Review of Income and Wealth
Series 43, Number 4, December 1997

PRIMARY VERSUS SECONDARY PRODUCTION TECHNIQUES IN U.S. MANUFACTURING

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In this paper we analyze the determinants of material inputs into individual production activities as a function of their outputs. We use observations on a large cross-section of U.S. manufacturing plants from the Census of Manufactures, including those that make goods primary to other industries, to study differences in production techniques. We find that in most cases material requirements do not depend on whether goods are made as primary products or as secondary products. We thus elucidate support for the commodity technology model as a useful working hypothesis.

I. INTRODUCTION

In multi-sectoral modelling it is customary to use an input–output core for the intermediate input requirements. In this paper we shed some light on the soundness of this strategy by analyzing the determinants of material inputs into individual manufacturing plants as a function of their outputs. The basic data refer to no less than 96,515 plants, 71 separate inputs, and 370 outputs.

The immediate relevance of our study pertains to Stone's 1961 commodity technology model. Stone distinguishes between activities and commodities, and his commodity technology model postulates input–output relations between the commodities, irrespective of the pattern of activities at the producing units. In this context, activities can be represented as alternative linear combinations of the elementary multiple-input/single-output processes used to make commodities.

In national accounting and input–output analysis, researchers usually rely on data which aggregates the activities of individual producing units to a sectoral level. The commodity technology coefficients must be inferred from a use table (with dimensions commodity by sector) and a make table (with dimensions sector by commodity). Assuming that there are the same number of sectors as activities and commodities, the input–output coefficients are exactly identified and obtained by multiplication of the use table and the (transposed) inverse of the make table. In this paper, however, we steer closer to Stone's framework by letting activities represent the behavior of individual plants. The wealth of plant data can be

Note: We thank an anonymous referee and participants at numerous seminars for helpful comments. The bulk of this research was completed while Mattey was a Research Associate at the Center for Economic Studies (CES), U.S. Bureau of the Census, for the Board of Governors of the Federal Reserve System. The paper presents the authors' own views, not those of the Census Bureau or the Federal Reserve System.

used for various tests of the commodity technology model (although a single comprehensive, system-wide test is not feasible). As it turns out, our results elucidate a great deal of support for the commodity technology model as a useful working hypothesis.

Our findings about material inputs also address one part of a more general issue, whether differences in factor intensities tend to reflect patterns of specialization or the co-existence of alternative techniques to produce outputs. For example, the traditional Heckshers-Ohlin trade-theory explanation of labor- vs. capital-intensive modes of production is that economies favor relatively abundant factor inputs. Equilibrium differences in factor intensities are explained by patterns of specialization in final goods and services. Per commodity, the co-existence of multiple techniques is not admitted.

In practice, patterns of specialization seldom conform to the sharp implications of such theory; specialization is not complete. To prevent such obvious contradictions, applied trade models often posit differences between seemingly identical commodities, either in terms of their price or perceived quality.[1] Alternatively, trade models following the Ricardian tradition consider differences of technologies as exogenous and exploit them to determine comparative advantages. The co-existence of multiple techniques is taken as given, without explanation. Similar issues arise with respect to materials usage, which is the main interest here.

Distinguishing between the alternative explanations of existing patterns of factor intensity—specialization or differences in production techniques—also confronts us at the level of measurement. Inputs are not reported by product or activity separately; the micro reporting units generally are conglomerates of production activities, establishments or legal forms of organization such as corporations. Moreover, applied studies generally use even more aggregative data. The traditional approach to aggregation is to classify reporting units into sectors, $j=1, \ldots, n$ and to label the commodities primarily associated with these sectors accordingly. In national accounts, the inputs of all commodities to sector j are listed in column vector $u_{\cdot j}$, and the make of all commodities by sector j is given in the row vector $v_{j\cdot}$ (U.N., 1993). Many of the off-diagonal elements of the corresponding make matrix V are non-zero. In considering perturbations of the patterns of production of final goods—changes in row vectors of the make matrix—a modeler needs to decide whether analysis can proceed on an element-by-element basis; alternatively, if this form of separability cannot be imposed, one must specify the nature of joint production.

[1]For example, a wide range of posited differences between seemingly identical commodities appears in the models used to study the effects of North American free trade agreements. The early work of Wonnacott and Wonnacott (1967) assumed that violation of the law of one price could explain the existing patterns of specialization; they argued that because of substantial tariff and non-tariff trade barriers between the U.S. and Canada, Canadian manufacturers attempted to take advantage of economies of scale through product diversification. More recently, Hamilton and Whalley (1985) among others, explain patterns of specialization by following Armington (1969) in assuming that the demand for a good depends on its country of origin. Alternatively, Brown and Stern (1989) allow for monopolistic competition created by firm-specific product differentiation, such as that established by brand-name advertising.

