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Econ 458

Measuring Markup and the Returns to Scale in the U.S. Storage Battery Manufacturing Industry 1958-2016

Abstract: This paper shows the evolution of the markup of price over marginal cost and output elasticity of cost for the US storage battery manufacturing industry, which is NAICS sector 335911. Based on our research, we have found that firms in the storage battery manufacturing industry do not have significant market power, which can help explain why the markup in this sector decreases over the time period. This industry became less concentrated over the time period, which is consistent with this decrease in markup as firms become more competitive. Firms in this industry operated at a long run output level above minimum efficiency scale, which means that they operated with decreasing returns to scale. This indicates that firms in this industry received less in return for each additional input. This could be attributed to the influx of firms entering the industry. There is a downward trend of output elasticity, which also explains the decreasing returns to scale.

Introduction

Our research of the US storage battery manufacturing industry is important because we learn how markup and scale elasticity change as the composition of inputs change. We calculated the markup ratio as a point-estimate by using regression on a modified version of Hall's equation. Then we performed time-series analysis to see how the markup equation changed over time. Since the markup ratio and the scale elasticity are related, we were able to calculate a time-dependent model for scale elasticity. This research was important because it showed how we can extend economic analysis and increase our knowledge of markets. We can treat markup and scale elasticity as a constant ratio, and we can treat the two variables as time dependent. By considering how markup and scale elasticity change over time, we are able to see how concentrated markets are. Our research concluded that the storage battery manufacturing industry became less concentrated over the interval of 1958 to 2016.

Data regarding the exact number of firms in the storage battery manufacturing industry vary across sources. The US Census reports 135 firms in 1997 and 207 firms in 2017. Another part of the US Census website reports 97 firms in 2012 and 120 in 2017. Regardless of the exact numbers, we can see that the industry is becoming less concentrated as more firms have entered in recent years.

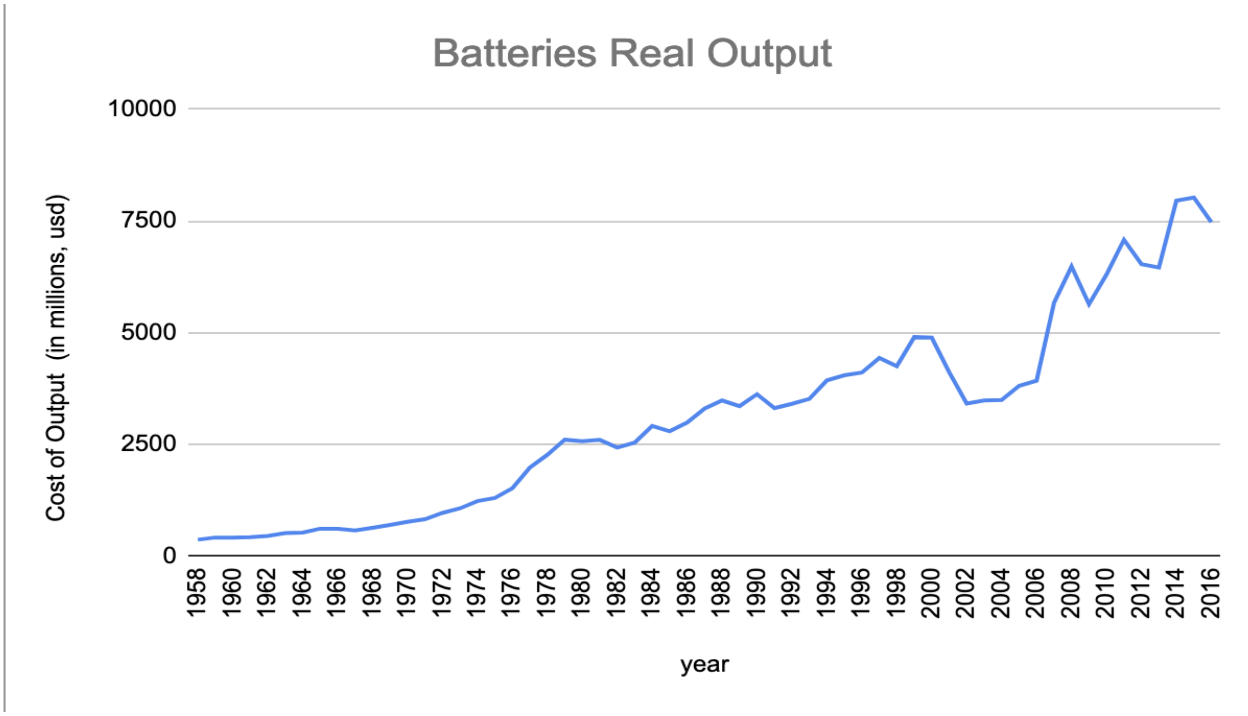
Beyond market concentration, there were many other changes that occurred in the storage battery manufacturing industry over this time period. It is important to note the decrease in output elasticity to all factors over this interval, especially when considering that the industry is becoming less concentrated. We also see that the total factor productivity falls over the interval which further highlights the decreasing returns to scale we see in the industry.

Data

Our data was collected from two sources. First, we downloaded a spreadsheet from the "National Bureau of Economic Research." After navigating to "NBER-CES Manufacturing Industry Database" we downloaded the "2012 NAICS version." This excel file provided data on twenty-three variables from 1958-2018. The data contained aggregate information about production inputs and outputs. The data was not adequate enough to examine how inputs were decomposed so we had to find other data sources. The second data source was found from "The Federal Reserve." It had time-series data for sixteen variables. These variables measured capital and investment inputs. After downloading "Manufacturing Investment and Capital, 6-digit NAICS," we had adequate information to set up our research. Lastly, we restricted the years of interest to 1958-2016 so that we could use both data sets.

NAICS Sector 335911 appears to be diverse. The sector shows battery storage manufacturing can be separated based on composition and uses. Batteries can be composed of different materials such as alkaline cells, lead-acid cells, lithium and more. They are used in different settings such as cars, home, and boats. Another way they can be divided is by the ability to recharge the battery. This sector appears to be much more diverse than NAICS Sector 3121220, which describes the brewing industry.

(Figure 1)



From 1958 to 2016, the output of the battery industry appears to experience exponential growth. Figure 1 has some unique features. From 1958 to 1976, output increased at a relatively constant rate. Then, from 1976 to 2000, output increased at a higher and rougher rate. The increased rate of output combined with the rough line may indicate that many firms entered the industry during the period. The next most interesting thing about Figure 1 is that output plummeted in 2000, and then output grew at its highest rate yet. The dip in 2000 most likely indicates either industry restructuring or TFP shocks. Perhaps, a combination of restructuring and changes in technology were responsible for the drastic changes in output from 2000 to 2016.

