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Research article

Determining a proportion of labor and equipment to achieve optimal production: A model supported by evidence of 19 U.S. industries from 2000 to 2020

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Abstract: This study examines two decades of labor and capital costs and gross output to evaluate production in 19 industries. A lesson learned is the need to have more input cost variables specifically defined to capture the production environment. Simply evaluating production by two categories alone—labor and capital—is not sufficient. This study tests a new production equation, producing an ordinary least squares regression model to explain changes to labor and capital resources in the U.S. economy. I found that increasingly growing capital intensity might not be optimal. Labor continues to play a role in production. Applied in proper proportion—neither too much nor too little—labor can be effective in producing maximum output. This study contributes to the literature by quantifying capital intensity with a measure that generalizes about U.S. production across industries. Evidence shows that 12 out of 19 industries had low capital intensity; in other words, most industries were labor intensive with relatively small utilization of equipment.

Keywords: productivity; production function; labor economics; capital usage; microeconomics

JEL Codes: E23, D24, L23

Abbreviations: BEA: Bureau of Economic Analysis; BLS: Bureau of Labor Statistics; GDP: Gross Domestic Product; GO: Gross Output; IPP: Intellectual Property Products; NAICS: North American Industry Classification System; NIPA: National Income and Product Accounts; QCEW: Quarterly Census of Employment and Wages.

1. Introduction

Can advanced computer software programs, automatic machines, robots, and other equipment produce greater output than what workers can do? Can labor be totally replaced by equipment? If not, how many workers should be retained in a production environment that uses both labor and equipment? What is the optimal mix of workers and machines?

The debate on choosing machines over workers has a long history that goes back to the Industrial Revolution. The question continues to be asked as artificial intelligence and other advanced computing technologies develop.

Previous research studies indicate that the answer is not as simple as substituting machines for workers. Given that a machine can break down and stop production for a certain amount of time, Levhari and Sheshinski (1970) developed a model to factor in the probability of machine failure and the need to have workers to repair machines. Levhari and Sheshinski's study suggests that not all workers can be eliminated. Baron and Bielby (1982) examined how workers relate to machines and found that the way in which firms distribute jobs and tasks among workers (suborganization factors) can be decisive in affecting the structure of work.

By drilling deeper into specific skills, productivity can be better analyzed. In the iron ore industry, Schmitz (2005) explained how mines in the Great Lakes region had turned around inefficient production by allowing machine operators to carry out tasks previously done by maintenance and repair workers. The consolidation of tasks reassigned to machine operators allowed machines to produce more output continuously throughout the day. Revealing firms' capacity to scale up operations, Foster et al. (2006) surveyed the effect of increased information technology investments during the 1990s in retail and found a considerable shift in the type of establishments, in so far as the industry moved from lower productive single-unit establishments to higher productive national chains. Bartel et al. (2007) studied the effects of information technology on worker skills in the valve manufacturing industry and found that implementation of computer numerically controlled (CNC) machines required operators to have fewer routine skills and deeper technical and problem-solving skills. In a wide range of service-related industries from education to finance and health care to accommodation and food, Rust and Huang (2012) explored the trade-off between productivity and customer service and articulated the point that better service tends to require more labor but at lower productivity. Revisiting production in the Industrial Revolution, Bessen (2012) found increased production of cotton cloth in the nineteenth century occurred not because of more machines but because of improved skills of cotton weavers. A number of cotton weavers were employed to monitor and operate power looms. Acemoglu and Restrepo (2019) analyzed how various kinds of tasks are either eliminated or created by automation to a point at which automation displaces labor on one hand and reinstates it on the other. From the nineteenth century to the present day, the use of labor and capital to produce goods and services has been a complex dynamic that leverages the power of machines on one hand and extracts the abilities of humans on the other.

All the foregoing studies share a common feature. Researchers applied different methods to evaluate productivity, taking into consideration job quality and specific work requirements. Studies factored in additional variables beyond the conventional output, labor, and capital variables based on price and quantity. The approaches overcome methodological issues in estimating a production function, typically a two-input or two-variable equation that forms the basis of a Cobb–Douglas production function (see Levinsohn and Petrin, 2003; Van Biesebroeck, 2007; Ackerberg et al., 2015).

A drawback to conducting firm-level inquiries is that it can be difficult to extrapolate the results to other firms and other industries. Such studies tend to be narrowly tailored to a particular industry. They also can be expensive to conduct since a greater amount of planning must go into research design. With each study applying a method, it can be difficult to apply one's method to another to replicate results.

There is value in developing a standard method of measuring productivity and labor changes in context of technology. Brooks (1983, page 117) pointedly remarked: "It is misleading to look at the effects of increasing productivity due to technology only within the context of single firms or single industries. The effects of technology depend on what happens to employment in the whole economy, not just the industry immediately affected."

Brooks understood the difficulty in calculating job quality in precise ways that can be generalizable to all industries. Job quality and work requirements are abstractions that require descriptions in the context of how they are applied. These qualitative terms need to be translated into a quantified form. This is why conventional measures continue to rely on market prices. Price is a concrete metric and can be quickly measured and reproduced. Unlike an abstract term such as job quality, market price is readily understood on its own without having to explain further in some particular context.

A drawback to relying on market prices in a production function and in productivity measures is that the calculated output does not produce an exact figure. There can be some variability. The result represents an approximated value—an estimate. Levhari and Sheshinski (1970) concluded that a Cobb–Douglas production function can be sufficient with only the costs of labor and capital but, if calculating an optimum is crucial, then additional cost factors have to be used. The problem with conventional productivity measures can emerge as firms employ more computers and information technology in their operations. Studies in the literature have examined the Solow paradox (e.g., Whelan, 2002; Acemoglu et al., 2014). Solow (1987, page 36) critiqued a book about the status of the manufacturing industry at the time and remarked, "You can see the computer age everywhere but in the productivity statistics." Whelan (2002) found that the National Income and Product Accounts (NIPA) measures underestimate the contributions of computers to productivity by a wide margin.