Typically, jointness in production is ignored, and modelers adopt the commodity-technology assumption that the requirements for intermediates depend just on the commodity being made, not on what else is being produced at the same location.[2] To apply the commodity technology assumption, one assumes that a technical coefficient a_{ij} represents the requirements for commodity i per unit of commodity j. Summing across the outputs v_{jk} of sector j of commodities k, the overall requirements for the i-th input are $\Sigma_k a_{ik} v_{jk}$. Equating observed inputs, u_{ij}, to requirements yields, given obvious matrix notation, $AV' = U$, where the superscript denotes transposition. If the matrices are square (the number of commodities equals the number of sectors), this equation can be solved for the commodity-specific input-coefficients A. Distinguishing between specialization and differences in production techniques as explanations for factor intensity is important to applied general equilibrium modeling; if the commodity technology assumption is invalid and techniques do differ, the predicted patterns of use will diverge from actual patterns.

With aggregated data, the ability to test the commodity technology assumption is limited. In fact, if the information on patterns of use and make are restricted to a single point in time, both the commodity technology assumption and the theoretically inferior alternatives critiqued by Kop Jansen and ten Raa, 1990 will fit the base-year data exactly, leaving no over-identifying restrictions to be tested.

In this paper we provide a stochastic framework for the measurement of production techniques, a framework that tests the commodity technology assumption and alternatives that allow for significant jointness of production. Instead of aggregating the reporting units—manufacturing plants—into sectors, we analyze the plant-level data. The micro data give us extensive variation in product mix and intermediate use; by simply regressing plant input on the whole vector of plant outputs, we investigate whether differences in factor intensities reflect patterns of specialization or the co-existence of alternative techniques to produce output. In terms of the above notation, we calculate the coefficients per material input for all products simultaneously; i.e. the estimation of input-coefficients is row by row, using the i-th row of the above equation, $u_{i\cdot} = a_{i\cdot} V'$.

In summary, we offer three contributions to the literature. First, we improve upon the traditional procedure of measuring technical coefficients from sectoral aggregates by allowing aggregation principles to be determined by the micro data. Second, by using raw data (reports from 96,515 U.S. manufacturing plants) we have a sound statistical basis for quantifying the accuracy of technical coefficient estimates; this lets us, for example, evaluate the so-called problem of negatives associated with the solution to the aggregate equation $AV' = U$. Last, but not least, we test for the co-existence of differing production techniques.

[2]For example, in the applied general-equilibrium model Lopez-de-Silanes, Markusen and Rutherford (1992) use to study the effect of a North American Free Trade Agreement on the motor vehicle industry, the intermediate input requirements of motor vehicle producers are assumed to just depend on whether they are making finished goods or parts (of two varieties), not on whether the production of finished vehicles and parts occurs jointly. More generally, the Social Accounting Matrices (SAMs) used to calibrate applied general equilibrium models (Reinert, Roland-Holst and Shiells, 1993) adopt this "commodity technology" assumption; see Pyatt (1993) for an explication of why the validity of the commodity technology assumption is critical in this context.

II. Data and Estimation Methods

To avoid the trap that variation of input intensities reflects specialization rather than a technical phenomenon, the definition of products must be disaggregated enough to render insignificant the concept of further specialization. We attempt to achieve product homogeneity by following the detailed U.S. benchmark input–output (I/O) table commodity classification system and the Census product code extensions of the U.S. Standard Industrial Classification (SIC) system. Specifically, each I/O sector is associated with a group of SIC industries, and each I/O commodity is associated with a list of Census products. For now, Census products are assumed to be homogeneous if they belong to the same I/O commodity category. This assumption seems modest, since there are hundreds of I/O commodities, and we do not aggregate them.

For each I/O commodity, producers are classified into two sets. For one set of producers, the make of the product is considered primary output because these producers are regarded as members of the corresponding I/O sector, and for the other set of producers, it is considered secondary output. This dichotomy of producers is known because the manufacturing industrial classification system has assigned producers to sectors on the basis of identifying their dominant products, and in the U.S. I/O system there is exactly one primary manufactured product for each I/O manufacturing sector.

Under the commodity technology assumption, this dichotomy into primary production—the make of the product characteristic to the sector—and secondary

TABLE 1

Coverage of Specified Materials Use in the 1982 Census of Manufactures

	Number of Plants	%	Amount of Materials[a]	%
1. Total Manufacturing	348,385	100	990,060	100
2. Nonreporters	251,870	72	149,881	15
3. Not required	135,042	39	29,168	3
4. Noncompliance[b]	116,828	34	120,713	12
5. Reporters	96,515	28	840,179	85
6. Materials n.e.c.[c]			180,094	18
7. Specified materials			660,085	67
Memo:				
8. Pure plants reporting[d]	62,757	18	384,554	39
9. Other plants reporting	33,758	10	455,624	46

[a]Millions of dollars of materials purchased and consumed. Excludes materials produced and consumed.

[b]For plants in industries asked to report specified materials use, includes non-administrative-record plants with materials use explicitly coded as n.s.k. and plants with only a positive balancing record in the detailed materials records.

[c]Also includes some unknown amount of materials of the types specified by kind but not reported under specified materials because the amount consumed was less than a censoring threshold, typically 10,000 dollars.