(Figure 2)

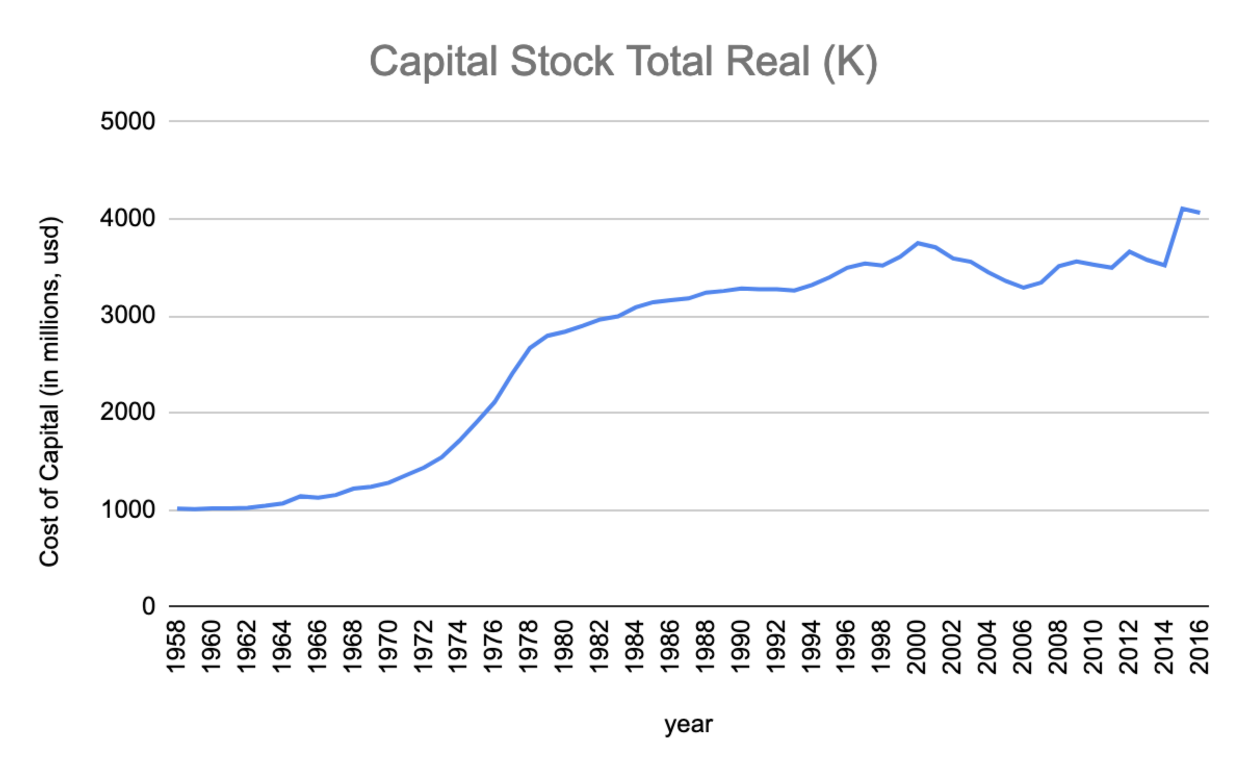


Figure 2 shows the total value of capital stock from 1958 to 2016. The graph can be divided into four unique sections. First, from 1958 to 1978, the value of capital stock increased at an exponential rate. Second, from 1978 to 2000, the value of capital stock in the industry appeared to increase at a constant rate. Third, from 2000 to 2006, there was a dip in the value of capital stock. Perhaps, capital stock was depreciating faster than they were replacing it and adding more capital. Another possibility is that the industry was experiencing restructuring or technological innovations. Based on the graph, both possibilities have merit. The fourth section is the most interesting part of the graph. It shows a sharp spike in capital stock starting in 2014. The world has seen a shift towards greener energy sources in the 2010s. The sharp spike may be reflective of the increased production of electric vehicles, solar power, and smart-grid technologies.

(Figure 3)

