extension of double deflation techniques, which account for inflation in both input and output markets.[9] We use the BEA's newly revised estimates for the net stock quantity index of private fixed assets, which include equipment, software and structures.[10] The estimates provide measures of the value of assets in the

---

[8] See Lum, Moyer, and Yuskavage (2000) footnote 8.

[9] Lum, Moyer, and Yuskavage (2000).

[10] See also *Survey of Current Business* (2001) for formulas to calculate quantity indices.

prices of the given period, which are end of year for net stocks and annual averages for depreciation. The index uses 1996 as the base year.[11]

The data were compiled by the BEA using two SIC codes. For 1947-1987, data were classified according to 1972 SIC codes, whereas data from 1987-1999 were compiled using 1987 SIC codes. To correct for the discrete change in the time series, the 1987 data from both classifications were compared. Using the proportional difference, we adjust the latter to fit with the earlier data. We use factor input and payments data for 28 two-digit SIC categories. The wage and rental rates were calculated by dividing the compensation to employees by the number of full-time equivalent employees, and property-type income by the net stock quantity index, respectively.

ECONOMETRIC RESULTS SPECIFICATION

We adopt equation (5) and apply standard time series econometric estimation techniques. We attempt to estimate the long-run elasticities that are appropriate for computable general (and partial) equilibrium models. Capital and labor adjustments to changes in rental and wage rates take time due to the lag involved in accumulating capital and other adjustment frictions. Therefore, we allow for time of adjustment in the estimation procedure.

We use the weighted-symmetric test to determine the order of integration for each series across industries, the ratio of capital to labor inputs, and the corresponding relative factor payments.[12] A group of non-stationary time series is cointegrated if a linear combination of them is stationary; that is, the combination does not have a stochastic trend. We tested for a long-run, stationary relationship between the two ratios for each industry using the Engle-Granger technique when the cointegrating variables had a unitary order of integration, I(1). This test was performed only when the ratio of factor inputs and the relative factor payments ratio were I(1).[13] The cointegration results allowed us to determine whether a single-equation error correction model would be an appropriate specification for each series.

Equation (7) was estimated separately for each industry category, using one of the three specifications laid out below, each utilizing different time-series properties of each series. The first specification is a parsimonious geometric lag model:

$$\ln y_t = \alpha_o + \beta_1 \ln x_t + \beta_2 \ln y_{t-1} + \varepsilon \qquad (8)$$

The autoregressive model of order one (AR(1)) specification is useful here because the long-run and short-run estimates are easily extracted. This estimation procedure generates efficient estimates in the presence of disturbances that exhibit first order serial correlation. The long-run elasticity is calculated as $\beta_1/(1-\beta_2)$ if $0<\beta_2<1$. The short run elasticity is simply β_1.

[11] *Survey of Current Business* (2000).

[12] The Weighted Symmetric test is recommended over the Dickey-Fuller test because it has (sometimes only slightly) higher power (see Pantula, Gonzalex, and Fuller, 1994).

[13] The theory is set forth in Engle and Granger (1987). The Engle-Granger test is only valid if all the cointegrating variables are I(1).

The second specification is based on using first differences of the dependent and explanatory variables only, and is appropriate for industries with data series that are both I(1) and not cointegrated, or with just one I(1) series:

$$\Delta \ln y_t = \alpha_o + \beta_1 \Delta \ln x_t + \varepsilon_t \qquad (9)$$

where $\Delta \ln y_t = \ln y_t - \ln y_{t-1}$ and $\Delta \ln x_t = \ln x_t - \ln x_{t-1}$, and ϵ is an i.i.d. error term. The short run elasticity is β_1.

Finally, a single equation error correction model is applicable to industries with data series that are both I(1) and cointegrated:

$$\Delta \ln y_t = \alpha_o + \beta_1 \Delta \ln x_t + \beta_2 \ln y_{t-1} + \beta_3 \ln x_{t-1} + \varepsilon_t \qquad (10)$$

This model allows the data to determine the short-run and long-run responses of factor inputs with respect to factor payments. Specifically, the long-run elasticity is $-(\beta_3/\beta_2)$ and the short-run elasticity is β_1.

We do not make any judgement about the dynamic structure and thus do not formally test among the estimation specifications described above. Allowing the data to inform the error structure implicitly assumes that the error structure can inform the dynamics of the model when, in fact, it cannot. Regardless of how well the time series model is fit to the data, it still has no statistical properties that correspond to the actual dynamic model with capital accumulation decisions. We do not submit any one of these as the true specification. However, we note that the estimation results demonstrate a lack of sensitivity across specifications.