[d]Pure plants make only primary products (I/O basis). Miscellaneous receipts are excluded from our calculation of this degree of specialization, but less than half of a pure plant's total receipts are allowed to come from miscellaneous activities.

production—the make of products characteristic to other sectors—has no special significance. However, we adopt the primary–secondary dichotomy in order to give our test of the commodity technology assumption power against likely alternatives. In other words, we assume that if a multiplicity of techniques really does exist, that the choice of techniques is likely to be highly correlated with the primary/secondary split.

For each material input, the observations are the consuming plants. Mattey, 1993 analyzed patterns of intermediate use for the subset of pure plants with no secondary production (Table 1, line 8) to focus on the role of data truncation and errors of measurement in the problem of negative coefficients. Since we are interested in possible differences in techniques, we also include the producers of secondary products (Table 1, line 9). About 10 percent of the manufacturing plants report some secondary production, but because these manufacturers tend to be larger than average, about 46 percent of overall materials use occurs in plants with some secondary production. When secondary production is present in a plant, it tends to comprise a significant portion of a plant's activities; about 11 percent of all manufacturing output is secondary production.[3]

With regard to the decision of how many materials to study, we chose to focus on the 71 commodities used significantly as intermediates in manufacturing.[4] For each of these 71 commodities (i), the null hypothesis of a commodity technology relation is represented in equations of the following form:

$$u_{im} = a_{i1} v_{m1} + a_{i2} + v_{m2} + \ldots + a_{i370} v_{m370}. \tag{1}$$

Here, u_{im} is the use of material (i) by a manufacturing plant (m). There are 370 manufacturing products in the I/O system, and the make of each of these products by the plant is denoted by the variables v_{m1} through v_{m370}. The unknown commodity technology coefficients a_{i1} through a_{i370} do not depend on the manufacturing plant or its industry affiliation. Thus, for estimating the unknown coefficients for use of material (i) we can stack the observations for all reporting plants in all manufacturing industries into an equation:

$$\mathbf{u}_i = a_{i1} \mathbf{v}_1 + a_{i2} \mathbf{v}_2 + \ldots + a_{i370} \mathbf{v}_{370}, \tag{2}$$

where $\mathbf{u}_i$ and $\mathbf{v}_1$ through $\mathbf{v}_{370}$ are now vectors with components representing the use or make entries for unique manufacturing plants.[5] Data is available for the 96,515 manufacturing plants that report some specified materials use in 1982 (Table 1). Thus, in principle the vectors in equation (2) have 96,515 elements.

[3]The benchmark make table for 1982 from the U.S. I/O accounts indicates that 11 percent of manufacturing output is secondary production.

[4]Specifically, we restrict the analysis to those 71 materials for which the median pure-plant commodity technology coefficient was at least 5 percent in at least one industry. The scrap commodity and non-comparable imports meet this 5 percent requirement but are excluded because of their heterogeneity. Five other materials also meet this 5 percent requirement but are excluded because their use is so broad-based (more than 100 industries report some use) that our econometric approach is intractable; the excluded materials with broad-based reporting are paperboard containers and boxes, plastics materials and resins, miscellaneous plastics products, blast furnace and steel mill products, and rolled or drawn aluminum products.

[5]The column-vector $\mathbf{u}_i$ of equation (2) is specified by the corresponding row of the use matrix U, and $\mathbf{v}_1$ through $\mathbf{v}_{370}$ are specified by the columns of the make matrix V.

TABLE 2

LIST OF SECTORS PRODUCING MATERIALS UNDER STUDY

Material-producing Sector	Sector Description	Material-producing Sector	Sector Description
	AGRICULTURAL MATERIALS		
1	Dairy farm products	9	Tobacco
2	Poultry and eggs	10	Fruits
3	Meat animals	12	Vegetables
5	Cotton	13	Sugar crops
6	Food grains	15	Oil bearing crops
7	Feed grains	19	Commercial fishing
	MINING MATERIALS		
23	Copper ore mining	28	Sand and gravel mining
26	Crude petroleum and natural gas	29	Clay, ceramic, and refractory minerals mining
27	Dimension, crushed and broken stone mining	30	Nonmetallic mineral services and misc. minerals
	FOOD AND TOBACCO MATERIALS		
91	Meat packing plants	120	Chewing gum
97	Condensed and evaporated milk	122	Malt
99	Fluid milk	124	Distilled liquor, except brandy
108	Flour and other grain mill products	126	Flavoring extracts and syrups, n.e.c.
117	Sugar	128	Soybean oil mills
119	Chocolate and cocoa products	139	Tobacco stemming and redrying
	TEXTILE, WOOD AND PAPER MATERIALS		
140	Broadwoven fabric mills and fabric finishing	196	Pulp mills
142	Yarn mills and finishing of textiles n.e.c.	197	Paper mills, except building paper
169	Logging camps and contractors	198	Paperboard mills
170	Sawmills and planing mills	202	Paper coating and glazing
175	Veneer and plywood	217	Blankbooks and looseleaf binders

Notes: The sector code ranges from 1 to 537, corresponding to the sequence of sectors in the benchmark U.S. I/O accounts for 1977. The 370 manufacturing sectors in this system are in the 85–454 range of codes.