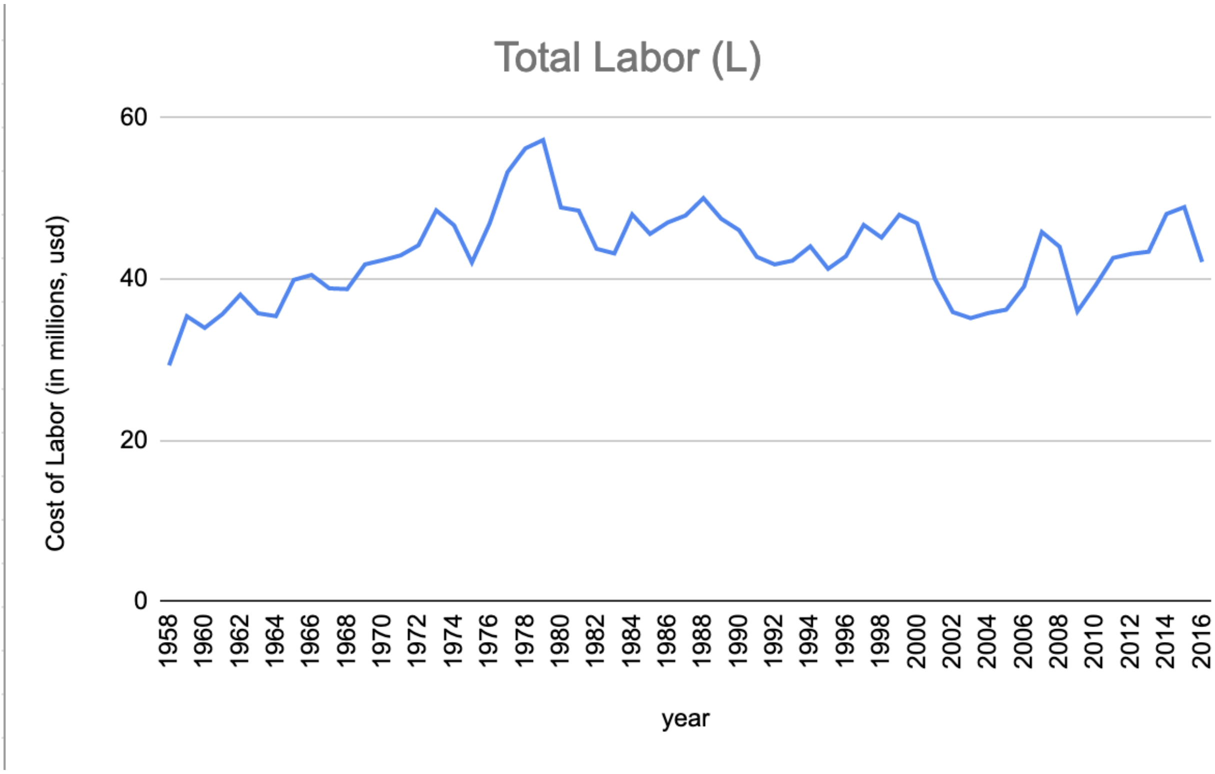


Figure 3 graphs the total cost of labor in the battery industry during the period. It is by far the most interesting graph because it has two unique properties. The first property is that it is much less costly than other inputs. The second property is that the cost has remained relatively constant over time. Figure 5 shows all the inputs in the same graph and the disparity between labor and other inputs is enormous. This is interesting because it may signal a few possible scenarios. The first scenario is that technology has been able to keep the price of labor constant. The second scenario is that workers in this industry do not require intensive training. A final possibility is that the price of labor in this industry has steadily increased with inflation.

(Figure 4)

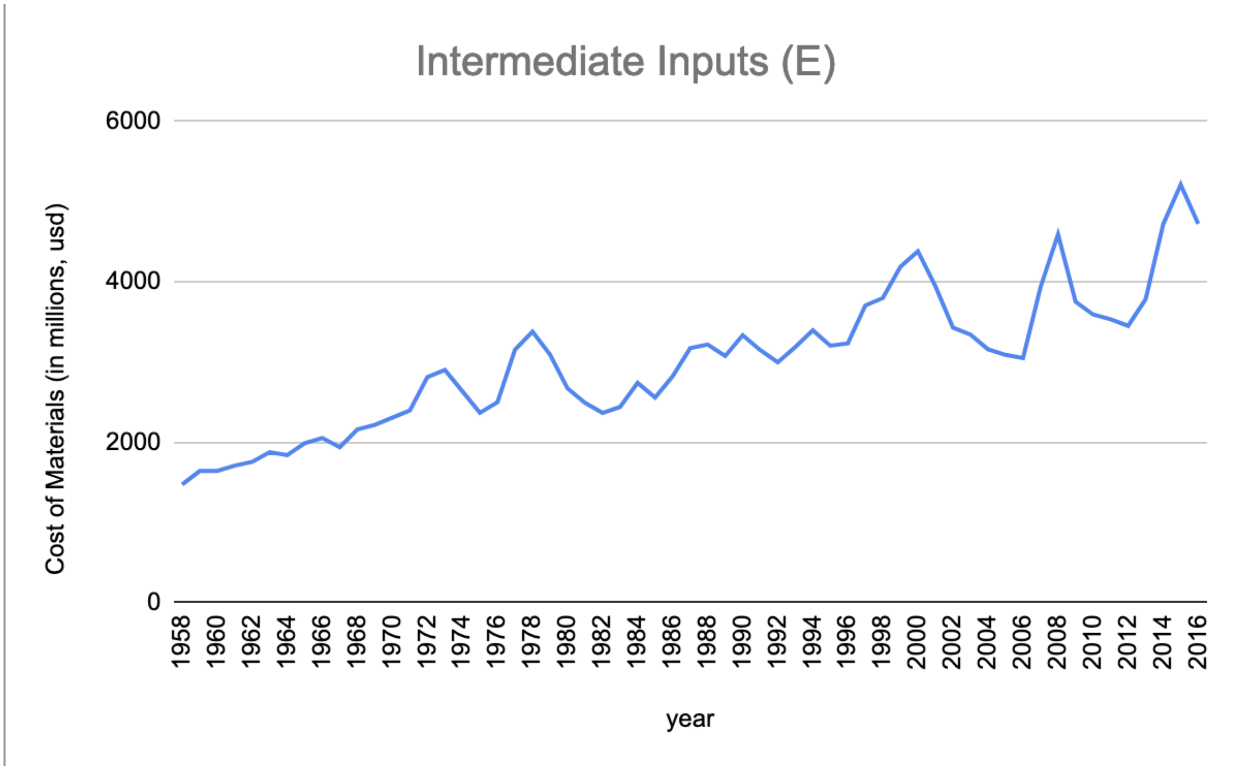


Figure 4 shows the total value of intermediate inputs from 1958 to 2016. We see dramatic increases in inputs over the time period. The total cost of intermediate inputs approximately doubles over the period. Comparing this to figure 5, we see that the capital and intermediate inputs follow a similar trend until around 2006 where intermediate inputs jump up to the same level as capital. The pattern from 2000 to 2016 has cyclical elements with an increasing trend. Given this pattern, we may be seeing firms massively upscale their factories. Another possibility is that the government may be playing a role; the peaks are eight years apart. Based on our data, we can not say with certainty what caused the unusual behavior. The best explanation our data supports is that demand for battery storage products has continued to increase. The increasing demand has resulted in firms entering the market. Therefore, firms may be competing for the same finite resources.

(Figure 5)