Estimation Results

In order to analyze the time series properties of the data, unit root and cointegration tests were performed for the capital-labor ratio and wage-rental ratio series.[14] Both series for each industry, with the exception of a few, were found to be stationary in first-differenced form, or I(1).[15] When series were found to be I(1), tests for second-order integration were easily rejected. Results from the Engle-Granger test for cointegration suggest that the series are not cointegrated for any of the industries.

The results from the three specifications—AR(1), first differenced, and single equation error correction—are presented separately. Overall, the elasticity estimates do not vary much across specifications either in terms of sign or magnitude.

On interpreting statistical significance, testing the null hypothesis that the elasticity estimate is equal to zero is equivalent to a test of the Leontief specification. Testing the null hypothesis that that elasticity estimate is equal to unity is equivalent to a test of the Cobb-Douglas specification. We fail to reject the Cobb-Douglas specification for 20 of the 28 industries (at the five-percent level) and for seven of those industries we fail to reject the Leontief specification. Serial correlation exists in 6 of the 28 individual industry-level regressions. For all of manufacturing industries combined, we reject the Leontief specification, but we cannot reject Cobb-Douglas.

---

[14] Unit root and cointegration tests were not performed for the following industries because of lack of continuous data: metal mining, other transportation equipment, and petroleum and coal products.

[15] Industrial machinery and equipment, motor vehicles and equipment, instruments and related products, and printing and publishing.

CONCLUDING REMARKS

We present econometric elasticity estimates for 28 2-digit sectors, utilizing newly available data. Our estimates have the advantage over earlier work in that they utilize a richer, more complete data set, cover a larger number of sectors, and provide an indication of the long-run versus short-run elasticities. We fail to reject Cobb-Douglas for 20 of the 28 industries, and for seven of those industries we fail to reject the Leontief specification. We also fail to reject Cobb-Douglas for manufacturing in the aggregate. Further, value-added weighted averages for various aggregations are compared against the econometric estimates from those aggregations. The calculations reveal the possibility of an aggregation bias and suggest a reconsideration of averaging methods in flexible aggregation models.

Our results provide some support for using the Cobb-Douglas specification as a starting point. However, we show some estimates with very wide confidence intervals and even some negative point estimates. We do not claim to offer estimates that are superior to industry-level studies that look at detailed production functions. Rather, we present these estimates and their distributions to give the reader a consistent, transparent analysis of this new data source. We leave a more detailed and intensive econometric study of the new data to future research. Our estimates and the arguments we forward should be of interest to researchers needing a starting point for specifying a substitution rate between capital and labor.

REFERENCES

Arrow, K. J., H. B. Chenery, B. S. Minhas, R. M. Solow, 1961. "Capital-Labor Substitution and Economic Efficiency," *The Review of Economics and Statistics*, Aug., vol. 43, no. 3, 225-250.

Barro, Robert J. and Xavier Sala-i-Martin, 1995. *Economic Growth*, New York: McGraw-Hill, Inc.

Bureau of Economic Analysis (1996), *Survey of Current Business,* January-February.

Bureau of Economic Analysis (1998), *Benchmark Input-Output Accounts of the United States, 1992,* September

Cochrane, D. and G. H. Orcutt, 1949. "Application of Least-Squares Regressions to Relationships Containing Autocorrelated Error Terms," *Journal of the American Statistical Association,* v.44, 32-61.

Dawkins, C., T.N. Srinivasan, and J. Whalley, 2001. "Calibration", in J.J. Heckman and E. Leamer, eds., *Handbook of Econometrics: Volume 5*, Elsevier Science.

Dixon, P.B. and M.T. Rimmer (2001), *Forecasting, Policy, History and Decomposition: the MONASH Model of the Australian Economy,* completed draft available from the authors at the Centre of Policy Studies, Monash University

Dixon, P.B. and M.T. Rimmer (December22, 2000) "MONASH-USA: Early Steps", the Centre of Policy Studies, Monash University, pp. 22.

Dixon, P.B. and M.T. Rimmer (2001), Dynamic General Equilibrium Modelling for Forecasting and Policy: a practical guide and documentation of MONASH, completed draft available from the authors at the Centre of Policy Studies, Monash University

Francois, J., 2001. "Flexible Estimation and Inference Within General Equilibrium Systems," Conference Proceedings – Volume I: Fourth Annual Conference on Global Economic Analysis, June, 2001.