Uechi (2023) expands a Cobb–Douglas production function to create an equation that includes labor, equipment, raw materials, processed materials, land, and a residual of all other input costs.[1] Uechi defined capital more specifically as machine equipment and distinguished the general category of materials between raw materials defined as a mineral resource or an unprocessed commodity and

[1] The new equation moves beyond the current convention in economics. Instead of examining production by simply calculating labor and capital, Uechi argues that the production function needs to be inclusive of specific input factors. The additional factors are a breakdown of capital. If one continues to use the conventional production function, equipment, materials, land, and the residual of all other inputs would be aggregated into capital.

processed materials defined as a supply item or a manufactured material. Processed materials would be intermediate inputs that firms require to produce final products. For example, an automobile manufacturer needs bolts, wheels, seats, and other parts to build an automobile; all of those parts are produced by other firms, each one of which has its own process to produce the individual part. Uechi further explained that each variable is the product of the variable's price and quantity and that the sum of all variables and the residual amounts to the total cost of production. "The total production cost would be less than or equal to total revenue" (Uechi, 2023, page 11) or equivalent to total output of produced goods and services.

In Uechi's production equation, each variable can be an aggregate of several sub items differentiated by price. Uechi (2023, page 15) teaches, "If any resource category has one or more subcategories with different unit costs, then the category needs to be broken down by subcategories." For example, a firm's total labor cost can consist of many different job positions with each position having a different wage. Each job position is a sub item or a subcategory of the labor variable. The total labor cost is the summation of each job position's wage and number of workers hired for that position. This logic can be applied to other variables in the production equation. In the instance of capital, a firm can have different types of capital with each having a different unit price and quantity demanded.

The example of disaggregating labor takes into consideration various types of occupations that a firm would need to produce goods or services. From executive staff through department managers to production workers, all job positions can be included in the calculation. Uechi seems to have found a precise way to capture job quality through the specificity of job positions or occupations in a simple calculation. A specific type of job position would indicate a level of quality inherent in the job. Different levels of the same job classification marked by skill or seniority (e.g., master, journeyman, and apprentice) can be captured in the calculation. A firm would hire a number of individuals at a given wage commensurate with their level of skill or seniority.

This paper seeks to test whether Uechi's production equation can, in general, measure the output of the U.S. economy and, in particular, evaluate changes to labor affected by changes to capital resources. I modify Uechi's equation given the availability of public data. The production equation requires a substantial amount of firm-level data from a large sample of firms encompassing all industries. An ideal research study would collect data on many types of job positions, many types of machines, and many types of raw and processed materials. For the purpose of this research study, I limit the scope to assessing macroeconomic growth at the national level. While firm-level data would produce an accurate measure of productivity, aggregate data would suffice to produce a macroeconomic indicator of capital intensity. The results will answer the questions posed at the start of the introduction. Direction for further research is provided at the end of the paper.

2. Data

The data set used in the analysis is a composite of national level employee wages, capital inputs, and gross output data from the U.S. Bureau of Labor Statistics (BLS) and the U.S. Bureau of Economic Analysis (BEA). I started with a compilation of annual average data files from the Quarterly Census of Employment and Wages (QCEW) program (BLS, 2021). The QCEW data include 19 private-sector industries from 2000 to 2020, selecting aggregation level code 14, which is "National, NAICS

Sector—by ownership sector." Industries are identified by the following two-digit North American Industry Classification System (NAICS) codes:

1. NAICS Code 11: Agriculture, Forestry, Fishing, and Hunting
2. NAICS Code 21: Mining, Quarrying, and Oil and Gas Extraction
3. NAICS Code 22: Utilities
4. NAICS Code 23: Construction
5. NAICS Code 31–33: Manufacturing
6. NAICS Code 42: Wholesale Trade
7. NAICS Code 44–45: Retail Trade
8. NAICS Code 48–49: Transportation and Warehousing
9. NAICS Code 51: Information
10. NAICS Code 52: Finance and Insurance
11. NAICS Code 53: Real Estate and Rental and Leasing
12. NAICS Code 54: Professional and Technical Services
13. NAICS Code 55: Management of Companies and Enterprises
14. NAICS Code 56: Administrative and Waste Services
15. NAICS Code 61: Educational Services
16. NAICS Code 62: Health Care and Social Assistance
17. NAICS Code 71: Arts, Entertainment, and Recreation
18. NAICS Code 72: Accommodation and Food Services
19. NAICS Code 81: Other Services, except Public Administration.

References to industries in the text and tables use the two-digit NAICS codes. The NAICS code is written in the form, NAICS plus its number (e.g., NAICS 11) for brevity. Readers can return to the foregoing list to find the definition of each code. Industry names may be spelled out for emphasis.

I add to the QCEW data five asset categories of capital input costs for the same industries and years from the "Capital Details for Major Sectors and Industries" data file prepared by BLS and released on 24 March 2022 (BLS, 2022). The selected measure is capital cost levels in billions of dollars. I exclude productive capital stock, gross investment, wealth stock, asset share, and depreciation rate. The asset categories include (1) equipment, (2) intellectual property products (IPP), (3) structures, (4) inventories, and (5) land. According to BLS, equipment covers a wide range of 39 types from household furniture to electromedical instruments, from tractors to vehicles and vessels, and from machinery to computers—all of which are in some physical form that is tangible. Intangible forms are included. IPP encompasses products created principally from the mind for use in a variety of venues; IPP covers computer software programs, artistic works, and research and development. Structures include 35 types of facilities and physical installations, such as buildings, warehouses, hospitals, hotels, shopping and restaurant establishments, and infrastructure for mining, energy, electrical and water distribution, waste disposal, transportation, and telecommunications. Inventories and land are self-explanatory.

I finally add annual gross output (GO) for the same industries and years from the "Gross Output by Industry" data file prepared by BEA and published on 30 March 2022 (BEA, 2022). I use only amounts in millions of dollars, excluding real gross output in chain dollars. GO reflects current dollars for the years in which they were reported. It needs to be noted that GO is substantively different from gross domestic product (GDP). GO figures are much less than GDP figures, because gross output does not include consumer spending, business spending, government spending, and net exports; GDP includes all of those types of spending and net exports[2] (BEA, 2021). GO is a focused economic measure on total sales and receipts of goods and services produced by industries for consumers and other industries (BEA, 2021).

The combined data set contains six cost variables and one output variable—a total of seven variables. The output variable is gross output. The cost variables are (1) total labor cost, (2) total equipment cost, (3) total IPP cost, (4) total structures cost, (5) total inventories cost, and (6) total land cost. Total labor cost is total annual average wages paid to employees. Conversions had been applied to cost and output variables to align all amounts in billions of dollars.

The combined data set also contains eight variables derived from the cost and output variables. The sum of all six cost variables amounts to an approximated total production cost. I assume additional costs exist and were not collected. A combined equipment and IPP variable was produced by adding those two cost variables together to form one composite measure. In the next section, I explain the rationale for that step. The quotient of the aforementioned composite variable and total labor cost produces a ratio of equipment and labor (equipment–labor cost ratio). The remaining five calculated measures represent a share of the total production cost. The shares of labor cost, the combined equipment and IPP cost, structures cost, inventories cost, and land cost were calculated by dividing the respective resource cost by total cost.