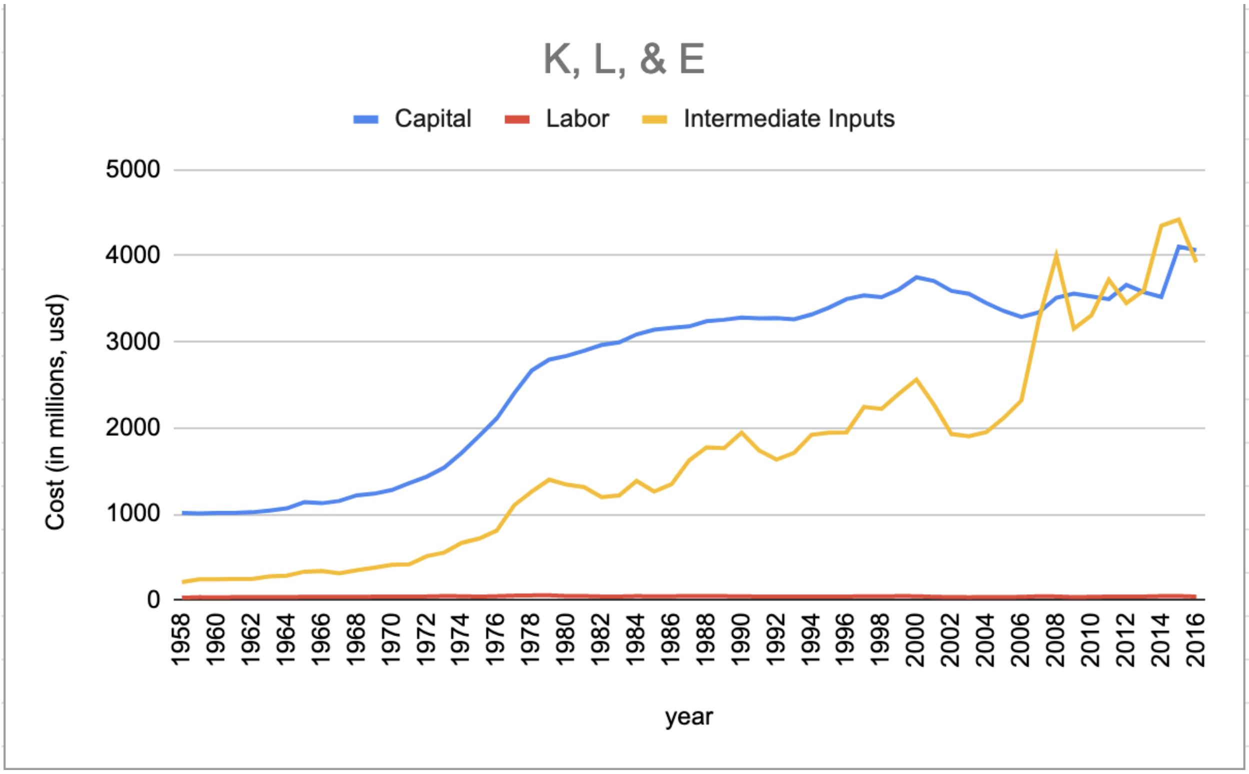


Figure 5 shows the input costs for the storage battery manufacturing industry by input type. The trends of these factors are explained above, but it is useful to view the graph to further understand the relationship between each input type and how the costs of each factor change over time.

(Figure 6)

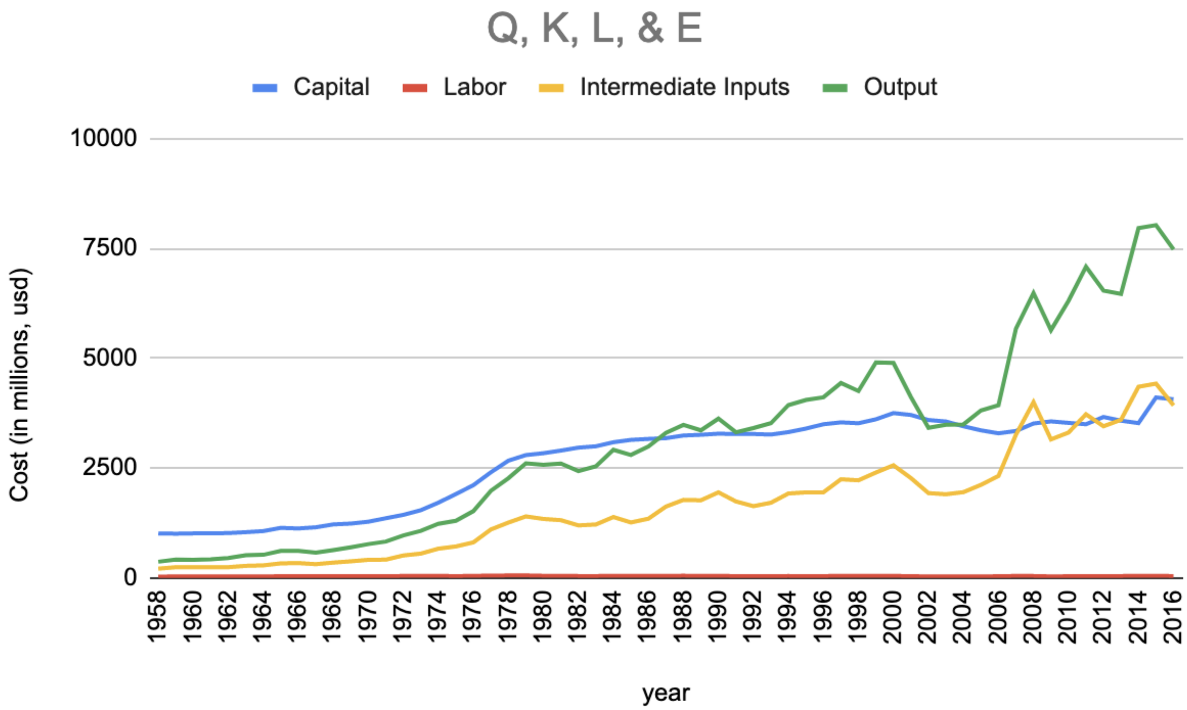
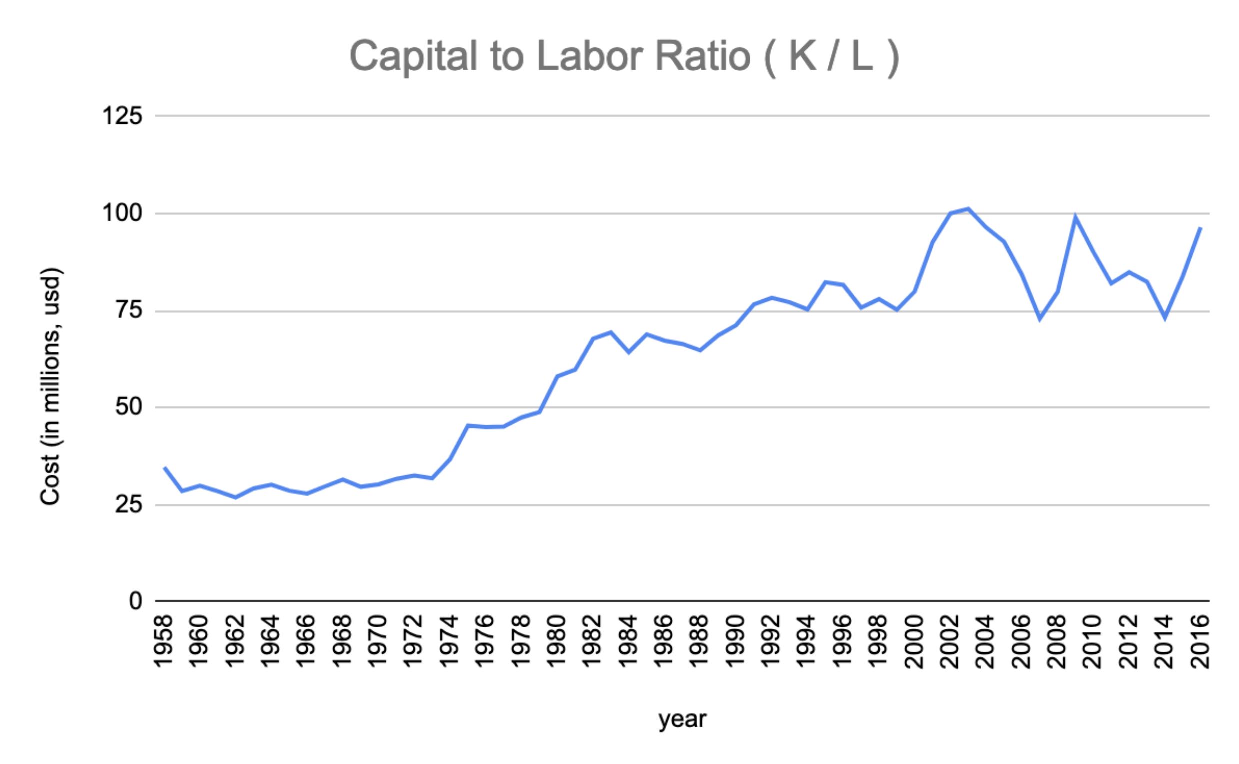


