Economies of Scope and Common Inputs in Multi-Output Production*

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March 15, 2024

Abstract

The dominant theoretical explanation for the existence of large, multi-product producers is economies of scope arising from common inputs across production lines of business. I assess the degree of economies of scope using data from the FTC's Line of Business surveys, which provide information on inputs at the line of business level as well as common inputs to the firm. I estimate a production function allowing for common inputs and find substantial economies of scope; eliminating the common input would reduce output by 11% for the average firm.

Keywords: productivity, economies of scope, multiproduct firms, production functions

*The views expressed in this article are those of the author. They do not necessarily represent those of the Federal Trade Commission or any of its Commissioners. I thank Bram De Rock, Glenn Magerman, Subal Kumbhakar, Ariel Pakes, Ted Rosenbaum, Dave Schmidt, David Slichter, and Philip Ushchev for their comments as well as Steve Puller for discussing this paper.

1 Introduction

Large, multi-product firms are responsible for a substantial share of US output (Gabaix, 2011) and the R&D spending that contributes to productivity growth.[1] The dominant explanation for the existence of such multi-product firms is economies of scope (Baumol, Panzar and Willig, 1988; Panzar and Willig, 1981). Panzar and Willig (1981) show formally that economies of scope imply the existence of inputs that are shareable across different production lines.

Despite this theoretical result, data limitations have caused the recent empirical literature examining multi-output production to largely ignore such common inputs, and indeed economies of scope themselves. Typical production datasets separate out outputs, but not inputs, by product line, and do not identify whether inputs are "common" to the firm or specific to a given product line.

Researchers have responded to these data limitations by taking two basic approaches. First, one could fully allocate inputs to different production lines (De Loecker et al., 2016; Orr, 2022; Valmari, 2023), which implicitly assumes no common inputs or economies of scope arising from such inputs. Alternatively, one could estimate a transformation function from firm-level inputs to multiple outputs (Diewert, 1973; Lau, 1976); however, such a transformation function is likely to be firm specific for large firms that operate in unique sets of business lines.

In this article, I examine how inputs common across product lines affect economies of scope by using microdata from the FTC's Line of Business surveys of large US manufacturing firms from the 1970s (Ravenscraft and Wagner III, 1991). The FTC surveys collected data on both outputs and inputs at the line of business level, and asked how much of specific inputs, such as capital and management and marketing expenses, were specific to a given

[1] Gabaix (2011) document that the sales of the top 100 US firms represent 29% of US GDP on average, and account for one-third of the volatility in output growth. The NSF finds that firms with more than 20,000 employees constitute 38% of all corporate R&D spending, and above 10,000 employees 55% of corporate R&D spending, in 2021. See https://ncses.nsf.gov/pubs/nsf24317.

line of business.[2] This data allows me to estimate production functions at the firm-line of business level, and to include common inputs in the production function. I can then assess how much common inputs contribute to output, and the degree of economies of scope that they provide.

The FTC's line of business surveys were discontinued in the 1980s as part of the Reagan era reforms to antitrust enforcement. Senator Amy Klobuchar has recently argued in favor of restarting this data collection program.[3] In this article, I show that the design of the FTC's line of business surveys provides valuable information not available from other data sources such as the US Census of Manufactures or Compustat.

I first document three stylized facts in the line of business data that break common assumptions of the multi-output production literature. First, approaches that allocate inputs to product lines assume specific allocation rules, such as that the share of each input allocated to a given product line is the same across inputs. However, the labor share of variable cost typically varies substantially across lines of business of the same firm in ways inconsistent with such allocation rules. Second, a substantial share of capital, and an even larger share of management and marketing expenses, are reported as not specific to any one line of business. I consider such inputs to be shareable or common inputs in production. Finally, a minority of firms report that significant output of one line of business is used as an input into its other lines of business; models that fully allocate inputs to product lines assume that there are no internally generated inputs.

I then model production as a nested CES function between a Cobb-Douglas function of line of business specific inputs and a common input at the firm-line of business level. This

[2] Nichols (1989) provide an early attempt to examine economies of scope using the line of business data by regressing measures of efficiency on several variables, and find that shared management/marketing expenses increase productivity.

[3] She writes "The FTC used to collect industry data on lines of business in an effort to make sure particular sectors did not become too concentrated, and antitrust officials today also have a need to get accurate information so that they can closely monitor industries for monopoly power and consolidation. Although the data collection program was stopped in the mid-1980s, if antitrust agencies are adequately funded, they will be better able to use modern-day technology to effectively track anticompetitive or exclusionary conduct." See Klobuchar (2022).

common input – measured as the combination of management and marketing expenses not traceable to any line of business – is what allows economies of scope across different product lines. I identify this production function using an approach similar to Gandhi, Navarro and Rivers (2020) by using both the revenue share equations from first order conditions as well as moments based on the innovation in productivity being orthogonal to pre-determined inputs.

Following this identification approach, I estimate this production function using the line of business data. I find an elasticity of substitution slightly above one and a substantial weight placed on the common input in the production function. The median and mean output elasticities for the common input for firms reporting any common input are 0.08 and 0.09, indicating a substantial contribution for common inputs in production.