To summarize, the data set is a sample of 399 national-industry observations covering 19 major industry sectors and spanning 21 years. The sample is broken down by each industry sector reporting annual cost and output data from 2000 to 2020 (i.e., 21 years of annual industry data for 19 industries). The data represent the U.S. economy in the first two decades of the twenty-first century. Fifteen variables are used to assess macroeconomic growth and changes to labor and capital inputs.

3. Methodology

I sought publicly available data sources from government agencies, which would closely align with Uechi's production equation. The BEA provides numerous input variables, covering all industries, including NAICS 92 (public administration). However, nearly all the BEA's variables are not suitable for Uechi's equation. Chain-type indexes must be disaggregated to specific item prices and quantities in order to use the data. The BEA's gross output is the only variable that can be used.

Alternatively, the BLS's input costs are suitable for Uechi's equation. An assumption is made that the aggregated totals were calculated based on prices and quantities of numerous items. Inventories would fit under Uechi's processed materials. Structures would fit appropriately under Uechi's residuals. With various types of structures captured, it cannot be determined without disaggregating the category which specific types would fit under equipment. Some structures that can contribute directly to output (e.g., certain types of infrastructure) would fit under equipment. Without knowing the details of structures, the aggregated structures cost is assumed to belong in residual costs.

[2] The term net exports means the exports of goods and services minus the imports of goods and services.

IPP is closely aligned with equipment and logically fits into the broad equipment category. In many cases, finished IPP products would be incorporated into physical forms of equipment in order to be used. For example, computer software requires computer hardware for executing program code. In another example, an artistic motion-picture film product requires a film projector and a large screen (specific types of equipment). A particular IPP product is not useful in production without combining it with some type of equipment. For this reason, IPP can be combined with Uechi's equipment.

Raw materials is the only category that appears to be missing from the BLS's asset categories. Perhaps raw materials might be captured in inventories, but it cannot be determined without disaggregating inventories.

Although some costs are missing and category names are different, the BLS's variables capture the concept of what Uechi's equation is intended to measure. The BLS's input costs and the BEA's gross output together form the variables to include in Uechi's production equation—albeit in modified form that deviates from the original design. The equation in modified form is as follows:

$$G \geq C_L + C_E + C_S + C_M + C_D \tag{1}$$

G is gross output. Each input cost is represented by C_L, C_E, C_S, C_M, and C_D for labor cost, equipment and IPP cost, structures cost, inventories cost, and land cost, respectively. IPP cost is included as a part of equipment cost in a composite measure.

To reiterate from the previous section, the annual cost and output data in the data set correspond to the variables specified in Equation (1). All the amounts reflect current dollars for the years in which they were reported. I do not adjust for inflation because the purpose of the study is not to compare economic growth or contraction over time. Several years of data provide for a large sample in which I can examine how industries change their inputs to produce output. In this regard, factoring inflation is appropriate since price changes influenced by external forces would affect the business decisions of firms to purchase machines and hire workers. Firms may change the mix of labor, equipment, and other inputs in their budgets from one year to the next, based on various internal and external reasons (e.g., management decisions, consumer demand, changes to the market, and economic recession).

To answer my research questions, an ordinary least squares (OLS) regression was conducted. All the input costs are the independent variables. Gross output is the dependent variable. An initial analysis examined equipment cost and IPP cost separately as two independent variables in the regression model. A subsequent analysis used the combined equipment and IPP cost in the regression model, reducing the number of independent variables from six to five. These two initial models examined whether it is appropriate to combine equipment and IPP. In the first two analyses, none of the variables was transformed. A third analysis transformed three variables, applying the natural logarithms of gross output, labor cost, and equipment and IPP cost in the regression model. The other three variables remained untransformed in the third analysis. A fourth analysis applied the natural logarithm of structures cost. The natural logarithms of inventories cost and land cost cannot be calculated, unless negative values are removed from the data set. Additional analyses examined just two independent variables in the model (labor cost and equipment and IPP cost) to compare the difference between the full and partial regression models. This last examination created a conventional model that resembles a production function that only factors labor and capital.

I devised hypothetical scenarios to demonstrate application of the selected regression model. Each scenario represents, in theory, a production budget that allocates a certain amount of dollars to each input. The regression model is then used to compute the input costs to generate an estimated output (predicted output). Through 11 scenarios, I hold the costs of structures, inventories, and land and the total cost constant while systematically changing the costs of labor and equipment in a logical manner. Incremental changes to labor and equipment indicate what output could be from a high-cost labor scenario to a low-cost labor scenario. It is assumed that a firm would develop a number of production scenarios in which different combinations of labor and equipment would be used. A firm analyzes these scenarios to determine which one would produce maximum output. It is this assumption that the hypothetical scenarios are based upon.

In theory, the scenarios could be for a single firm or numerous firms. I propose that the regression model can be used to analyze business activities of multiple industries to calculate economic output in the aggregate. This would be accomplished using the described methodology on a sample of firms. In this case, the cost and output data would be those reported by firms in a survey. Alternatively, a single firm would compile its own cost and output data and determine how much to spend on each input to produce the most output.

Correlations were calculated on the cost and output variables to compare the relative strength of the relationship between a given pair of variables. The cost and output variables—both transformed and untransformed—were plotted on a graph, comparing an input cost variable against the output variable. Descriptive statistics, specifically the mean and the standard deviation of the input costs, gross output, equipment–labor ratio, and input cost shares were calculated for the national average and each individual industry across the same time frame. The data set was segmented by industry.

A script was written and saved to generate the scatter diagrams and to calculate the natural logarithms, descriptive statistics, correlations, and OLS regression. Segmenting of the data set by industry was also written in the script. The script was then executed in the R statistical software program. Outputs from R were saved and analyzed in Microsoft Excel. The R statistical software program generated the scatter diagrams and had saved them as images.

4. Results

Over the first two decades of the twenty-first century, the U.S. had annual gross output of less than $1.3 trillion[3], on average, in a total of 19 private-sector industries. That level of output would have fluctuated year by year by as much as $1.2 trillion. In terms of total production cost, the U.S. spent an annual mean of $484.4 billion with a standard deviation of $399 billion in 19 industries.