Gregory, A. W., and G. W. Smith, 1991. "Calibration As Testing: Inference in Simulated Macroeconomic Models," *Journal of Business and Economic Statistics*, vol. 9, 297-303.

Harberger, A. C., 1962. "The Incidence of the Corporation Income Tax," *Journal of Political Economy*, vol. 70, 215-240.

Jorgenson, D.W., 1984. "Econometric Methods for Applied General Equilibrium Analysis," in: H.E. Scarf and J.B. Shoven, eds., *Applied General Equilibrium Analysis*, Cambridge University Press, Cambridge.

Jorgenson, D.W., D.T. Slesnick, and P.J. Wilcoxen, 1992. "Carbon Taxes and Economic Welfare," Brookings Papers on Economic Activity, Microeconomics 1992, 393-441.

Kaldor, Nicholas, 1963. "Capital Accumulation and Economic Growth," in Friedrich A. Lutz and Douglas C. Hague, eds., *Proceedings of a Conference Held by the International Economics Association*, Macmillan, London.

Kydland, F. E., and E. C. Prescott, 1982. "Time To Build and Aggregate Fluctuations," *Econometrica*, vol. 50, no. 6, 1345-1370.

Leamer, Edward E., 1983. "Let's Take the Con Out of Econometrics," *American Economic Review*, March, vol. 73, no. 1, 31-43.

Liu, J., C. Arndt, and T. Hertel, 2001. "Parameter Estimation and Measures of Fit in A Global, General Equlibrium Model," Conference Proceedings – Volume I: Fourth Annual Conference on Global Economic Analysis, June, 2001.

McKibbin, W.J., R. Shackleton, and P.J. Wilcoxen, 1998. "What to Expect from an International System of Tradable Permits for Carbon Emissions," unpublished manuscript, revised: 9 December, 1998.

McKitrick, R.R., 1995. "The Econometric Critique of Applied General Equilibrium Modelling: the Role of Parameter Estimation," Discussion Paper 95/27, University of British Columbia, Department of Economics.

Perroni, C., and T.F. Rutherford, 1998. "A Comparison of the Performance of Flexible Functional Forms for Use in Applied General Equilibrium Analysis," Computational Economics, vol. 11, no. 3, 245-263.

Rutherford, T.F., 1995. "Constant Elasticity of Substitution Functions: Some Hints and Useful Formulae," notes prepared for GAMS General Equilibrium Workshop held December, 1995 in Boulder Colorado.

Shoven, J. B., and J. Whalley, 1972. "A General Equilibrium Calculation of the Effects of Differential Taxation of Income from Capital in the U.S.," *Journal of Public Economics*, vol. 1, 281-322.

U.S. Department of Commerce, 2000. Bureau of Economic Analysis, CD-ROM *Gross Product by Industry for the United States and States*, December, 2000.

U.S. Department of Commerce, 2000. "Fixed Assets and Consumer Durable Goods for 1925-1999," *Survey of Current Business,* September 2000, pp. 19-30.

U.S. Department of Commerce, 2000. "Improved Estimates of Gross Product by Industry for 1947-98, *Survey of Current Business,* June 2000, pp. 24-54.

Uzawa, H., 1962. "Production Functions with Constant Elasticity of Substitution," *Review of Economic Studies*, vol. 30, 291-299.

Wilcoxen, P.J., 1988. *The Effects of Environmental Regulation and Energy Prices on U.S. Economic Performance*, Doctoral Thesis, Harvard University, Cambridge, December, 1988.