However, not all plants in all industries are asked about the use of every type of material, so no particular material input regression has this many observations.[6]

To illustrate the scope of the dataset with regard to types of materials, Table 2 lists the sectors in which the materials under study are produced as primary products. The analysis covers a wide range of materials. We study the use of particular agricultural materials such as dairy farm products. We also analyze the available reports on the use of mining materials such as copper ores, processed

[6]We implicitly assume that all plants making a particular product combination use the same production techniques. Another possibility is that some plants use inferior production techniques. If such plants could be identified, it would be interesting to eliminate them from the sample and to just estimate the techniques which define an efficient frontier. However, data limitations prevent us from identifying the relative efficiency of plants. In particular, the Census includes estimates of total output, total labor costs, and total materials costs for each plant, but capital costs and expenditures on purchased business services are not separately identified.

TABLE 2—continued

LIST OF SECTORS PRODUCING MATERIALS UNDER STUDY

Material-producing Sector	Sector Description	Material-producing Sector	Sector Description
	CHEMICAL, PLASTICS AND PETROLEUM MATERIALS		
224	Industrial inorganic and organic chemicals	237	Organic fibers, noncellulosic
225	Nitrogenous and phosphatic fertilizers	243	Paints and allied products
229	Adhesives and sealants	244	Petroleum refining
233	Chemical preparations, n.e.c.	249	Tires and inner tubes
235	Synthetic rubber	255	Leather tanning and finishing
	STONE, CLAY AND GLASS MATERIALS		
264	Glass and glass products	266	Cement, hydraulic
265	Glass containers	285	Minerals, ground or treated
	METAL MATERIALS		
298	Primary copper	304	Copper rolling and drawing
299	Primary lead	307	Nonferrous wire drawing and insulating
300	Primary zinc	312	Metal cans
301	Primary aluminum	331	Hardware, n.e.c.
302	Primary nonferrous metals, n.e.c.	334	Miscellaneous fabricated wire products
	EQUIPMENT COMPONENTS AND PARTS		
340	Internal combustion engines	412	Motor vehicles and car bodies
377	Refrigeration and heating equipment	413	Motor vehicle parts
	MISCELLANEOUS MATERIALS AND PARTS		
436	Jewelers' materials	443	Pens and mechanical pencils

Notes: The sector code ranges from 1 to 537, corresponding to the sequence of sectors in the benchmark U.S. I/O accounts for 1977. The 370 manufacturing sectors in this system are in the 85 454 range of codes.

foods such as packed meat, and various textiles, wood, and paper materials. There are several chemicals, plastics and petroleum materials. We also study the use of manufactured materials such as stone, clay and glass and metals. Only a few equipment components and parts are included in the dataset.

To illustrate the scope of the dataset with regard to the identity of the users of the materials, Table 3 lists the industry availability of reports on specified materials use of selected commodities. The use of dairy farm products is reported by plants in five manufacturing industries, those which produce butter, cheese, condensed milk, ice cream, and fluid milk. The plants in these five industries make a variety of products, including those primary to twenty-five other industries, which are as diverse as cereal breakfast foods and manufactured ice. Correspondingly, for this first material, indexed by the subscript $i=1$, equation (2) has a vector of observed dairy products use as the left-hand-side variable, and there are thirty right-hand-side variables describing the product composition of these plants, five for the primary products and twenty-five for the secondary products. The commodity technology equations (2) explaining the use of copper ores, meat packing plant products, or other materials have a similar form: observations on use of the materials by plants in several industries are explained by the wide-ranging product composition of these plants.

TABLE 3

AVAILABILITY OF REPORTS ON SPECIFIED MATERIALS USE FOR SELECTED COMMODITIES BY SECTOR

Sector Reporting Use	Sector Description	Sector Reporting Use	Sector Description
	USE OF DAIRY FARM PRODUCTS (1)		
95	Creamery butter	98	Ice cream and frozen desserts
96	Cheese	99	Fluid milk
97	Condensed and evaporated milk		
	USE OF COPPER ORES (23)		
224	Industrial inorganic and organic chemicals	298	Primary copper
	USE OF MEAT PACKING PLANT PRODUCTS (91)		
91	Meat packing plants	132	Shortening and cooking oils
92	Sausages and other prepared meats	238	Drugs
101	Canned specialties	244	Petroleum refining
102	Canned fruits and vegetables	245	Lubricating oils and greases
107	Frozen specialties	255	Leather tanning and finishing
115	Bread, cake and related products	256	Boot and shoe cut stock
116	Cookies and crackers		
	USE OF LOGGING CAMP PRODUCTS (169)		
170	Sawmills and planing mills	180	Particleboard
171	Hardwood dimension mills	181	Wood products n.e.c.
172	Special product sawmills	182	Wood containers
173	Millwork	196	Pulp mills
175	Veneer and plywood	197	Pulp mills
178	Wood preserving	198	Paperboard mills
179	Wood pallets and skids	201	Building paper and board mills
	USE OF SYNTHETIC RUBBER (235)		
229	Adhesives and sealants	256	Boot and shoe cut stock
249	Tires and inner tubes	283	Asbestos products
250	Rubber and plastics footwear	284	Gaskets, packing and sealing devices
252	Fabricated rubber n.e.c.	307	Nonferrous wire drawing
254	Rubber and plastics hose	451	Hard surface floor coverings
	USE OF PRIMARY LEAD (299)		
289	Blast furnaces and steel mills	306	Nonferrous rolling and drawing n.e.c.
291	Steel wire and related products	312	Metal cans
299	Primary lead	313	Metal barrels, drums and pails
303	Secondary nonferrous metals	405	Storage batteries
304	Copper rolling and drawing		
	USE OF REFRIGERATION AND HEATING EQUIPMENT (377)		
375	Automatic merchandising machines	410	Truck and bus bodies
376	Commercial laundry equipment	411	Truck trailers
377	Refrigeration and heating equip.	412	Motor vehicle and car bodies
379	Service industry machines n.e.c.	421	Travel trailers and campers
389	Household refrigerators	423	Motor homes