Table 1 breaks down the cost and output by industry and input cost. NAICS 31–33 (manufacturing) stands out with the highest output and costs on four measures. The manufacturing industry produced an annual mean gross output of less than $5.2 trillion with an annual mean total cost of more than $1.6 trillion. Manufacturing exceeded the national average by a wide margin. The difference between output

[3] All output figures are estimates of GO, not estimates of GDP. As explained in the data section, GO is an economic measure that captures sales and receipts of goods and services. The result produces a GO estimate that is less than a GDP estimate.

and cost produces a substantial net profit, which allows manufacturing firms to reinvest in production (i.e., improve machinery, expand operations, provide employee bonuses, or raise wages). The manufacturing industry further had the highest mean labor cost at $744.9 billion and the highest mean equipment and IPP cost at $600.2 billion. More than half of the equipment and IPP cost went into IPP products alone.

NAICS 53 and NAICS 52 ranked second and third in the highest annual mean gross output at $2.9 trillion and $2.1 trillion, respectively. NAICS 62 and NAICS 54 ranked fourth and fifth in the highest annual mean gross output at $1.8 trillion and $1.7 trillion, respectively. NAICS 71, NAICS 61, NAICS 11, NAICS 55, and NAICS 21 ranked among the lowest in annual mean gross output from nineteenth to fifteenth, respectively. The penultimate industry was educational services. Five industries close to the national average in annual mean gross output were NAICS 23, NAICS 42, NAICS 44–45, NAICS 48–49, and NAICS 51. These five industries included a diverse mix from construction and transportation to retail trade and information.

The distribution of input costs is reported in Table 2. Most industries spent a fraction of 1%, on average, in inventories. In terms of both percentage share and dollar value, NAICS 42, NAICS 44–45, NAICS 31–33, and NAICS 11 spent a relatively high amount in inventories. This is not surprising since agriculture, manufacturing, retail trade, and wholesale trade depend on certain levels of stocks and supplies.

Costs in both structures and land show variability among industries with a few spending higher amounts than others. In both percentage share and dollar value, NAICS 11 and NAICS 53 had the highest annual mean land cost of all industries. This result is expected, since land contributes to these two industries' output. Agriculture, forestry, fishing, and hunting consumed relatively the most in land cost by a wide margin at a mean share of 39.3%. Real estate and rental and leasing followed behind at a mean share of 14.6%.

NAICS 21 (mining) and NAICS 22 (utilities) had the highest annual mean share of structures cost of all industries at 60.1% and 43.4%, respectively. In terms of dollar value, however, NAICS 31–33 spent the highest in structures cost at $176.7 billion on average. Manufacturing's share of structures cost amounted to 10.7% on average—below the national average. NAICS 52 showed a similar pattern with a mean structures cost at $133 billion and mean share at 13.7%. The results of structures cost create a complex picture of variation.

Figures 1 and 2 help to explain variation in the structures cost and other input costs. Panel C1 in Figure 1 shows the observations of structures cost loosely organized in such a way that multiple patterns can be discerned. By applying a natural logarithm to structures cost, Panel C2 in Figure 2 shows a smoother pattern, but numerous observations remain outside the patten. Structures cost shows variability in both diagrams.

Panel E1 in Figure 1 shows the observations of land cost spread apart with no linear pattern. Most observations are clustered together with outliers far from the cluster.

Panel D1 in Figure 1 shows an interesting finding in inventories cost. Most of the observations create a vertical line. The pattern suggests that inventories cost is inelastic. A firm would not be responsive to changes to inventories in relation to changes to output. The cost in inventories would remain relatively the same at any amount of output.

Table 1. Average annual input costs and gross output in billions, by industry (2000–2020).

Descriptive Statistic	U.S. National	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31–33	NAICS 42	NAICS 44–45	NAICS 48–49	NAICS 51
Labor Cost ($)										
Mean	282.9	33.5	57.0	49.3	335.2	744.9	370.0	418.5	199.7	236.6
SD	235.2	8.2	18.0	8.2	74.2	74.1	66.1	62.0	50.2	54.0
Eqp. & IPP Cost ($)										
Mean	112.8	26.9	26.8	65.4	58.8	600.2	109.5	75.7	77.1	345.4
SD	152.0	5.5	8.4	12.5	18.8	134.4	22.0	18.9	23.2	97.7
IPP Cost ($)										
Mean	44.4	0.1	2.9	5.7	4.3	319.3	29.4	16.9	5.4	213.8
SD	87.4	0.0	0.7	1.4	1.7	94.0	10.4	7.0	2.2	68.8
Structures Cost ($)										
Mean	57.6	17.9	146.7	92.5	10.2	176.7	50.4	57.4	44.6	71.6
SD	55.9	2.4	61.4	26.3	4.8	38.9	26.2	18.4	17.3	38.8
Inventories Cost ($)										
Mean	12.0	7.3	1.2	0.9	6.1	72.5	96.8	31.5	1.0	2.8
SD	29.2	1.7	0.9	1.0	4.8	28.2	47.9	13.1	0.4	1.1
Land Cost ($)										
Mean	19.1	57.6	7.6	1.7	25.9	41.4	34.3	23.9	7.2	10.5
SD	23.3	18.8	4.6	0.4	13.2	10.3	16.5	11.4	2.3	7.9
Total Cost ($)										
Mean	484.4	143.1	239.2	209.8	436.3	1,635.7	661.1	606.9	329.7	666.9
SD	399.0	33.3	88.1	46.4	109.9	260.1	174.1	106.0	87.6	191.3
Gross Output ($)										
Mean	1,291.3	376.4	459.8	464.0	1,262.4	5,188.2	1,460.8	1,415.3	930.7	1,308.5
SD	1,202.9	86.0	158.5	71.1	260.1	719.6	438.8	308.0	242.3	314.9