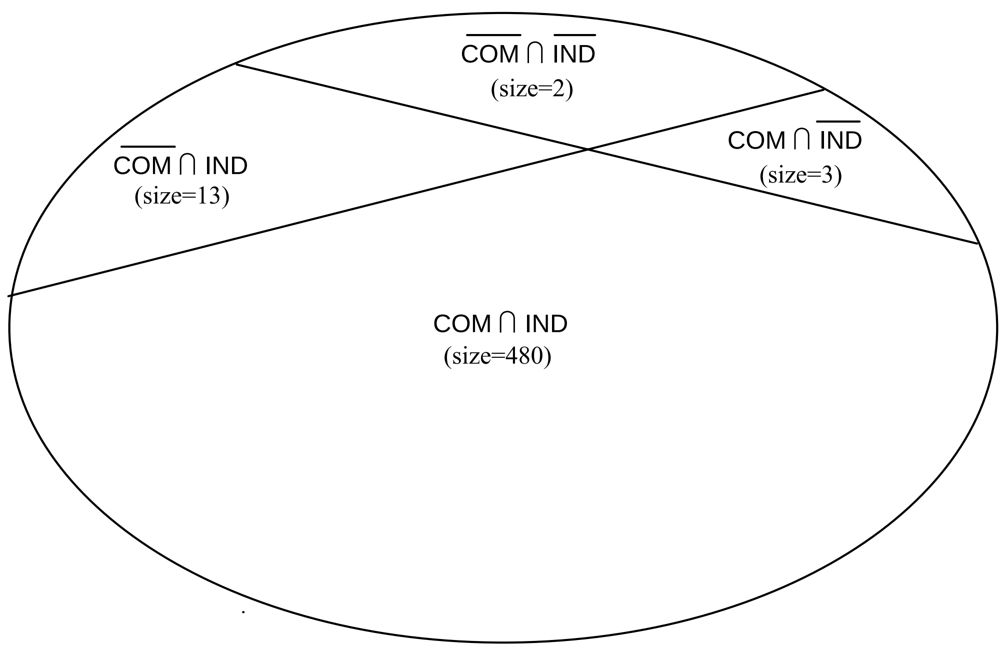
Figure 1. Schematic Representation of BEA Benchmark Input-Output Data for 1992

		Absorption Matrix						
		Producers	Investors	Households	Exports	Government	Inventories	-Imports
	Size	$\leftarrow I \rightarrow$	$\leftarrow 1 \rightarrow$	$\leftarrow 1 \rightarrow$	$\leftarrow 1 \rightarrow$	$\leftarrow 35 \rightarrow$	$\leftarrow 1 \rightarrow$	$\leftarrow 1 \rightarrow$
Commodity flows	$\uparrow C \downarrow$	PV1	PV2	PV3	PV4	PV5	PV6	-PVM
Margins	$\uparrow C \times N \downarrow$	MAR1	MAR2	MAR3	MAR4	MAR5	MAR6	0
Labor	$\uparrow 1 \downarrow$	LAB						
Taxes	$\uparrow 1 \downarrow$	TAX0						
Other value added	$\uparrow 1 \downarrow$	OVA						

C = Number of commodities (= 483)
I = Number of industries (= 493)
N = Number of commodities used as margins (= 8)

	Joint Production Matrix
Size	$\leftarrow I \rightarrow$
$\uparrow C \downarrow$	MAKE

Figure 2. Commodity and industry identifiers in the BEA 1992 Benchmark IO data



COM is the set of identifiers of genuine commodities, and $\overline{\text{COM}}$ is the set of identifiers for which there is no genuine commodity. Similarly, IND is the set of identifiers of genuine industries, and $\overline{\text{IND}}$ is the set of identifiers for which there is no genuine industry.

Table 1. Industry categories with no corresponding commodity categories

	Industry		Main commodity
020701	Forest products	030001	Forestry products
180201	Knit outerwear mills	180400	Apparel made from purchased materials
180202	Knit underwear and nightwear mills	180400	Apparel made from purchased materials
270202	Fertilizers, mixing only	270201	Nitrogenous and phosphatic fertilizers
370104	Cold-rolled steel sheet, strip, and bars	370101	Blast furnaces and steel mills
370105	Steel pipe and tubes	370101	Blast furnaces and steel mills
380600	Secondary nonferrous metals	380400	Primary aluminum
780200	Federal electric utilities	680100	Electric services (utilities)
790100	State and local government passenger transit	650200	Local and suburban transit and interurban highway passenger transportation
790200	State and local government electric utilities	680100	Electric services (utilities)
381200	Copper foundries	381100	Aluminum castings
381300	Nonferrous castings n.e.c.	381100	Aluminum castings
180203	Knitting mills n.e.c.	190200	Household furnishings n.e.c.

Table 2. Specification of BLS Input-Output Data

192 commodities and 192 industries. These are straight-forward aggregations of the BEA 6-digit categories.
131 categories of final demand. These are made up of 80 categories of private consumption, 38 categories of private investment, 1 category of inventories, 2 categories of exports, 2 categories of imports and 8 categories of government activities.
Commodity flows are valued in producer prices.
Imports are allocated indirectly.
Only 1 category of value added.
No separate identification of margins.
192 by 192 make matrix.
16 years, 1983 to 1998.
All tables are available in current and 1992 prices.