My estimates allow me to examine the degree of economies of scope stemming from the common input. I examine the counterfactual of removing the common input; output falls by 11% on average, with larger declines in output for firms operating in more lines of business.

Economists have largely taken two approaches to estimating multi-output production functions. First, one can fully allocate firm level inputs to the product level and then estimate production functions at the firm-product level (De Loecker et al., 2016; Gong and Sickles, 2021; Itoga, 2019; Orr, 2022; Valmari, 2023). These approaches require symmetry assumptions across the firm's products, such as no product-level productivity differences (De Loecker et al., 2016) or no differences in input mix across products (Orr, 2022). Second, one could estimate a transformation function from firm-level inputs to multiple outputs (Dhyne et al., 2022; Grieco and McDevitt, 2017; Maican and Orth, 2021; Malikov and Lien, 2021). Most of these papers have examined a setting with a small number of outputs (such as beef and dairy milk from cows, or quality and quantity from dialysis), although Dhyne et al. (2023) examine the assumptions required to estimate transformation functions with many outputs.

Khmelnitskaya, Marshall and Orr (2023) apply a complementary approach to estimating economies of scope – they use estimates of the demand function to recover marginal costs, and then identify the degree of economies of scope using cost data. Applying this approach to the beer industry, they find that shutting down economies of scope increases marginal costs by 26% and prices by 14%.

In addition, a large literature has examined how management and marketing affect firm output and productivity. For example, researchers have found that firms with better management practices have higher productivity (Bloom and Van Reenen, 2007), that hiring management consultants leads to improved productivity (Bloom et al., 2013), and that managers improve in productivity after receiving management education (Bianchi and Giorcelli, 2022; Giorcelli, 2019). In marketing, the main challenge has been to measure how different marketing campaigns affect revenue (for one example, see Shapiro, Hitsch and Tuchman (2021)).

The rest of this paper proceeds as follows. Section 2 explains the data from the FTC Line of Business surveys, while Section 3 examines several stylized facts from this data. Section 4 lays out the model of production and the strategy used to identify its parameters. Section 5 details the estimates of this production function and examines counterfactuals that illustrate the degree of economies of scope from common inputs. Finally, Section 6 concludes.

2 Data

In the 1970s, the FTC developed a new program to collect disaggregated data on revenue and costs from the largest manufacturing firms in the US. The FTC piloted the survey in 1973 and then ran four waves from 1974 to 1977. This data effort experienced considerable headwinds, as hundreds of corporations sued to stop the data collection. While the FTC won in court, the General Accounting Organization (GAO) asked the FTC to evaluate the benefits and costs of the surveys.[4] Data collection was paused pending this cost-benefit

[4]The FTC won in district court and at the DC Circuit Court of Appeals, and the Supreme Court denied *certiorari*. See Whipple (1979) for details of the litigation.

Table 1: Number of Firms and Lines of Business Per Year

Year	Firms	Lines of Business	Manufacturing Lines of Business
1974	436	4,291	3,383
1975	469	4,507	3,536
1976	466	4,572	3,598
1977	456	4,650	3,693

analysis; the FTC ended up concluding that the costs exceeded the benefits in 1984 and so the program was discontinued.

The FTC asked large manufacturing firms to provide data at the "line of business". The FTC developed 289 lines of business. For manufacturing, these lines of business were roughly at the 3/4 digit SIC level; for example, for glass products, flat glass (SIC 321), glass containers (SIC 3221), pressed and blown glass, not elsewhere classified (SIC 3229), and products of purchased glass (SIC 323) are all separate lines of business. In addition, the data include information on 14 non-manufacturing lines of businesses at a roughly one digit SIC level of aggregation (e.g., Construction or Retail Trade).

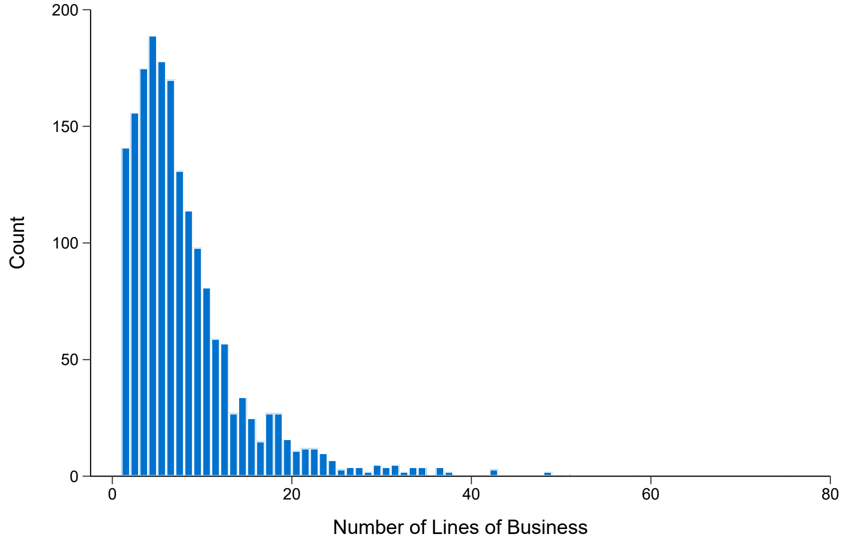
Table 1 provides details on the number of firms, total lines of business, and manufacturing lines of business in the dataset. Each year has between 436 and 469 firms; on average, firms operate in about 10 lines of business, of which 7 to 8 are in manufacturing.