Continued on next page

Descriptive Statistic	NAICS 52	NAICS 53	NAICS 54	NAICS 55	NAICS 56	NAICS 61	NAICS 62	NAICS 71	NAICS 72	NAICS 81
Labor Cost ($)										
Mean	503.6	96.6	629.1	200.0	275.2	105.5	714.6	65.7	206.7	132.9
SD	110.4	23.5	194.9	63.7	69.1	31.9	207.6	15.5	54.3	26.5
Eqp. & IPP Cost ($)										
Mean	286.7	139.1	134.0	12.3	47.8	4.4	63.0	24.7	31.5	13.1
SD	95.9	29.4	35.4	4.5	15.3	1.7	17.6	4.7	6.3	1.9
IPP Cost ($)										
Mean	97.4	4.5	85.0	8.2	18.9	1.6	8.4	16.0	2.3	3.2
SD	47.3	1.8	25.5	3.9	8.2	0.8	3.2	2.5	0.9	0.8
Structures Cost ($)										
Mean	133.0	97.2	23.5	14.8	13.9	15.1	66.3	12.7	44.0	5.7
SD	46.6	33.0	9.8	3.0	4.9	6.4	28.3	4.6	14.4	1.7
Inventories Cost ($)										
Mean	1.0	1.8	2.5	0.1	0.6	0.1	0.3	0.2	1.6	0.3
SD	1.7	0.5	0.8	0.1	0.3	0.0	0.2	0.1	0.7	0.5
Land Cost ($)										
Mean	25.6	66.6	4.8	7.4	4.1	1.8	11.9	4.0	23.3	3.6
SD	4.8	51.1	1.9	2.1	1.5	0.8	4.5	1.1	6.9	1.0
Total Cost ($)										
Mean	949.8	401.3	793.9	234.7	341.7	126.9	856.2	107.3	307.2	155.7
SD	253.6	129.8	238.7	72.9	89.6	40.4	256.3	24.7	81.0	29.3
Gross Output ($)										
Mean	2,149.6	2,854.0	1,696.2	451.6	749.8	272.8	1,795.8	251.6	803.1	571.6
SD	586.0	693.1	443.4	135.2	232.5	79.7	516.0	63.9	209.4	100.8

Note: Eqp. means equipment. Source: Author’s analysis of data from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis.

Table 2. Average annual input cost shares and equipment–labor cost ratio, by industry (2000–2020).

Descriptive Statistic	U.S. National	NAICS 11	NAICS 21	NAICS 22	NAICS 23	NAICS 31–33	NAICS 42	NAICS 44–45	NAICS 48–49	NAICS 51
Eqp.–Labor Ratio										
Mean	0.48	0.82	0.48	1.32	0.17	0.80	0.29	0.18	0.38	1.45
SD	0.47	0.11	0.06	0.08	0.02	0.12	0.01	0.02	0.05	0.24
Labor Share (%)										
Mean	59.2	23.5	24.9	23.8	77.4	46.1	57.4	69.2	61.1	36.5
SD	22.7	2.8	5.2	1.9	3.6	4.5	5.9	2.1	4.4	6.3
Eqp. & IPP Share (%)										
Mean	19.5	19.0	11.7	31.5	13.3	36.3	16.9	12.3	23.2	51.7
SD	12.5	1.9	2.1	2.7	1.0	2.6	1.3	1.3	1.8	3.2
Structures Share (%)										
Mean	14.1	12.9	60.1	43.4	2.3	10.7	7.1	9.3	13.1	9.9
SD	14.3	2.1	6.1	4.0	0.5	1.4	2.4	1.9	2.6	3.7
Inventories Share (%)										
Mean	1.8	5.2	0.4	0.4	1.3	4.3	13.8	5.3	0.3	0.4
SD	3.5	1.2	0.3	0.5	0.8	1.2	3.7	2.4	0.1	0.2
Land Share (%)										
Mean	5.4	39.3	2.9	0.8	5.8	2.5	4.9	3.8	2.3	1.4
SD	8.9	4.6	1.3	0.2	2.2	0.5	1.6	1.4	0.8	0.9

Continued on next page

Descriptive Statistic	NAICS 52	NAICS 53	NAICS 54	NAICS 55	NAICS 56	NAICS 61	NAICS 62	NAICS 71	NAICS 72	NAICS 81
Eqp.–Labor Ratio										
Mean	0.56	1.45	0.22	0.06	0.17	0.04	0.09	0.38	0.16	0.10
SD	0.08	0.10	0.03	0.01	0.02	0.01	0.00	0.03	0.02	0.01
Labor Share (%)										
Mean	53.6	24.7	79.2	85.1	80.8	83.8	83.8	61.3	67.3	85.2
SD	3.2	3.0	2.3	1.0	1.9	2.9	1.4	2.0	0.9	1.8
Eqp. & IPP Share (%)										
Mean	29.8	36.0	17.0	5.2	13.8	3.4	7.4	23.2	10.5	8.5
SD	2.5	5.1	1.8	0.6	1.4	0.6	0.4	1.4	1.3	1.0
Structures Share (%)										
Mean	13.7	24.2	2.9	6.5	4.0	11.4	7.4	11.5	14.1	3.6
SD	1.5	3.5	0.6	0.8	0.7	2.1	1.5	1.9	1.2	0.6
Inventories Share (%)										
Mean	0.1	0.5	0.3	0.0	0.2	0.1	0.0	0.2	0.5	0.3
SD	0.1	0.2	0.1	0.0	0.1	0.0	0.0	0.1	0.2	0.4
Land Share (%)										
Mean	2.8	14.6	0.6	3.2	1.2	1.3	1.4	3.9	7.6	2.4
SD	0.5	7.4	0.2	0.4	0.3	0.3	0.3	1.2	0.8	0.9

Note: Eqp. means equipment. Source: Author’s analysis of data from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis.