Figure 3. Schematic Representation of BLS Input-Output Tables

		Absorption Matrix						
		Prod-ucers	Invest-ors	House-holds	Exports	Govern-ment	Invent-ories	Negative of Imports
	Size	← 192 →	← 38→	← 80 →	← 2 →	← 8 →	← 1 →	← 2 →
Commod-ity flows	↑ 192 ↓	PV1T	PV2T	PV3T	PV4T	PV5T	PV6T	-PVM
Value added	↑ 1 ↓	VA						

	Joint Production Matrix
Size	← 192 →
↑ 192 ↓	MAKE

*Table 3. Output growth and contributions, 1983 to 1998: Selected BLS input-output commodities**

Rank[1]	Commodity	Output	Intermediate use	Investment demand	Household demand	Exports	Government demand	Inventory demand	Imports
128	**1 AgricProd**	**35.4**	**18.5**	**0.0**	**6.8**	**2.4**	**-0.1**	**13.6**	**-5.8**
			20.1	*0.0*	*64.2*	*23.8*	*-14.4*	*-131.5*	*188.0*
23	**2 VetServ**	**122.8**	**-18.1**	**0.0**	**140.3**	**0.0**	**0.7**	**0.0**	**0.0**
			-56.0	*0.0*	*208.1*	*0.0*	*278.3*	*0.0*	*0.0*
18	**3 LandHort**	**136.8**	**117.4**	**0.0**	**0.0**	**0.0**	**19.4**	**0.0**	**0.0**
			132.5	*0.0*	*0.0*	*0.0*	*170.4*	*0.0*	*0.0*
71	**4 AFFservnec**	**58.4**	**56.5**	**0.0**	**4.7**	**0.4**	**-3.0**	**0.0**	**-0.1**
			58.6	*0.0*	*102.7*	*282.2*	*261.0*	*0.0*	*1083.1*
118	**5 ForFishHntTr**	**38.8**	**49.7**	**0.0**	**11.2**	**1.9**	**-2.5**	**2.2**	**-23.6**
			40.4	*0.0*	*40.2*	*9.4*	*17.0*	*-131.8*	*43.5*
47	**6 MetalMin**	**81.5**	**32.5**	**-10.0**	**0.0**	**12.6**	**-0.8**	**-4.9**	**52.1**
			32.2	*-60.1*	*0.0*	*187.3*	*55.9*	*323.9*	*-243.9*
122	**7 CoalMin**	**37.5**	**34.3**	**0.3**	**-0.4**	**5.2**	**0.0**	**0.0**	**-2.0**
			40.2	*8.1*	*-50.8*	*51.0*	*9.1*	*-58.3*	*518.1*

Sample Industry Description:

BLS industry 45: Computer and office equipment (SIC 357)

The main products included in this classification are items of computer hardware.

In 1998, 97 per cent of US Computer and office equipment was produced by the Computer and office equipment industry and 92 per cent of the output of the Computer and office equipment industry was the Computer and office equipment commodity.

In 1983 the Computer and office equipment industry provided 475 thousand jobs, 0.46 per cent of total employment. Since 1983 employment in the industry has declined (Figure 45.1b). By 1998 the industry provided 384 thousand jobs, 0.28 per cent of total employment.

Despite declining employment, output of the Computer and office equipment industry grew by 18 per cent a year between 1983 and 1992 and 35 per cent a year between 1992 and 1998 (Figure 45.1a). Together the employment and output statistics for the industry imply average annual productivity growth between 1983 and 1998 of 34 per cent.

Consistent with very rapid productivity growth, the producer price of Computer and office equipment has declined sharply. By 1998 it was only 11 per cent of its level in 1983 (Figure 45.1b).

Figure 45.2 shows demand and supply for Computer and office equipment in 1983, 1992 and 1998. The first column for each year divides demand into four segments: intermediate, investment, exports and other (consumption, government and inventories). As can be seen from Figure 45.2 and Table 2.1, all segments of demand grew rapidly between 1983 and 1998. Output growth was damped slightly by very rapid growth in imports (about 36 per cent annually from 1983 to 1998). In 1983 imports satisfied 10 per cent of US demand (includes exports), by 1992 imports satisfied 31 per cent of demand and by 1998 they satisfied 32 per cent.