Figure 1 depicts the distribution of manufacturing lines of business per firm year. This distribution is quite skewed. While the modal firm has 5 lines of business and the median firm has 6 lines of business, 25% of firms have 10 lines of business or more and 5% have over 20 lines of business.

The dataset includes information on the standard productivity inputs and outputs – sales, payroll, materials, and capital (net plant, property, and equipment) – at the line of business level. In addition, it has information on three categories of additional expenses at the line of business level – advertising, other selling, and general/administrative expenses.

For both capital and the marketing/management expenses, the survey distinguished between assets or expenditure "traceable" to the line of business, as opposed to not traceable

Figure 1: Distribution of Manufacturing LBs per Firm-Year



to a specific line of business. I use this distinction to separate common inputs across the firm's lines of business to inputs specific to a given line of business. In addition, the survey distinguished revenue from sales to outside parties from transfers to different lines of business of the firm.

While the sample has less than 500 firms per year, these firms are quite large. Comparing to data from the US Census of Manufactures in 1977, the firms in the Line of Business database comprise 47 to 52% of manufacturing revenue, 49% of materials, and 53% of payroll. Since large firms are more capital intensive, they comprise an even larger share of gross capital, at 73% to 84% of manufacturing gross capital.[5]

I next clean the data by dropping all non-manufacturing lines of business as well as all observations with zero or negative records for sales, payroll, materials, traceable capital, and traceable management/marketing expenses. The latter restriction removes about 6% of all observations in the data.

[5]For revenue, materials, and payroll, I compare to data for manufacturing from the NBER Productivity Database for 1977. For revenue, the lower estimate is based only on revenue from outsiders while the higher estimate also includes within firm transfers. For capital, I compare to data for manufacturing from the 1977 Census of Manufactures; the lower number compares to gross capital at the end of 1977 and only includes "traceable" capital. The higher number compares to gross capital at the beginning of 1977 and includes both capital traceable and not traceable to the line of business.

3 Stylized Facts

I examine three key assumptions commonly made in the production literature with respect to multi-output production on the line of business data – symmetry across products for the same firm, no input common across products, and no vertical integration where the firm produces its own inputs.

3.1 Symmetry

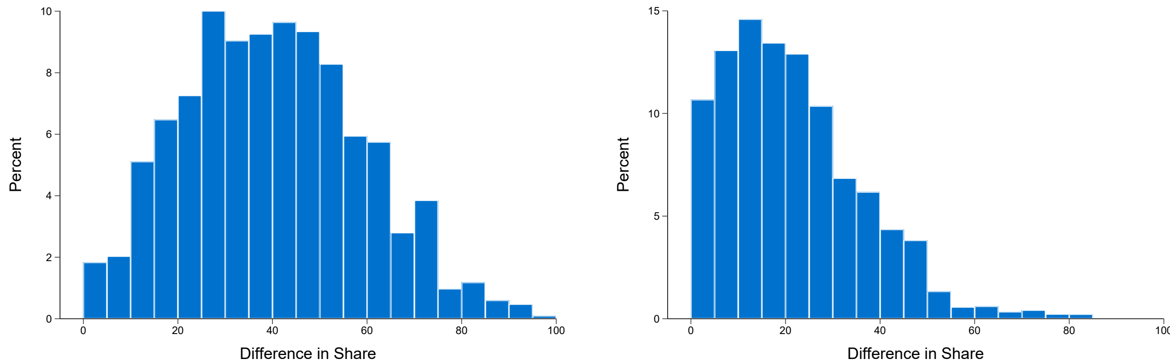
Models in the multi-output production literature typically include a symmetry assumption across products produced by the same firm in order to allocate inputs to products. For example, De Loecker et al. (2016) assume that all products of the same firm have the same productivity, while Orr (2022) assumes that the share of each input allocated to a given product is the same across inputs. For the latter assumption, for example, if product A is allocated 20% of capital, it should also be allocated 20% of labor and 20% of materials.

I examine both of these symmetry conditions on the line of business data. First, I assess Orr (2022)'s assumption that the input mix of each product is the same across all product lines in the same firm. I examine variation in the labor share of total labor and materials expenses across lines of business for a given firm; under the symmetry condition, this labor share should be the same across lines of business of the same firm.

In the left panel of Figure 2, I depict the difference between the maximum and minimum labor share of variable inputs within each firm. Lines of business vary substantially in their labor share. The median and mean differences between the maximum and minimum labor share are 40%; a quarter are below 26% and a quarter are above 53%.