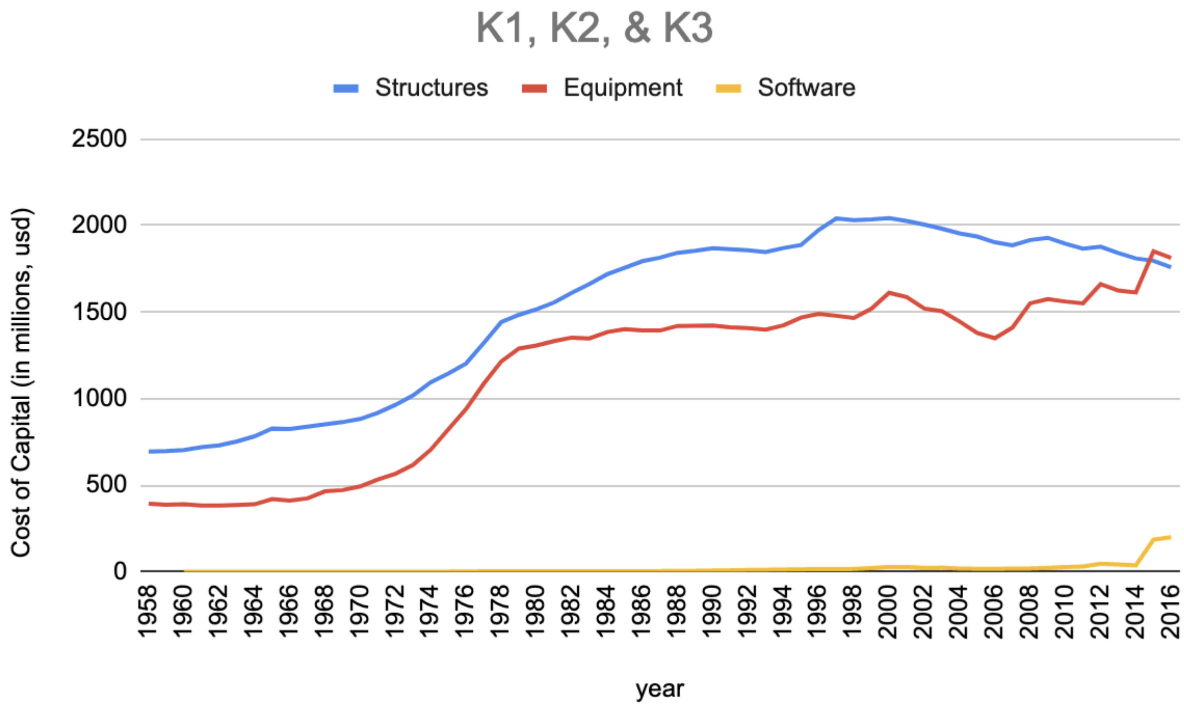
Figure 6 shows the relationship between inputs and overall output. We see that the graph of output nearly mirrors the intermediate inputs line. This suggests that the intermediate inputs are a stronger indicator of output level than capital or labor. It is also important to note that the graph of output does not perfectly reflect the changes in profit margin that we see in Figure 11. Although we do see that larger events such as the dip in output in 2002 is reflected on the graph of evolution of the profit margin as well. This shows that there are numerous factors that contribute to the overall output level. The growth of output as shown on this graph is indicative of the scaling of the industry as more firms enter the market.

(Figure 7)



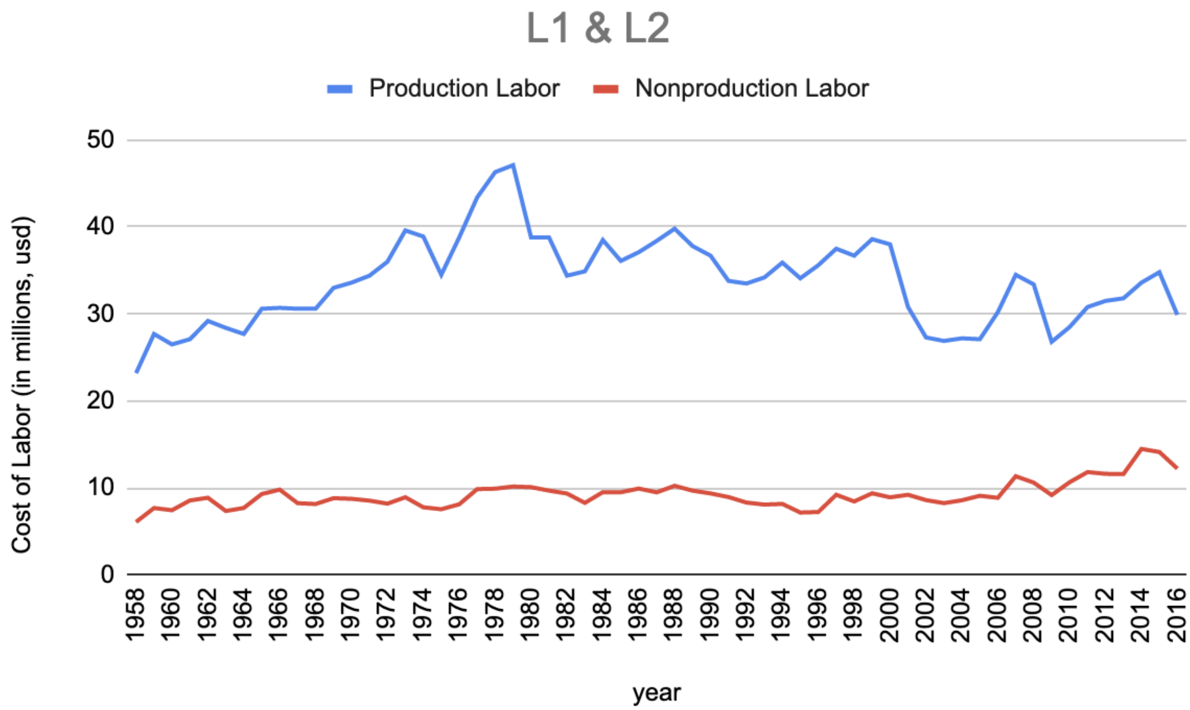
The capital to labor ratio approximately quadrupled over the interval. The industry clearly became more capital intensive. What is interesting about the graph is that capital appears to grow at an exponential rate until 2000. Then the capital to labor ratio has distinct, major influxes of capital occurring in cyclical patterns. The cyclical pattern may be indicative of government funding. The government has made substantial investments towards electric vehicles and sustainable sources of energy. Public support for sustainable technologies (electric vehicles, solar power, wind power, smart grid) have also substantially increased from 2000 to 2016. Another explanation of the major, cyclical influxes of capital may just be from companies shifting production to achieve their goals in greener technologies.