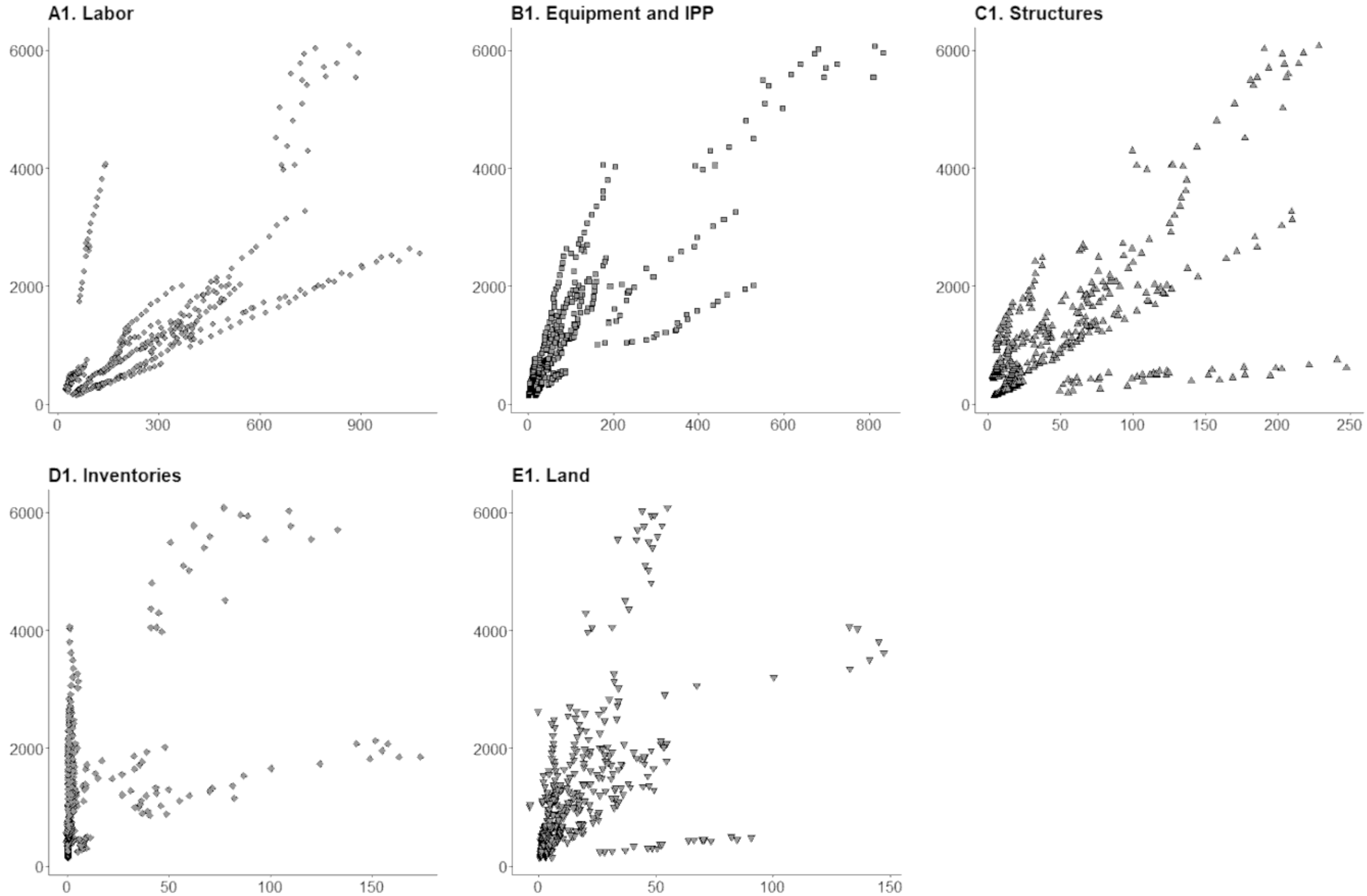

Figure 1. Scatter diagrams of relationships between various input costs and gross output (2000–2020). Note: Gross output is the Y-axis in all scatter diagrams. A1 is labor cost and gross output. B1 is equipment and IPP cost and gross output. C1 is structures cost and gross output. D1 is inventories cost and gross output. E1 is land cost and gross output. Source: Author's analysis of data from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis.

Figure 2. Scatter diagrams of relationships between the logs of input costs and the log of gross output (2000–2020). Note: The scatter diagrams show the observations of the natural logarithms of labor cost, equipment and IPP cost, structures cost, and gross output. Gross output is the Y-axis in all scatter diagrams. A2 is labor cost and gross output. B2 is equipment and IPP cost and gross output. C2 is structures cost and gross output. Compare these diagrams with the corresponding ones in Figure 1. Source: Author's analysis of data from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis.

Table 3. Relative strength in relationships between various input costs and gross output (2000–2020).

Variable	Labor Cost	Eqp. & IPP Cost	Equipment Cost	IPP Cost	Structures Cost	Inventories Cost	Land Cost	Gross Output
Labor Cost	1.00	0.57	0.55	0.54	0.35	0.38	0.10	0.70
Eqp. & IPP Cost	0.57	1.00	0.94	0.96	0.68	0.44	0.30	0.85
Equipment Cost	0.55	0.94	1.00	0.81	0.75	0.44	0.45	0.90
IPP Cost	0.54	0.96	0.81	1.00	0.56	0.41	0.16	0.74
Structures Cost	0.35	0.68	0.75	0.56	1.00	0.30	0.34	0.66
Inventories Cost	0.38	0.44	0.44	0.41	0.30	1.00	0.33	0.50
Land Cost	0.10	0.30	0.45	0.16	0.34	0.33	1.00	0.50
Gross Output	0.70	0.85	0.90	0.74	0.66	0.50	0.50	1.00

Note: Eqp. Means equipment. The equipment cost variable and the IPP cost variable are included in the table to show their relationships to other variables. The equipment-related variables can be compared against each other relative to other variables with particular attention to their relationships to structures cost. Source: Author's analysis of data from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis.

Panel B1 in Figure 1 also shows an interesting pattern. The observations of equipment and IPP cost create a slope that appears rather steep. Applying a natural logarithm to the values makes an improvement in the way the observations are organized. Panel B2 in Figure 2 shows a stronger pattern that is curvilinear in the observations of equipment and IPP cost.

Panel A1 in Figure 1 shows a pattern that is remarkably linear for the observations of labor cost. Outliers remain outside of the pattern. With the natural logarithm applied, Panel A2 in Figure 2 shows a stronger linear pattern with a slight curve in the observations of labor cost.

The visual pattern depicted in Panel A2 is confirmed quantitatively. The correlation between labor cost and gross output is high at 0.70. However, labor cost has the weakest relationship with gross output in comparison with equipment cost and IPP cost. Among all the input cost variables listed in Table 3, the correlation between equipment and IPP cost and gross output is the second strongest at 0.85. If equipment cost is examined alone, the relationship between equipment cost and gross output has a correlation of 0.90—a very strong relationship. The relationship between IPP cost alone and gross output has a correlation of 0.74. The correlation of the *combined* equipment and IPP cost represents an average of the two individual cost variables.

The other input costs show a moderately strong relationship with gross output. However, structures cost, inventories cost, and land cost show weak relationships with other variables. Land cost shows the weakest in relationships with labor cost, IPP cost, equipment and IPP cost, inventories cost, and structures cost. Inventories cost shows weak relationships with labor cost and structures cost and moderate to weak relationships with equipment cost and IPP cost. Structures cost has a weak relationship with labor cost as well but shows moderately strong relationships with IPP cost and equipment and IPP cost. Structures cost has the strongest relationship with equipment cost alone.