One explanation for these wide differences is that input shares vary across industries for technological reasons. Thus, in the right panel of Figure 2, I examine the same difference between the maximum and minimum share with 2 digit SIC industries. While these differences are smaller, they are still quite large; the median is 19.5% and mean is 22%. A quarter of the differences are below 10% and a quarter are above 30%.

Figure 2: Max-Min Difference in Labor Share of Variable Inputs Across Lines of Business Within Firm



a) Within Firm b) Within Firm / 2 Digit SIC Industry

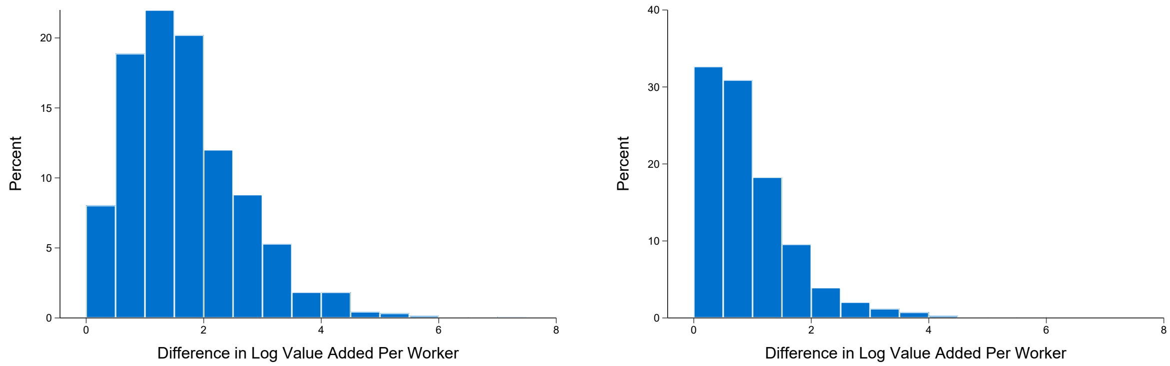
Notes: I only include firms with more than one line of business in the left figure, and firms with more than one line of business for a given 2 digit SIC industry in the right figure.

Second, I examine De Loecker et al. (2016)'s assumption that all product lines of the same firm have the same productivity. I calculate a simple measure of labor productivity as log value added per worker dollar (as I only have data on payroll). In the left figure of Figure 3, I depict the difference between the highest and lowest labor productivity across lines of business in the same firm. The median firm's most productive line of business is 4.5 times as productive as its least productive line of business; the 25th and 75th percentile firms' most productive business line are 2.6 and 8.7 as productive as the least productive line. These differences persist after controlling for 2 digit SIC industry. In the right figure of Figure 3, I depict the max-min difference in labor productivity within firm and 2 digit SIC industry. For the median firm, the most productive line of business is 2.1 times as productive as the least productive line of business; this difference is 1.5 and 3.7 times as productive for the 25th and 75th percentile firm.

3.2 Common Inputs

The multi-output production literature also typically assumes that all inputs are specific to a given product.Perhaps the most unique aspect of this data is that firms were required to

Figure 3: Max-Min Difference in Log Value Added Per Worker Across Lines of Business Within Firm



a) Within Firm b) Within Firm / 2 Digit SIC Industry

Notes: I only include firms with more than one line of business in the left figure, and firms with more than one line of business for a given 2 digit SIC industry in the right figure.

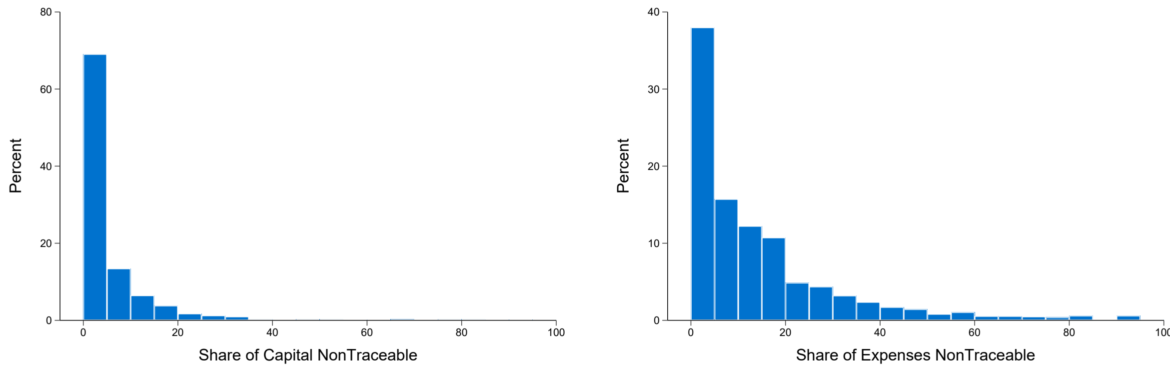
report how much of certain inputs were "traceable" to a given line of business. I examine the firm-level non-traceable share of each input for two such inputs – capital and management and marketing expenses (defined as the sum of advertising, other selling, and general and administrative expenses).