Figure 45.1a Computer and office equipment: indexes for productivity and output

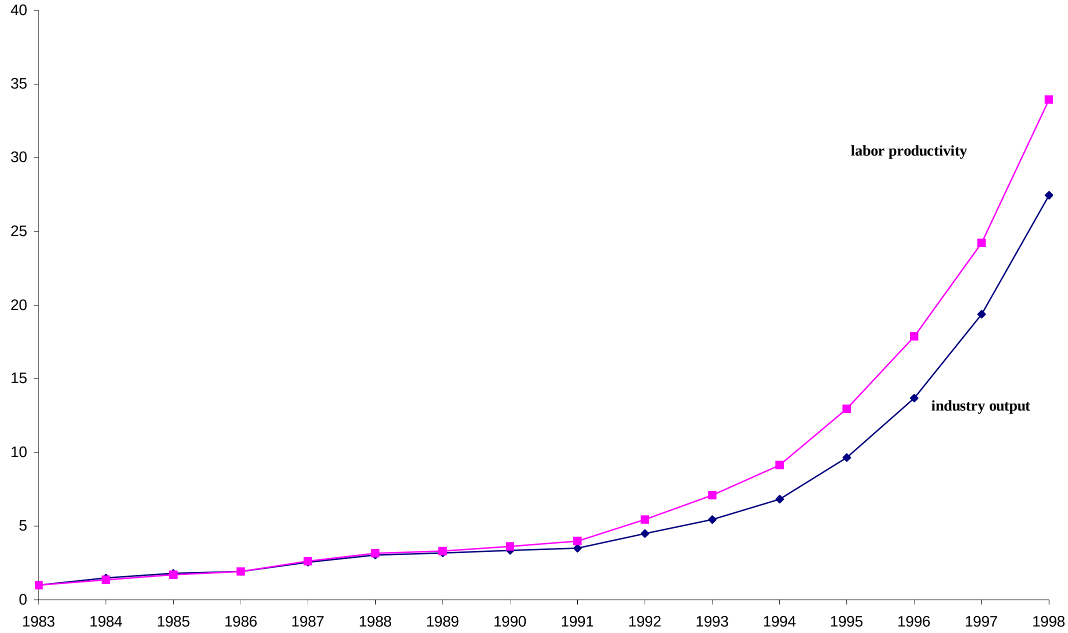


Figure 45.1b Computer and office equipment: indexes for employment and price

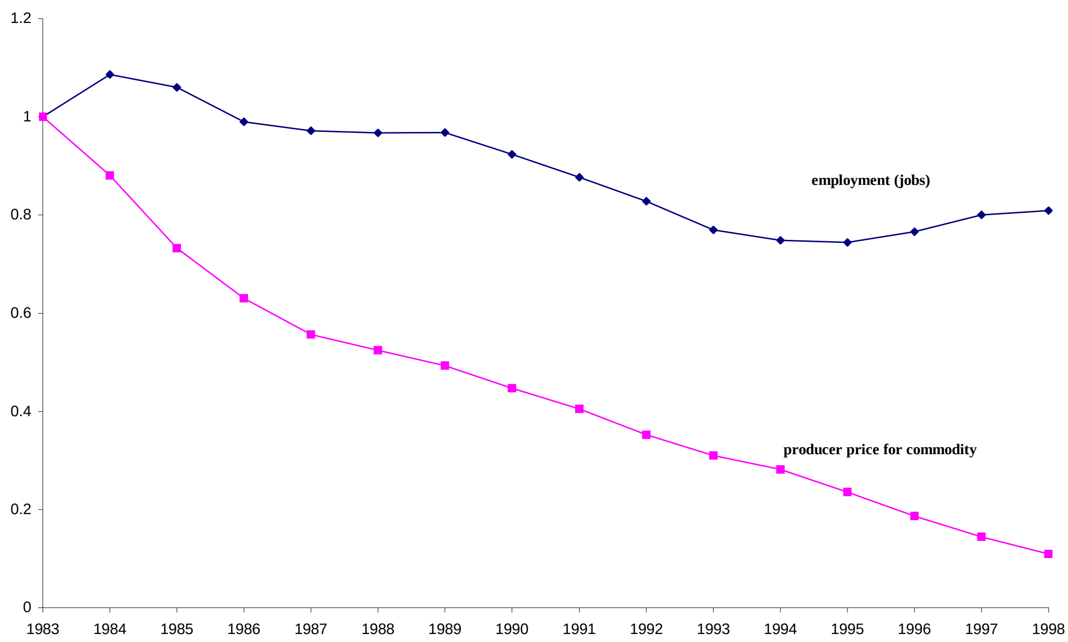


Figure 45.2 Computer and office equipment: quantity indexes for the commodity