(Figure 8)



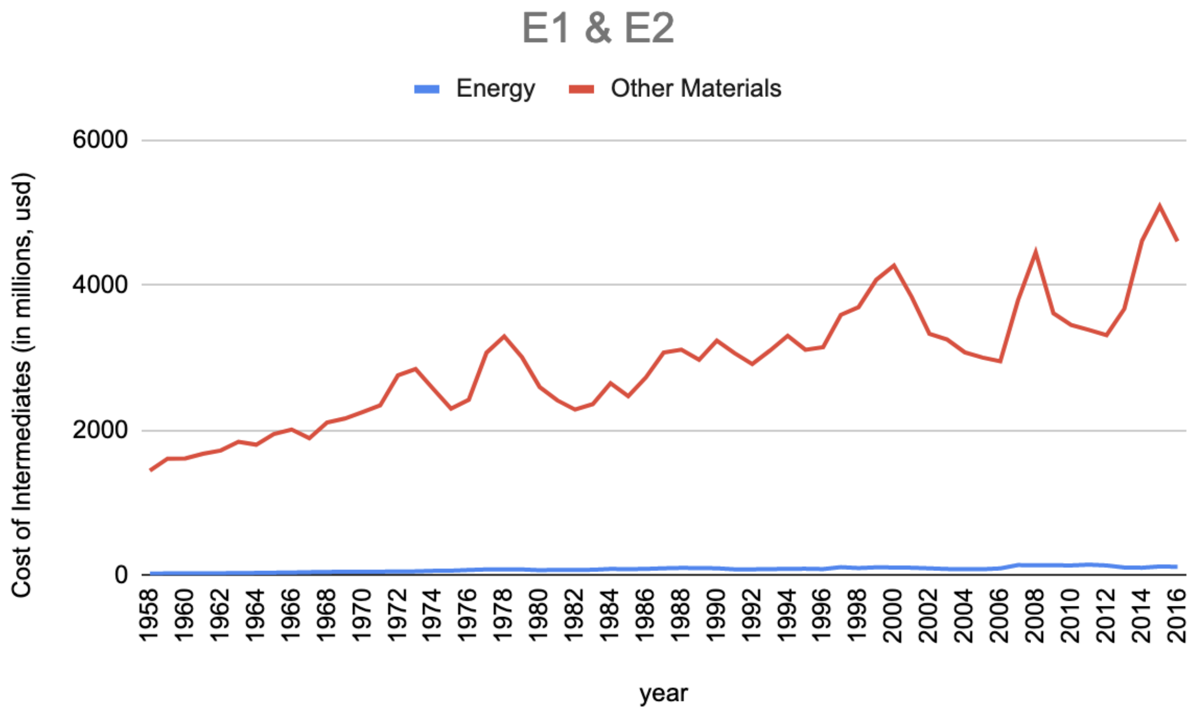
The cost of structures is the most expensive category of capital. The next most expensive category is equipment. The least expensive category is software. An interesting pattern in the graph is that the cost of structures falls below the cost of equipment in the last two years of the period. The cost of equipment has been increasing since 2006 while the cost of structures has been decreasing. The cost of software has seen explosive, near-vertical growth over the last two years of the period. Even though software has been a much more important input over the last two years, the total cost is negligible compared to structures and equipment.

(Figure 9)



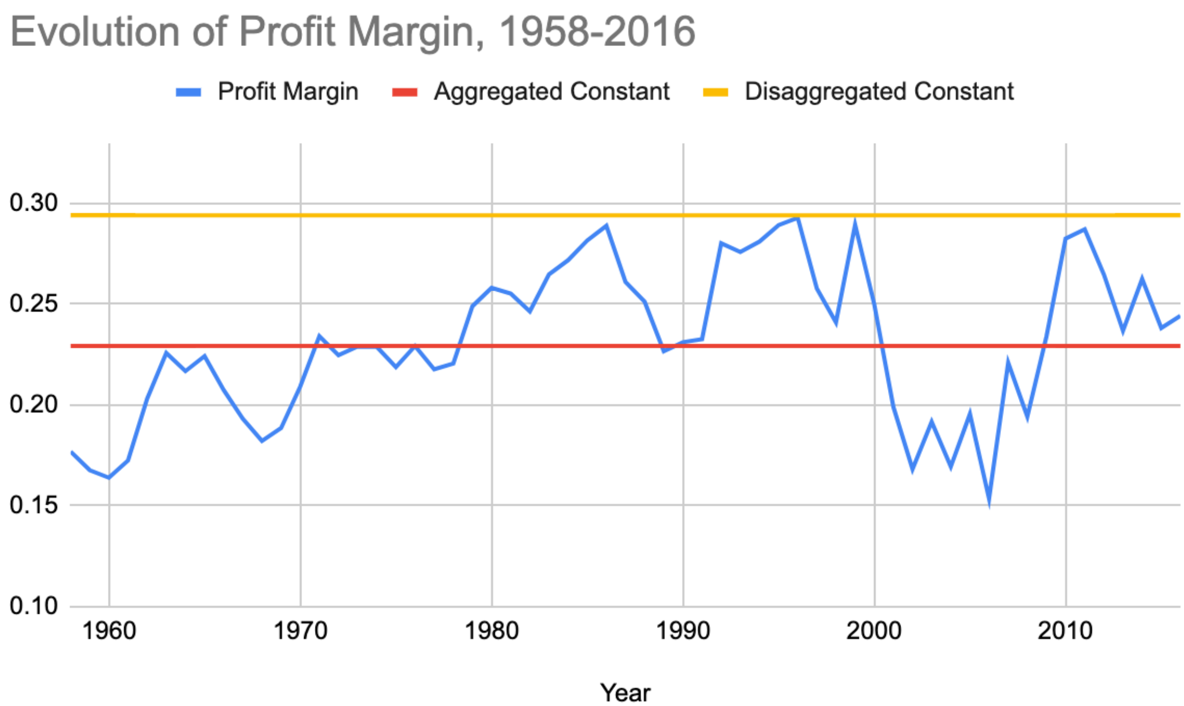
The cost of nonproduction labor has remained approximately constant over the period. The interval from 2006 to 2016 is starting to show modest growth. The cost of production labor peaked in 1978. Since then, the industry has experienced a decrease in the importance of production labor. The shift away from production labor is explained by the rise of capital starting in 1978. Firms prioritized capital over labor in every period. During the same intervals production grew, therefore, the marginal product of capital is more productive than the marginal product of labor. Firms will prioritize inputs that maximize their output. The elasticity of output for labor and capital are equal; since the cost-share of capital is so much larger than the cost-share of labor, firms' total spending on labor is almost negligible.