In Figure 4, I depict the share of each input that is non-traceable. For both inputs, a substantial share of each input is common to the firm, although the common input share is higher for management/marketing expenses than for capital. For the median firm, 2% of capital and 8.5% of expenses are common to the firm. The distribution is, however, highly skewed; the mean share is 6% for capital and 14% for expenses. For capital, 30% report zero common capital, while 10% report a share above 16% and 5% report a share above 26%. For expenses, 25% report zero common expenses, while 10% report a share above 36% and 5% report a share above 52%.

3.3 Vertical Integration

Finally, the multi-output literature typically assumes that products produced by the firm are not used by other parts of the firm. Here, I examine the degree of such vertical integration through the share of revenue that is not sold to outside parties, that is, the share of revenue

Figure 4: Share of Input that is Common to Firm



a) Capital

b) Management and Marketing Expenses

Notes:

attributable to transfers.[6]

In Figure 5, I depict the distribution of the share of transfers across lines of business. While about 70% of firm lines of business report any transfers, only a minority of lines of business report substantial transfers to other parts of the firm. The median line of business has 1.4% of revenue as transfers; the mean is 8%. However, 10% of the sample have a transfer share of 23% and 5% of the sample have a transfer share of 40%.

4 Model and Identification Strategy

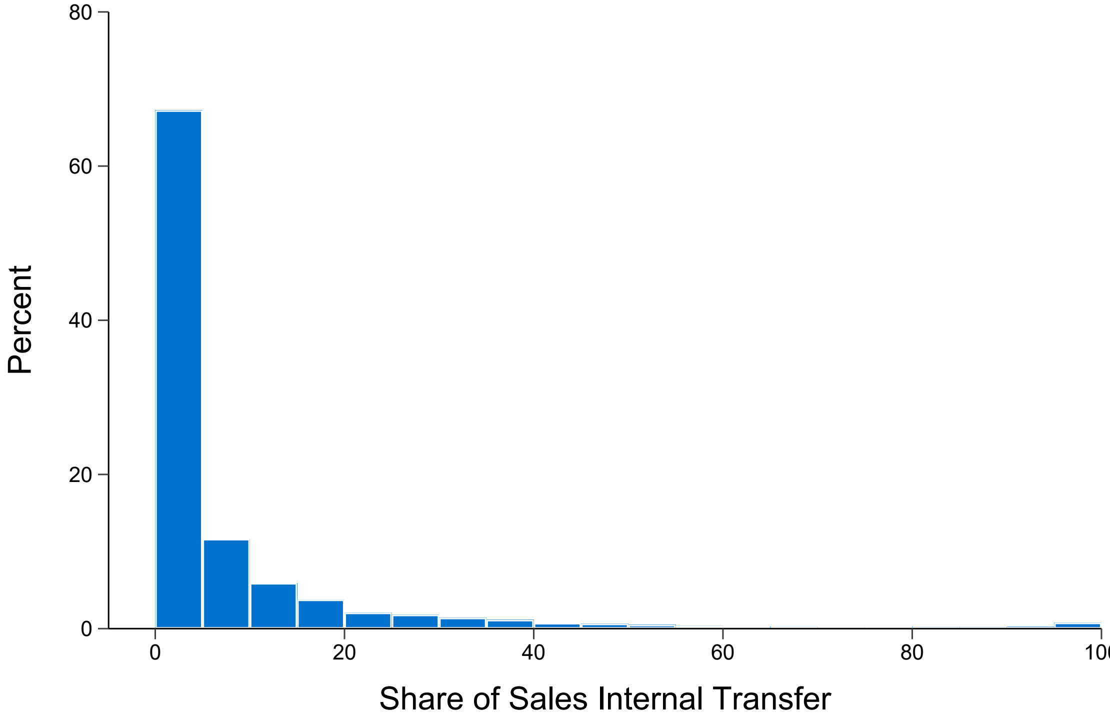
4.1 Model

I assume a nested CES revenue production function at the firm-line of business level as follows:

$$Y = A[\alpha(K^{\beta_k} L^{\beta_l} M^{\beta_m} E^{\beta_e})^{\frac{\sigma-1}{\sigma}} + (1-\alpha)C^{\frac{\sigma-1}{\sigma}}]^{\gamma\frac{\sigma}{\sigma-1}}, \tag{1}$$

[6]The data report three sources of transfers – to other lines of business in the dataset, to foreign parts of the firm, and to domestic parts of the firm regulated by other federal regulators (These are domestic corporations included in the Total Reporting Company. but not in the LB Reporting Section because either: (1) a corporation is primarily engaged in banking, finance, or insurance; or (2) a corporation is required to file annual financial statements with the Interstate Commerce Commission, Civil Aeronautics Board, Federal Communications Commission, or Federal Power Commission.). I combine all three sources for these estimates.