With a review of correlations and scatter diagrams, different regression models were examined to find the one that would produce the most accurate predictions. I selected the model that applied the natural logarithms of gross output, labor cost, and equipment and IPP cost. A model that applied the natural logarithm of structures cost produced a weak coefficient for the inventories cost variable (see Appendix Table A.1). Adding the natural logarithm of structures cost did not substantially change the other variables' coefficients, the adjusted R-squared, and the residual standard error. Although the coefficient of the transformed structures cost variable did increase, the standard error of the natural logarithm of structures cost grew larger. The selected best-fit model showed strong coefficients for all variables as indicated by their corresponding small standard error and a very small p-value (see Table 4). The selected regression model produced the following equation:

$$\ln Y = 3.012 + 0.448 \ln L + 0.291 \ln E + 0.002S - 0.001M + 0.009D \tag{2}$$

Table 4. Regression model for efficient production.

Variable	*b*	SE	p-value
Intercept	3.012	0.076	0.000
Log of Labor Cost	0.448	0.017	0.000
Log of Equipment and IPP Cost	0.291	0.016	0.000
Structures Cost	0.002	0.000	0.000
Inventories Cost	–0.001	0.001	0.028
Land Cost	0.009	0.001	0.000

Note: The model is representative of a sample consisting of 399 observations of aggregate national-industry data from 2000 to 2020 (n = 399). The adjusted R-squared is 0.91. The residual standard error is 0.25 on 393 degrees of freedom. The natural logarithms of gross output, labor cost, and equipment and IPP cost were used in the model. The other variables were not transformed. Source: Author's analysis of data from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis.

lnY is the natural logarithm of the predicted output. *lnL* is the natural logarithm of labor cost. *lnE* is the natural logarithm of equipment and IPP cost. Variables *S*, *M*, and *D* are structures cost, inventories cost, and land cost, respectively.

The adjusted R-squared in this model is 0.91. The residual standard error is 0.25 on 393 degrees of freedom. All the variables' coefficients including the intercept's coefficient have a standard error of 0.076 or smaller.

The model shows that a change to any of the input variables would have an effect on output. In the case of inventories, the effect could be negative. For every one dollar increase in the total cost of inventories, output would decrease by 0.1%. All other variables would have a positive effect on output. For every one dollar increase in the total cost of structures, output would increase by 0.2%. For every dollar increase in the total cost of land, output would increase by 0.9%. Interpretation of the coefficients of labor cost and equipment and IPP cost is different, but the outcome follows the same pattern. For every 1% increase in the total cost of labor, output would increase by 0.45%. For every 1% increase in the total cost of equipment and IPP, output would increase by 0.29%.

The effects of labor and equipment are both revealing and surprising. If a regression model were generated without structures, inventories, and land, the coefficients would be switched around for labor cost and equipment and IPP cost; that is, the coefficient of equipment and IPP cost would be larger than the coefficient of labor cost (see Appendix Table A.2). By adding more cost variables to the equation, equipment and IPP cost has a smaller effect on output. This outcome could seem counterintuitive in that one would assume that equipment plays a larger role in production. If you evaluate labor and equipment alone, then equipment would contribute more to output than labor. However, by including additional cost variables in the equation, the distribution of labor and equipment completely changes.

Does the regression model indicate that labor contributes *more* to output than equipment? Is labor really more productive than equipment?

The predictions in Table 5 suggest that the answer could be positive. I use the model to calculate 11 hypothetical production scenarios (Scenarios A to K). While the costs to structures, inventories, and land are held constant, I adjust labor cost and equipment and IPP cost in a way that answers the question. Labor cost decreases progressively from Scenario A to Scenario K. I reverse the cost progression to show equipment and IPP cost increasing progressively from Scenario A to Scenario K. In each scenario, total cost does not change. Through this simple demonstration, predicted output increases from Scenario A to Scenario D and then decreases to Scenario K. This trend will show a curved line when predicted output is plotted on a graph.[4] Productivity would rise, reach a peak, and finally fall.

[4] A deeper cost analysis of total costs, marginal costs, total revenues, marginal revenues, profit, and output would generate various cost curves. These cost curves serve to identify points at which a firm can make key decisions to operate (e.g., breakeven point and efficiency or optimization).

A firm that chooses to spend progressively more on equipment and IPP and less on labor might not produce increasing output. On the other hand, a firm that spends too much on labor and too little on equipment and IPP could fall short of producing the maximum number of goods and services possible. Based on the calculations shown in Table 5, the optimal level of production would be a point at which the amount spent on equipment is moderately less than the amount spent on labor. This level of production translates to employing more workers and fewer machines.

Table 5. Predicted outputs of different production scenarios from a high-cost labor scenario to a low-cost one.

Scenario	Eqp.–Labor Ratio	Labor Cost ($)	Eqp. & IPP Cost ($)	Structures Cost ($)	Inventories Cost ($)	Land Cost ($)	Total Cost ($)	Predicated Output ($)	Percent Diff. (%)
A	0.33	150	50	20	5	10	235	679	189
B	0.43	140	60	20	5	10	235	694	195
C	0.54	130	70	20	5	10	235	702	199
D	0.67	120	80	20	5	10	235	704	200
E	0.82	110	90	20	5	10	235	701	198
F	1.00	100	100	20	5	10	235	692	195
G	1.22	90	110	20	5	10	235	679	189
H	1.50	80	120	20	5	10	235	661	181
I	1.86	70	130	20	5	10	235	637	171
J	2.33	60	140	20	5	10	235	607	158
K	3.00	50	150	20	5	10	235	571	143

Note: Production scenarios are hypothetical, representing a progression from very high labor cost (Scenario A) to very low labor cost (Scenario K). The dollar amounts of input costs are theoretical with no reference to a particular scale of operations. In theory, the scenarios could be for a single firm seeking to adjust its internal organization or for numerous firms seeking similar adjustments to their operations on average. The costs of structures, inventories, and land are held constant, so that the effect on output can be clearly observed by changes to labor cost and equipment and IPP cost. Predicted output is calculated using the regression model shown in Equation (2). Source: Author's calculation based on the regression model in Table 4.

Comparing the model's proportion of labor and equipment with empirical data (see Table 2) suggests that most NAICS industries were labor intensive with relatively small utilization of equipment. The situation was particularly acute in the service-related industries, where labor's share of the total cost far outweighed that of equipment and IPP cost. Over the first two decades of the twenty-first century, 12 out of 19 industries had a mean equipment–labor cost ratio from as low as 0.04 to as high as 0.38. Construction, wholesale trade, retail trade, and transportation and warehousing had low capital intensity. Industries with the lowest equipment–labor cost ratio were NAICS 61, NAICS 55, NAICS 62, and NAICS 81, all of which provide some kind of service. Table 1 shows that these service-related industries had a very high mean labor cost and a very low mean equipment and IPP cost. Industries with very low capital intensity included educational services and health care and social assistance.