Note: The I/O sector codes of the materials are shown in parentheses.

III. PRIMARY VS. SECONDARY PRODUCTION TECHNIQUES

In fact, the most natural division of plants to test for differences in technical coefficients is between primary and secondary producers. So, in the estimation we

TABLE 3—continued

AVAILABILITY OF REPORTS ON SPECIFIED MATERIALS USE FOR SELECTED COMMODITIES BY SECTOR

Sector Reporting Use Sector	Description	Sector Reporting Use Sector	Description
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229	Adhesives and sealants	256	Boot and shoe cut stock
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299	Primary lead	313	Metal barrels, drums and pails
303	Secondary nonferrous metals	405	Storage batteries
304	Copper rolling and drawing		
	USE OF REFRIGERATION AND HEATING EQUIPMENT (377)		
375	Automatic merchandising machines	410	Truck and bus bodies
376	Commercial laundry equipment	411	Truck trailers
377	Refrigeration and heating equip.	412	Motor vehicle and car bodies
379	Service industry machines n.e.c.	421	Travel trailers and campers
389	Household refrigerators	423	Motor homes

Note: The I/O sector codes of the materials are shown in parentheses.

focus on a subset of material-product combinations for which it is possible to estimate requirements for make as a primary product, a^p, separately from the requirements for make as a secondary product, a^s. Our regression equations are a less restrictive form of equation (2):

$$\mathbf{u}_i = a^p_{i1}\mathbf{v}^p_1 + \ldots + a^p_{i370}\mathbf{v}^p_{370} + a^s_{i1}\mathbf{v}^s_1 + \ldots + a^s_{i370}\mathbf{v}^s_{370}, \tag{3}$$

where the superscripts p and s on $\mathbf{v}_1$ through $\mathbf{v}_{370}$ now index primary and secondary production of the specific commodities indexed 1 through 370. This dichotomy is useful for investigating whether multiple production techniques are present. If techniques do differ substantially across manufacturing plants, it is likely that the distribution of techniques will be correlated with the product mix.

Table 4 summarizes the distribution of regression summary statistics. Estimates are computed from 71 separate OLS regressions, one regression for each of the materials.[7] The goodness-of-fit tends to be quite high; only about 5 percent of the regressions explain less than 50 percent of the variation in materials use, and most of the regressions explain more than 80 percent of the variation.

The number of products of material users ranges from a low of 5 products in the regression explaining the use of sugar to a high of 205 products in the regression explaining the use of rolled or drawn copper. Most regressions reflect the make of 84 or more products. There are at least 27 manufacturing plant

[7]In Tables 4 and 5, each regression statistic is sorted relative to the same statistics from other regressions. Thus, for example, the smallest goodness-of-fit is 38 percent, but this lowest R^2 does not necessarily arise in the regression with the fewest products (5).

TABLE 4

DISTRIBUTION OF REGRESSION SUMMARY STATISTICS FOR USE OF 71 SPECIFIC MATERIALS BY MANUFACTURERS WITH USE DEPENDENT ON MAKE AS PRIMARY OR SECONDARY PRODUCT

	Fit and Scope of the Regression		
Quantile of Statistic	Goodness of Fit	Number of Products	Number of Plants
0	0.38	5	27
5	0.50	10	75
10	0.53	28	98
25	0.66	46	373
50	0.80	84	934
75	0.89	129	1,816
90	0.97	154	3,239
95	0.98	170	4,585
100	0.99	205	6,360

Notes: There are 1,073 observations on the statistics in the columns, one observation per material-product combination with reports of specified materials use available from manufacturing plants; material-product combinations with too few reports to identify both the primary- and secondary-production requirements parameters are excluded. The regression statistics in each column are sorted separately. Thus, for example, the smallest goodness-of-fit is 38 percent, but this does not necessarily arise in the regression with the fewest products (5).

observations in each regression. Most regressions attempt to explain the use by more than 934 manufacturing plants of a specific material. The high numbers of observations facilitates estimation and testing of technologies and their differences.