Figure 5: Share of Line of Business Revenue from Transfers



Notes:

where Y is revenue and A is Hicks neutral productivity. The production function nests between a Cobb-Douglas aggregate of line of business specific inputs – capital (K), labor (L), materials (M), and traceable management/marketing expenses (E) – and the common input C. The elasticity of substitution between common and non-common inputs is σ. The production function has two sets of distributional parameters; α is the weight on the Cobb-Douglas aggregate compared to the common input, while the β terms are the Cobb-Douglas weights. In addition, γ indexes returns to scale and is one with constant returns to scale; the β Cobb-Douglas coefficients are constrained to sum to 1.

Figure 4 showed that a substantial share of firms report no common inputs. In that case, the production function above condenses to a simple Cobb-Douglas production function:

$$Y = \tilde{A} K^{\gamma\beta_k} L^{\gamma\beta_l} M^{\gamma\beta_m} E^{\gamma\beta_e}, \tag{2}$$

where $\tilde{A} = A\alpha^{\gamma\frac{\sigma}{\sigma-1}}$.

4.2 Identification Strategy

I estimate this production function through a two step approach. In the first step, primarily using firms with zero common input, I estimate the Cobb-Douglas parameters of the sub-production function for the line of business specific inputs. Here, I apply an identification strategy similar to Gandhi, Navarro and Rivers (2020), estimating the Cobb-Douglas parameters of the variable inputs using revenue share equations and those of the fixed inputs assuming that productivity evolves following an AR(1) process. In the second step, I use the variable input's share of revenue for firms with positive common inputs to estimate the elasticity of substitution between the common input and aggregate of line of business specific inputs, as well as the distribution parameter for the common input. This approach is thus again similar to Gandhi, Navarro and Rivers (2020).

To illustrate this approach, assume that labor and materials are the only two variable inputs. In this case, I use two sets of moment conditions based on the first order conditions for labor and capital to estimate $\gamma\beta_l$ and $\gamma\beta_m$:

$$E_{C=0}[\frac{p_m M}{Y}] = \gamma\beta_m \quad (3)$$

$$E_{C=0}[\frac{wL}{Y}] = \gamma\beta_l \quad (4)$$

$$E_{C>0}[\frac{p_m M}{wL}] = \frac{\gamma\beta_m}{\gamma\beta_l} \quad (5)$$

Here, the first two moments – the revenue share of materials and labor – identify $\gamma\beta_m$ and $\gamma\beta_l$ for firms for which the common input is zero. In addition, the ratio of materials costs to labor costs identifies the ratio of β_m to β_l for all firms, including those with positive common inputs.

Next, I assume that log productivity a_{it} follows an AR(1) process:

$$a_{it} = \rho a_{i,t-1} + \xi_{it}. \tag{6}$$

In that case, the remaining Cobb-Douglas parameters are identified through moments for which the innovation of productivity ξ_{it} is orthogonal to factors of production decided before the innovation shock:

$$E[\xi_{it} K_{it}] = 0 \tag{7}$$

$$E[\xi_{it} E_{i,t-1}] = 0 \tag{8}$$

In addition, γ is identified because of the normalization that all of the Cobb-Douglas coefficients sum to 1. Thus, the first step identifies γ together with the Cobb-Douglas coefficients β_i, as well as the subproduction function $F = K^{\beta_k} L^{\beta_l} M^{\beta_m} E^{\beta_e}$.

In the second step, I identify the elasticity of substitution σ and distributional parameter α based upon the revenue share equation for the variable inputs for firms with positive common inputs:

$$\frac{p_m M + wL}{PY} - (\gamma\beta_m + \gamma\beta_l)\frac{\alpha F^{\frac{\sigma-1}{\sigma}}}{\alpha F^{\frac{\sigma-1}{\sigma}} + (1-\alpha)C^{\frac{\sigma-1}{\sigma}}} = \nu = 0 \tag{9}$$

I then take a non-linear least squares type approach and identify σ and α given that the residual ν is mean zero and orthogonal to F and C:

$$E_{C>0}(\nu) = 0$$

$$E_{C>0}(\nu \log F) = 0$$

$$E_{C>0}(\nu \log C) = 0.$$

5 Results

I estimate equation (1) using the identification strategy laid out in Section 4. I then examine the output elasticities for the common input, as well as the economies of scope generated by the common input.

5.1 Implementation

I measure output as total sales and transfers at the line of business level, capital as net traceable plant, property, and equipment, labor as total payroll (the data does not include the number of workers), and materials as the total cost of materials. The traceable part of management/marketing expenses enters the Cobb-Douglas subproduction function, while the common input is the non-traceable part of those expenses.

I deflate the values of all of these variables to 1977 dollars. For output and materials, I match shipment and materials deflators from the NBER Productivity Database (Bartlesman and Gray, 1996) using line of business to SIC 1977 and SIC 1977 to SIC 1987 concordances. For capital, I use a combined deflator of the investment deflator from the NBER Productivity Database with the ratio of current cost to historical cost of fixed assets, available from the BEA at the 2 digit SIC level. Finally, for labor and management/marketing expenses, I deflate using the CPI.

Table 2 provides the summary statistics for each of the variables (in logs) entering the production function.