(Figure 10)



According to figure 10, the total spent on energy doubled over the time period. Interestingly, the price of energy has remained constant and negligible when compared to the cost of other materials. Storage battery manufacturing depends on many intermediate inputs. Since the price of electricity and fuel is negligible, we have to wonder where these massive costs come from. Batteries are made from chemicals. These chemicals have to be mined from the Earth and gathered from recycled materials. Both processes can be time consuming and expensive. The constant rise in the price of other materials may result from increased firms competing for the same inputs. Another possibility is that the total supply of materials has dwindled from 60 years of mining. The simplest explanations are often correct. However, a cyclical pattern with an increasing trend appears starting in 2000. This pattern indicates a substantial, industrial wide shift. This trend is interesting because there are decreasing returns to scale over the interval, yet production continues to increase.

Model and Empirical Results
(Figure 11)



Because future investments are funded by previous profits, it is important to observe investment trends over this same period. We see that the profit margin in the storage battery manufacturing industry increases gradually over the period. We see a severe decline in the profit margin just before the turn of the century. The years around 2000 have shown interesting results in every preceding figure indicating that a major event took place just before 2000. Furthermore, the steep dip from 1999 to 2006 was followed by a quick recovery. This action may indicate structural shifts in the industry such as mergers, changes in demand, or investment in research and development.

(Figure 12)

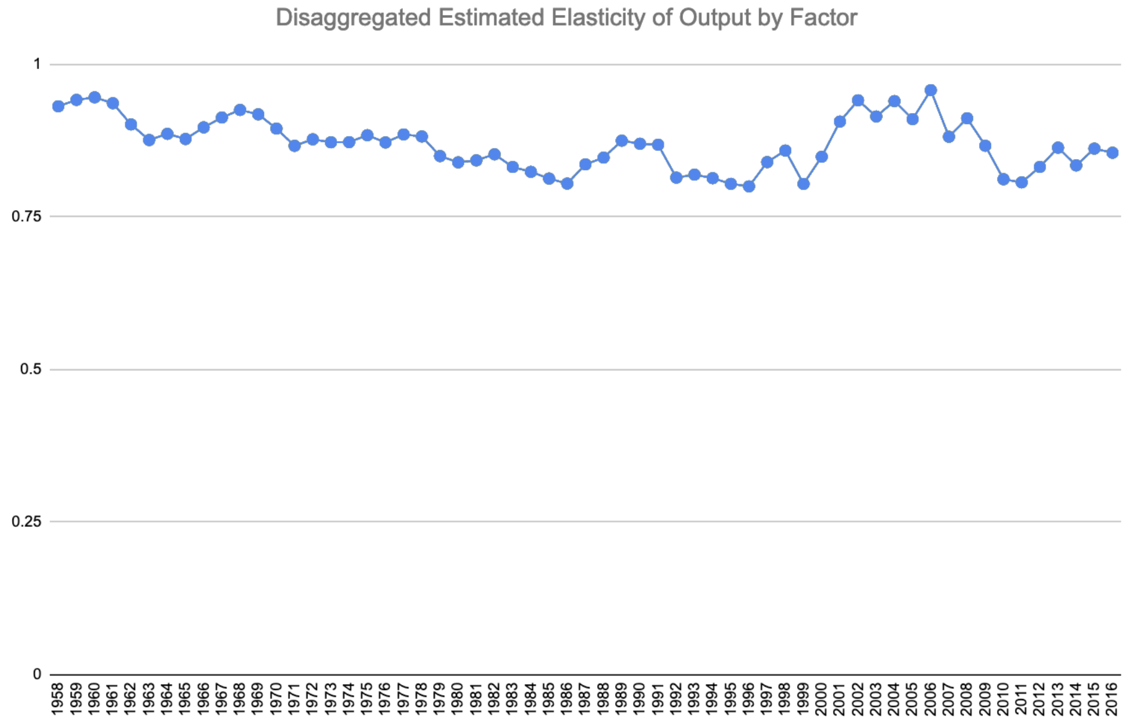


Figure 12 graphs the elasticities of all inputs across time. All inputs have identical elasticities so the figure has only one line. As listed in our graph of estimated elasticity of output by factor, we noticed that the elasticity of all factors faced a sudden increase from 1998-2010. An increase of the output elasticities of K, L, and M signals a path toward diseconomies of scale. We observed a similar pattern in this graph of the evolution of the profit margin. In this same time period, the profit margin dropped from roughly 0.3 to 0.15. This insight leads us to draw a negative relationship between profit margin and the estimated elasticity of output by factor. One possible explanation is that the average costs per unit of output have been increasing with the increase in scale of the storage battery manufacturing industry. Another possible explanation is that the industry concentrated during this interval. Industry concentration is a likely explanation considering that the profit margin shot back up to all time highs during the 2007 to 2011 interval. The last possible explanation we will discuss is that profit margin dipped because of substantial investments in intangible assets such as Research and Development. Any investment into intangible assets must be financed by profits, therefore, the profit margin plummeted during a period of intense research and design. This theory does not have strong support because the resulting profit margin did not surpass its previous high.