As shown in Table 5, the estimates of requirements for make as a primary product generally are in the expected range from zero to one, with less than 5 percent clearly negative and statistically significant at the 5 percent significance level. The estimates of requirements for make as a secondary product are a bit more imprecise and wide-ranging. A bit more than 5 percent of the estimates are significantly negative, suggesting that there are a few secondary production techniques that use fewer of these specified materials than the use in primary production. Also, about 4.5 percent of the estimated requirements for secondary production exceed one, whereas very few of the estimated requirements for primary production exceed this upper threshold.

To more fully quantify the extent to which secondary production techniques really do tend to differ, we also have computed the difference between the parameter estimates and scaled the difference by its conventional standard error. This t-statistic for the difference between primary and secondary production requirements is significantly negative in about 7 percent of the cases and is significantly positive in another 10 percent of the cases (final column of Table 5). In all, there is no evidence of a significant difference between primary and secondary production techniques in about 83 percent of the 1,073 material-product combinations we tested. Thus, in the vast majority of cases, the results support the common assumption that material requirements for a product are not dependent on whether this production is the modal activity of a manufacturing plant.

TABLE 5

DISTRIBUTION OF REGRESSION RESULTS FOR USE OF 71 SPECIFIC MATERIALS BY MANUFACTURERS WITH USE DEPENDENT ON MAKE AS PRIMARY OR SECONDARY PRODUCT

Quantile of Statistic	Make as a Primary Product a^p	Primary Product t-statistic	Make as a Secondary Product a^s	Secondary Product t-statistic	T-statistic for Difference
0	−1.17	−5.00	−305.81	−18.38	−12.39
5	0.00	0.05	−0.38	−2.25	−3.22
10	0.00	0.05	−0.21	−1.04	−1.44
25	0.01	0.43	−0.03	−0.17	−0.37
50	0.02	1.55	0.02	0.13	0.04
75	0.09	6.33	0.13	0.91	0.57
90	0.23	16.75	0.43	2.85	2.07
95	0.37	29.05	0.90	5.79	3.32
100	232.48	348.89	29.85	46.81	19.98

Notes: There are 1,073 observations on the statistics in the columns, one observation per material–product combination with reports of specified materials use available from manufacturing plants; material–product combinations with too few reports to identify both the primary- and secondary-production requirements parameters are excluded. The regression statistics in each column are sorted separately.

The conclusion that techniques are mostly uniform across primary and secondary production is strengthened when the cases of different techniques are examined more closely. The 17 percent of the cases where material–product coefficients are different will be broken down into three, roughly equal subgroups. In one-third of these cases, the differences can be ascribed to possibly improper aggregation in the original tests. In a second third, the further examination is inconclusive due to insufficient reporting of the data needed for additional tests. Only in the remaining third, that is 6 percent of all the material–product combinations, do differences in primary and secondary production techniques withstand the tests with alternative specifications and, therefore, can be said to be indigenous. This share is low enough to be ascribed to measurement error. In other words, with regard to materials use, the neoclassical assumption that a single, most efficient technique is chosen for making each product appears to be a good one for most U.S. manufacturing products.

In examining in more detail the material–product combinations which appear to have different proportions in primary vs. secondary production, we note that the following specification issues could cause false rejections of the homogeneity test.

A. *Underlying Product Diversity*

Sometimes products are classified as primary to the same sector on the basis of similarities in the customer market, rather than similarities in production (Triplett, 1992). An example is the pet food sector, whose primary products include both "dog and cat food"—which contains significant amounts of beef and fish—and "other pet food"—which contains significant amounts of grains and seed for feeding pets such as birds. Pet food plants which make secondary products tend to have different underlying primary product mixes than pet food plants which make only primary products; for example, a tuna packing plant likely cans goods for both household and pet consumption, and the former counts as a secondary product in the pet food sector. Bird seed packagers likely do not make secondary products for household consumption. Too much aggregation in this pet food primary product group could lead us to infer that the technical coefficients differ across primary and secondary producers, when really they only differ because of product diversity within the primary product group. In principle, further disaggregation can be used to identify this source of technical difference.

To identify cases in which the apparent difference in primary and secondary production techniques is explained by product heterogeneity among the products classified as primary to the same sector, we modify equation (3) by further disaggregating the explanatory variables that gave rise to the finding of heterogeneity in techniques. If the significant differences between primary and secondary production techniques get resolved by further disaggregation, we count the case as an instance explained by product diversity among primary products. As shown in Table 6, about two-thirds of the cases can be tested for underlying product diversity. Of these, 53 material-product combinations no longer reject the test of homogeneity between primary and secondary production techniques. In other words, in 28 percent of the cases where we originally found an apparent difference,

TABLE 6

SUMMARY OF CLASSIFICATION OF APPARENT DIFFERENCES BETWEEN PRIMARY AND SECONDARY PRODUCTION TECHNIQUES

Explanation Code	Description	Number of Cases	Percent of Cases
	Total apparent differences	190	100
A	Underlying product diversity		
	Not testable	64	34
	Testable	126	66
	No Rejection	53	28
	Still Reject	73	38
B	Use of similar delivered materials		
	Not testable	152	80
	Testable	38	20
	No Rejection	16	8
	Still Reject	22	12
C	Use of produced-and-consumed materials		
	Not testable	148	78
	Testable	42	22
	No Rejection	23	12
	Still Reject	19	10
Memo:			
A, B, C	Any of the Explanations		
	Not testable	54	28
	Testable under at least one	136	72
	No Rejection under at least one	70	37
	Still Reject under all tested	66	35

Source: Calculations by the authors by the method described in the text.

primary and secondary production techniques did look similar at a more disaggregate product level; this 28 percent of the differences between techniques is ascribed to underlying product diversity.