5.2 Estimates

In Table 3, I report estimates of the production function parameters. The first column provides estimates using my baseline approach in which labor and materials are both considered variable inputs. Of the Cobb-Douglas parameters for the line of business specific inputs, materials gets the highest weight (0.46), followed by labor (0.29). Capital and line of business

Table 2: Summary Statistics for Production Inputs and Output

	(1)				
	count	mean	sd	min	max
Sales	13327	10.97	1.37	3.49	17.16
Capital	13327	9.68	1.69	0.44	15.90
Labor	13327	9.24	1.40	0.06	15.68
Materials	13327	10.14	1.47	0.69	16.99
Expenses	13327	8.65	1.54	0.21	14.60
Common Input	11057	9.93	1.22	1.39	14.03

specific expenses get similar weights, at 0.11 and 0.14 respectively. Returns to scale are close to constant at 0.97.

In addition, I find a substantial weight on the common input. Since α is 0.93, 7% of the weight in the CES aggregator is on the common input and I can reject the null hypothesis of zero weight for the common input. Finally, the elasticity of substitution σ is 1.6, indicating that the common input and Cobb-Douglas aggregate of line of business specific inputs are substitutes.

The next two columns of Table 3 examine alternative specifications in which either only materials is a variable input, or materials, labor, and line of business specific expenses are variable inputs. My estimates of the production function parameters are largely consistent across these specifications. However, the estimates are more imprecisely estimated using only materials as a variable input; with all three inputs as variable, the weight on the common input is higher ($\alpha = 0.90$) and the common input is less substitutable with the line of business specific aggregate ($\sigma = 1.3$).

In Figure 6, I display the distribution of the output elasticity for the common input for all firm-line of business observations with positive common inputs given the baseline estimates.[7] The median output elasticity is 0.08 and the mean output elasticity is 0.09; most output elasticities range between 4% and 15%. Thus, the output elasticity of the common input is

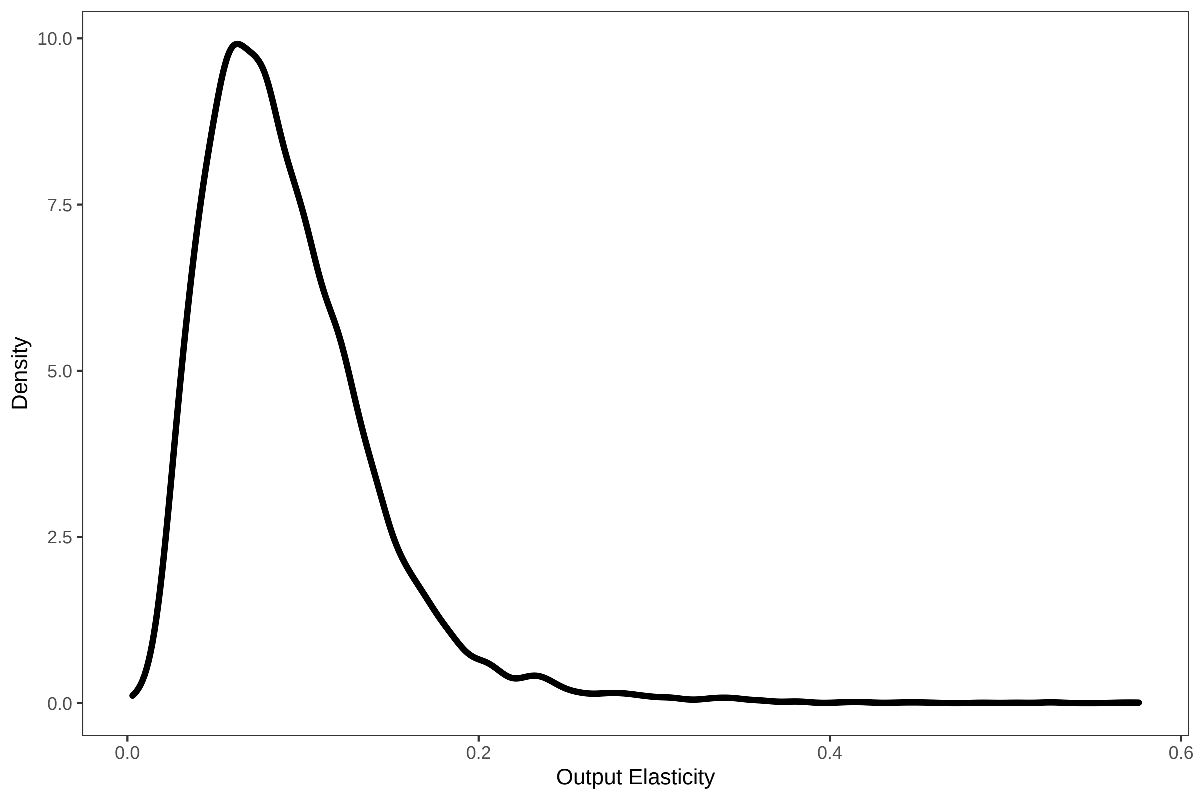
[7] The output elasticity of the common input is $\gamma(1-\alpha)\frac{C^{\frac{\sigma-1}{\sigma}}}{Y}(\alpha F^{\frac{\sigma-1}{\sigma}} + (1-\alpha)C^{\frac{\sigma-1}{\sigma}})^{\gamma\frac{\sigma}{\sigma-1}-1}$.