In contrast, few industries appeared to operate at a point at which the model suggests to be an optimal level. NAICS 11 (agriculture), NAICS 31–33 (manufacturing), and NAICS 52 (finance and insurance) had a labor cost that was moderately higher than equipment and IPP cost. These industries invested in machines and yet maintained levels of workers.

The wide difference in the equipment–labor ratio between manufacturing and service-related industries underscores how differently labor can be applied across industries. Baumol (1967) explained how labor is perceived in its role to produce products (e.g., automobiles, chairs, and shirts) on one hand and to deliver services (e.g., education, health care, and hospitality) on the other.[5] The contrasting results of shares of labor and capital confirm findings described in previous studies examining economic growth in the United States from 1948 to 2001 (Nordhaus, 2006) and in the European Union from 1995 to 2016 (Pariboni and Tridico, 2020).

5. Discussion

The regression model suggests that there needs to be a conscious balance in using capital and labor resources. A firm has to find a proportion of machines and workers that can reach maximum output. The number of workers should not be reduced to such a low point where machines dominate the production environment. Too much capital intensity might be unproductive. On the other side of the equation, too much labor intensity would not be productive either. A firm should not have a very low number of machines and a very high number of workers. An optimal level would be an environment where machines and workers are implemented in a balanced and strategic way.

The results of this study align with prior ones. As described in the introduction, firms would reconfigure their labor structure through a different organizational scheme. With increased investments in capital resources, firms would not eliminate all workers. They would retrain (upskill) a number of workers or hire new workers as determined by new skills required to meet the demands of new machines. This kind of organization has held across manufacturing from the nineteenth century to the present day. In this study, I confirm the organizational reconfiguration with the equipment–labor cost ratio.

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[5] Baumol advanced a tenuous argument to claim that labor is a means in certain activities to produce a good, while in other activities, labor is the end goal (Baumol, 1967, page 416). Recent technological advances may prove that productivity in administrative support, education, food services, and health care can be increased with the use of machines. Baumol's argument should be revisited given how much technology has progressed over the decades to solve problems in carrying out service-related jobs and tasks.

The use of Uechi's production equation to measure output and changes to labor and equipment demonstrates the importance of including other cost factors beyond the conventional labor and capital measures. Further analysis would show that evaluating labor and equipment alone generates a biased model in favor of capital. The inclusion of more defined capital resources redistributes the level of contribution more evenly across the variables. Additional variables in the equation lead to a more accurate representation of production. Moreover, defining variables with a greater degree of specificity is key. This finding is aligned with Levhari and Sheshinski's conclusion. It also disproves the conclusion that an OLS regression produces biased coefficients in a production function; prior research advanced such a conclusion based on using an equation with only two input variables (Van Biesebroeck, 2007). Indeed, Van Biesebroeck shows how using only labor and capital can produce biased results. Uechi's conceptual underpinnings of the production equation produces a regression model that is remarkedly robust.

On the topic of particular input costs, structures cost could be broken up into two or more asset categories or reexamined to see if specific types of structures fit better in another asset category. Results show large variability in this category. Structures is a broad category that includes specific types that both directly and indirectly contribute to output. Buildings and other facilities would contribute indirectly to output. Certain structures such as radio towers, transmission lines, and conveyance systems would contribute directly to output. Some structures could be categorized under equipment. With a large share of structures cost, the mining and utilities industries could be using large-scale machinery, which could be interpreted as either structures or equipment. The correlation result indicates a strong relationship between structures cost and equipment cost. Refining the structures asset category will provide clarity. As such, a narrowly defined structures category should produce a tighter pattern when comparing it against gross output in a scatter diagram.

6. Conclusions

Latest advances in technology raises the specter of the century-old debate on labor versus capital. Can robots and advanced computer software produce greater output than what workers can do? If labor is required, what is the optimal mix of workers and machines?

This paper addressed the foregoing questions by analyzing the economic fundamentals of input and output. In the case of the United States, I examined two decades of labor and capital costs and gross output to evaluate production in 19 private-sector industries. I collected data suitable to test Uechi's production equation for the purpose of assessing macroeconomic growth and capital intensity. Given available public data, Uechi's equation had to be adjusted to incorporate categories that differed in name. Nonetheless, the new production equation proves flexible in making accommodations while adhering to the concept for which the equation is intended to solve.

A lesson learned Is the need to have more input cost variables specifically defined to capture the production environment. Simply evaluating production by two categories alone—labor and capital—is not sufficient. Doing so could produce a biased model. A more accurate representation can be economically produced with additional cost factors.

Applying Uechi's equation in modified form produced an OLS regression model, which can explain changes to labor, equipment, and other capital resources in the U.S. economy. Prior microeconomic studies of specific industries support the predicted outputs of the model. The regression model predicts that output would gradually decrease after a certain point when a firm spends progressively more on equipment and less on labor. Increasingly growing capital intensity might not be optimal. Investing more in labor is preferable. A firm does not necessarily need to invest so much in equipment to produce maximum output. Even if it does, a firm needs to employ a number of workers—presumably to operate and repair the purchased machines.

To answer the question: can labor be totally replaced by equipment? According to the model, the answer is no. Labor continues to play a role in production. Applied in proper proportion—neither too much nor too little—labor can be effective in producing maximum output.

7. Further research

Will the results of this study hold with the use of firm-level data? A subsequent inquiry should be undertaken to answer the question. The present account was limited to analyzing sectoral cost and output data in the aggregate. A future, deeper project should analyze not just total input costs but the quantities and composition of labor and capital and the breakdown of gross output. It should also analyze the various types of workers, machines, and other resources that contribute to output. Not only would a future study confirm or refute this one's results, it could produce additional insights into what specific types of occupations and equipment should be used in production. Including such specificity of labor and capital in the equation would show which resources are and which are not in demand. Further research that uses firm-level data would result in a better understanding of the flows of employment between industries affected by changes to capital resources.

With that said, a caveat needs to be expressed. A greater degree of specificity imposes challenges on sampling all industries in a national economy. It might be difficult to apply all the input variables and produce coherent results where substantial heterogeneity exists. This is not to say that it cannot be done. The research design needs to be carefully thought through in structuring firm-level data across diverse industries and firms. An alternate approach is to apply Uechi's production equation in a specific sector where firms implement similar machines to produce similar products. This narrow design on a single industry would be easier to carry out, especially when the research goal is centered on microeconomics.

Use of AI tools declaration

The author declares that he has not used artificial intelligence (AI) tools in the creation of this paper.

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Conflict of interest

The author declares no conflicts of interest in this paper.

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