B. *Use of Similar Delivered Materials*

In this case, too little aggregation of materials could create differences in technical coefficients that really only reflect the use of close substitute materials which, for most purposes, could just as well have been counted as a single material in the original analysis. For example, there are separate sectors for primary production of fluid milk and of condensed or evaporated milk, so these items are counted as separate materials, even though the ultimate requirements on dairy farms from the use of the materials is similar.

To identify cases in which the apparent differences in techniques can be explained by very close substitutability of the materials, we aggregate close substitute materials and re-do the test at the more aggregate levels.[8] As shown in the second grouping of rows in Table 6, some use of similar delivered materials is reported by only enough respondents to apply this test to 20 percent of the cases. Of these, 16 cases, or 8 percent of the total 190 rejections, no longer indicate a difference between primary and secondary production techniques.

C. *Use of Produced-and-Consumed Materials*

The use of produced-and-consumed materials is relatively common in industries such as meat-packing. Under-reporting of materials use arises if the analysis is restricted to purchased materials, which is the conventional format of the data. To investigate the extent to which the omission of produced-and-consumed materials has introduced the appearance of heterogeneity, we also have estimated equation (3) under the broader definition of materials, that is including self-supplied inputs.[9]

As shown in the third group of rows in Table 6, some use of produced and consumed materials is reported by enough respondents to test this explanation for about 22 percent of the cases. Of these, 23 cases no longer reject the test of similarity. In other words, about 12 percent of all of the initial rejections can be resolved by the incorporation of the use of produced-and-consumed materials. Many of these are cases in which requirements for delivered materials are lower for secondary producers. Apparently, there is some tendency for the simultaneous production and consumption of materials to occur in conjunction with secondary production.

To summarize these results, underlying product diversity explains 28 percent of the original 190 findings of heterogeneity. Use of close substitute materials

[8]Again, we rely on the SIC as an indicator of substitutability. Specifically, materials use at the 6-digit materials code level is aggregated to a 3-digit level.

[9]The dependent and independent variables in equation (3) are measured in dollars, but the data on produced-and-consumed materials is available only in physical units. To aggregate across delivered and produced-and-consumed materials, we value the produced-and-consumed materials at the average price of the plant-specific delivered materials of the same kind.

explains 8 percent, and use of produced-and-consumed materials explains 12 percent of the original findings of heterogeneity. A bit over one-third (37 percent) of the differences are explained (eliminating the double-counting that could arise because more than one explanation could be applicable). In 35 percent of the cases, the rejection of the t-test is still there under all tested explanations. The remainder of 28 percent is not testable.[10]

IV. Sensitivity to Scale Effects

Our main results, shown in Table 5, are from estimating equation (3) by ordinary least squares (OLS) and testing the restriction that materials use requirements do not depend on whether products are made as primary products or as secondary products. The statistical properties of these coefficient estimators and tests depend both on the distribution of the explanatory variables—make as a primary or secondary product—and on the distribution of the implicit error term in equation (3). In this section, we discuss the sensitivity of these statistical properties to scale effects, the presence of very large and very small (in terms of output) plants in the sample, and the possibility that model should exhibit dependence on plant size.

The presence of both large and small plants in the sample contributes to the ability of the regressions to achieve a high goodness of fit (Table 4). However, we do not use the goodness of fit measures for any inferences about economic structure, and this wide size distribution does not, in and of itself, bias our OLS coefficient estimators or test statistics. Scale effects are potentially important for our statistical inferences only if these scale effects have contaminated the implicit error term in equation (3).

One possibility is that the standard deviation of the error term for equation (3) is directly proportional to a measure of plant size; in other words, there could be size-related heteroskedasticity of the first degree. To help us be specific in discussing this, note that the m-th row of equation (3) corresponds to the observation on the m-th manufacturing plant and can be written as

$$u_{im} = \sum_{k=1}^{370} (a_{ik}^{p} v_{mk}^{p} + a_{ik}^{s} v_{mk}^{s}) + \varepsilon_{im}, \tag{3'}$$

where ε_{im} is the implicit error term. Using the plant's level of primary production, v_{mj}^{p}, as a convenient measure of plant size, this type of size-related heteroskedasticity is a proportional relationship between the standard deviation of ε_{im} and v_{mj}^{p}. In this case, OLS estimators of the coefficients in equation (3′) remain unbiased, but OLS is not an efficient (minimum variance) estimator. A weighted least squares

[10]For product diversity, the explanation is not testable if there are not enough plants that report the make of the more disaggregate products; such additional detail must be available for both primary and secondary producers, but often the secondary producers specialize in a single product class. For the use of close substitute materials, the explanation is not testable if the questionnaires on materials use do not ask about close substitutes (other materials in the 3-digit class) in both the industry where production is primary and the industries where production is secondary. For the use of own-produced materials, the explanation is not testable unless such activity is reported by both primary and secondary producers.

procedure, using the v^p_{mj} as weights, would be more efficient. Also, heteroskedasticity would render invalid the conventionally-calculated OLS standard errors, biasing the test statistics, whereas the conventional standard errors and test statistics from the weighted least squares regression would be correct.