Table 3: Production Function Estimates

	Set of Variable Inputs		
	M & L	M	M & L & E
β_k	0.11 [0.06, 0.15]	0.13 [0.08, 0.20]	0.08 [0.06, 0.11]
β_l	0.28 [0.27, 0.31]	0.19 [0.01, 0.30]	0.27 [0.26, 0.29]
β_m	0.45 [0.44, 0.49]	0.48 [0.48, 0.53]	0.43 [0.41, 0.47]
β_e	0.14 [0.08, 0.20]	0.16 [0.09, 0.29]	0.19 [0.18, 0.22]
γ	0.97 [0.94, 0.98]	0.96 [0.92, 0.98]	0.98 [0.95, 1]
α	0.93 [0.89, 0.96]	0.94 [0.89, 0.98]	0.90 [0.87, 0.93]
σ	1.6 [1.4, 2.1]	2.2 [1.6, 9.1]	1.3 [1.2, 1.4]

substantial for most firm lines of business that have some common inputs.

Figure 6: Distribution of Output Elasticities for Common Input



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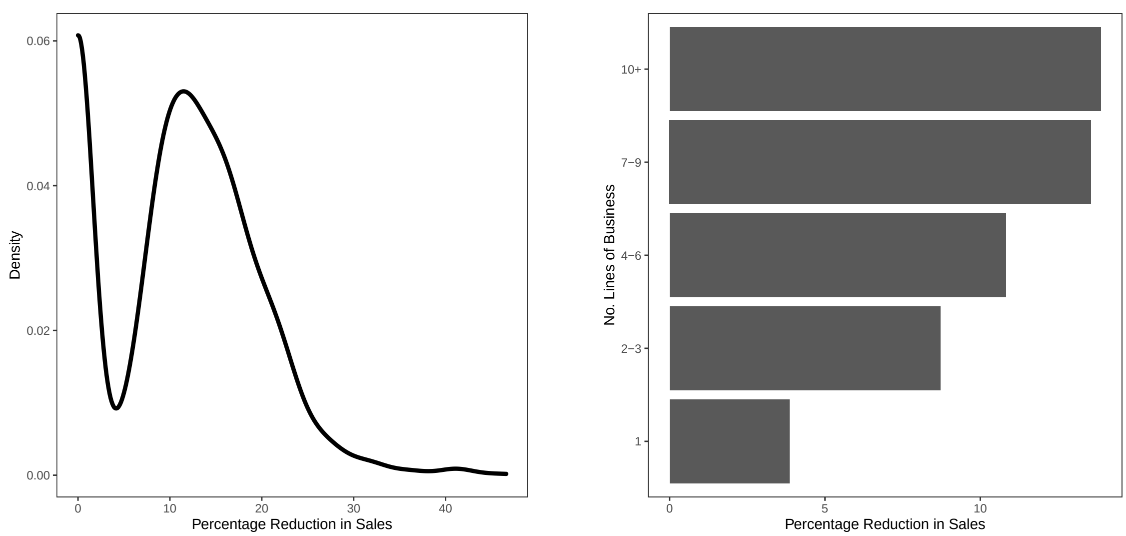
5.3 Counterfactuals

I conclude by assessing the degree of economies of scope through a counterfactual in which the common input is set to zero. I then examine the output losses stemming from eliminating the common input.

In the left figure of Figure 7, I depict the distribution of the firm level decline in output from eliminating the common input. This distribution has two modes, as there is no effect for firms without common inputs. However, median and mean firm experience a 11% decline in output, and the 90th percentile firm experiences a 21% decline in output.

In the right figure of Figure 7, I examine how the decline in output from eliminating the common input varies by the number of lines of business of the firm. As one would expect from economies of scope, the decline in output is larger for firms with more lines of business. I estimate an average decline of 4% for firms with one line of business, 9% for firms with two to three lines of business, 11% for firms with four to six lines of business, and 14% for firms with seven to nine or greater than ten lines of business.

Figure 7: Decline in Output from Eliminating the Common Input



a) Distribution

b) Average by Number of Lines of Business

6 Conclusion

In this article, I have examined the degree of economies of scope using data on large manufacturing firms from the FTC's Line of Business surveys. The Line of Business data provided me with inputs at the line of business level as well as information on the degree of shareable or common inputs to the firm as a whole. I found large differences in the input mix that firms used across different lines of business, as well as a substantial share of inputs that were shareable across lines of business

These facts motivated a nested CES model of production including a common input in production. I estimated this model using the line of business data and found that the common input had a non-zero output elasticity and was substitutable with an aggregate of line of business specific inputs. Finally, I found considerable declines in output from removing the common input from production.

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