Estimation of equation (3′) by such a weighted least squares procedure likely would be preferable to our OLS estimation of equation (3) and would be equivalent to estimating the following transformed equation by OLS:[11]

$$(3'') \qquad \frac{u_{im}}{v^p_{mj}} = \sum_{k=1}^{370} \left(a^p_{ik} \frac{v^p_{mk}}{v^p_{mj}} + a^s_{ik} \frac{v^s_{mk}}{v^p_{mj}} \right) + \frac{\varepsilon_{im}}{v^p_{mj}}.$$

Whether or not size-related heteroskedasticity is present and to what degree is an empirical matter which cannot be ascertained at this time.[12] However, the econometric theory in this area is well known and indicates that the OLS standard errors from the untransformed regression (3) generally will understate the true degree of estimation error which would be revealed by estimating (3″).[13] Tests based on (3) instead of (3″) of the equality of material requirements for primary and secondary production would be biased toward rejection. We found little evidence of differences with a test which might be biased toward finding evidence of frequent differences. Accordingly, the possible presence of such size-related heteroskedasticity reinforces our main conclusions.[14]

The recognition of another possible scale-related misspecification—the omission of an intercept from equation (3″)—also works to strengthen the support for our main conclusions. Allowing for overhead materials requirements in this form

[11]We thank an anonymous referee for suggesting tests based on equations like (3″) to avoid possible problems with scale effects.

[12]Our research affiliation with the Census Bureau has expired, and we no longer have access to the confidential Census data used in our original empirical work. Furthermore, this dataset is so rich—as many as 71 inputs and 370 outputs could be reported for each of 96,515 manufacturing plants—that exploring alternative forms for the regression would be quite burdensome computationally.

[13]See, for example, Theil (1971), p. 248.

[14]We conducted some Monte Carlo experiments to simulate how size-related heteroskedasticity could have affected our results. In particular, we generated random data on the use of materials and the make of primary and secondary products by one-hundred hypothetical manufacturing plants, supposing that twenty percent of these were large plants with output levels which averaged ten times that of the small plants. We split the plants into two industries and allowed for make of one additional secondary product, with eighty percent of production, on average, devoted to primary production. In one set of experiments, there was no size-related heteroskedasticity, and in the other set of experiments the standard deviation of the error term was proportional to the plant's level of primary production. We generated the artificial data one-thousand times for each of the one-hundred plants and calculated the regressions and tests corresponding to both equation (3) and equation (3″).

As expected, in the set of experiments without size-related heteroskedasticity and a true null hypothesis of no difference in requirements between primary and secondary production, the rejection frequencies for the 5 percent significance level hypothesis tests based on (3) were close to their theoretical values; no difference was detected in 4.4 percent of the one-thousand cases for the tests based on (3). In the set of experiments with size-related heteroskedasticity, the tests based on (3) rejected much too often; 41.5 percent of the one-thousand cases showed a false rejection. In contrast, the rejection frequency of the tests based on (3″) was relatively insensitive to the presence of size-related heteroskedasticity. These Monte Carlo experiments illustrate that tests based on (3″) are superior in the sense that they are robust to the possible heteroskedasticity. However, the Monte Carlo experiments also illustrate that our main conclusion that there is little apparent difference between material requirements for primary and secondary production is reinforced by the possibility of bias in the tests based on equation (3).

that allows for economies of scale would introduce in the model another parameter that would be capable of absorbing any originally-estimated differences in technical coefficients between primary and secondary producers. The commodity technology model does not allow for such economies of scale, and we did not find many estimated differences, so such richer parameterizations appear unneeded for evaluating the commodity technology model.

V. Conclusion

This paper lends support to the commodity technology model of material input use. Material input requirements can be reasonably well-approximated without considering joint production. Using raw data reports from almost 100,000 U.S. manufacturing plants, technical coefficients have been estimated and tested. The problem of negative coefficients in the presence of secondary production appeared to be significant in only about 5 percent of the material–product combinations. Moreover, after further testing, we find that in only about 6 percent of the cases (which is 35 percent of the initial rejections) the difference between primary and secondary coefficients withstands further scrutiny. In other words, generally we find that material requirements do not depend on whether the goods are made as primary products or as secondary products. Within U.S. manufacturing sectors, differences in material input factor intensities tend to reflect patterns of product specialization, not the co-existence of alternative techniques to produce output.

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