So far, mu has been a constant value. Logically, mu should change if industry concentration changes because the state of competition determines how much firms are able to markup their products. We performed time-series strategies to estimate how mu changes over time. Then we used our estimated values of mu to calculate gamma. Equation 1 shows the final form of mu we are solving for.

$$\mu(t) = \mu 0 + \mu 1(t) \qquad (equation\ 1)$$

At this point in the project we did not perform time-series analysis on disaggregated equations. We could have calculated mu for this but we felt that composing disaggregated, time-series calculations for mu was not unnecessary. In equation 2, we performed multivariate regression analysis on SWFG and SWFG multiplied by the interval.

$$\Delta Q/Q = a1 + \mu 0 SWFG + \mu 1(t\, x\, SWFG) + e \qquad (equation\ 2)$$

This multivariate regression was useful because it gave us values for equation 2. Our results in equation 3 were vital for calculating time-dependent values of mu.

$$\Delta Q/Q = 0.01253 + 1.2039\, x\, SWFG - 0.0032(t\, x\, SWFG) + e\, ,\ R^2 = 0.6552$$

t-stat (1.725043526) t-stat (5.064467596) t-stat (-0.540734482) (equation 3)

Analysis of equation 3. The R-squared value can range between zero and one. A value of zero means that the variables in the regression cannot explain changes in output. A value of one would indicate that the variables in the regression perfectly explain the changes in output. Since our calculated R-squared value is 0.6552, we can say that the variables in our regression adequately explain changes in output. The t-stats are also important in determining how well explanatory variables describe dependent variables. Since our calculated coefficients are between the calculated t-stat and zero, we can say that the model is adequate in predicting changes in output from changes in inputs. Another measure of accuracy is the p-value. The p-value for (t x SWFG) is 0.59 in a 95% confidence interval. Since the p-value is greater than 0.05, we must be wary of any conclusions we draw from equation 3, assuming a 95% confidence interval is the level of accuracy we are determined to provide.

(Figure 13)

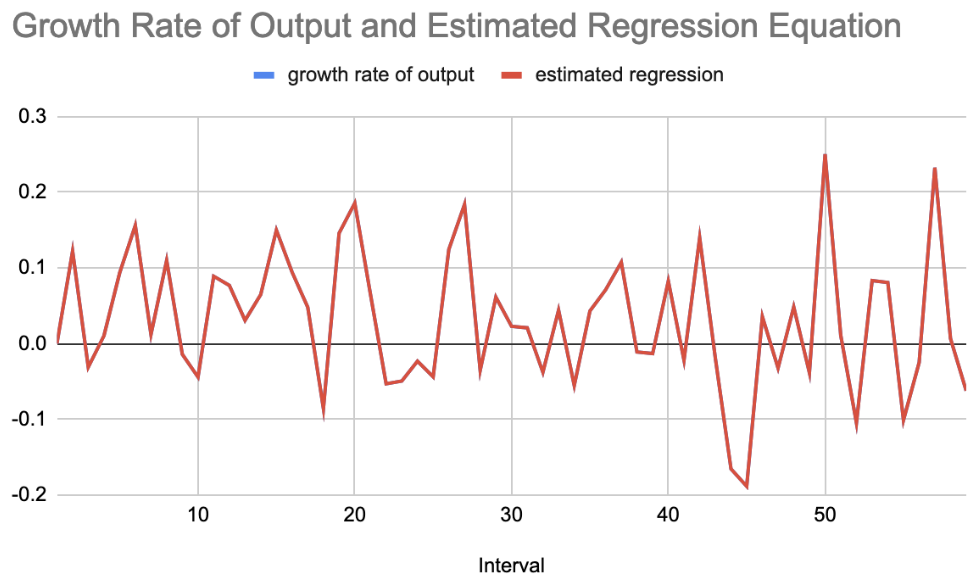


Figure 13 is a graph that shows that the growth rate of output and estimated regression equation are identical across all periods. The growth rate of output cannot be seen because it is behind the estimated regression equation.

(Figure 14)

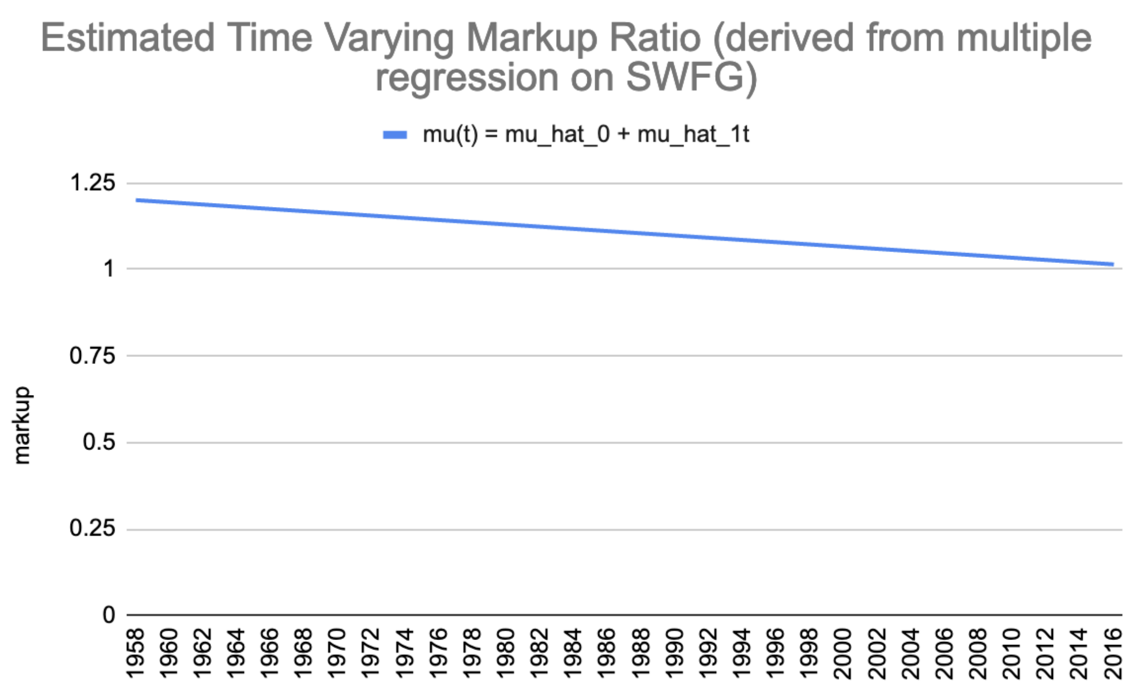
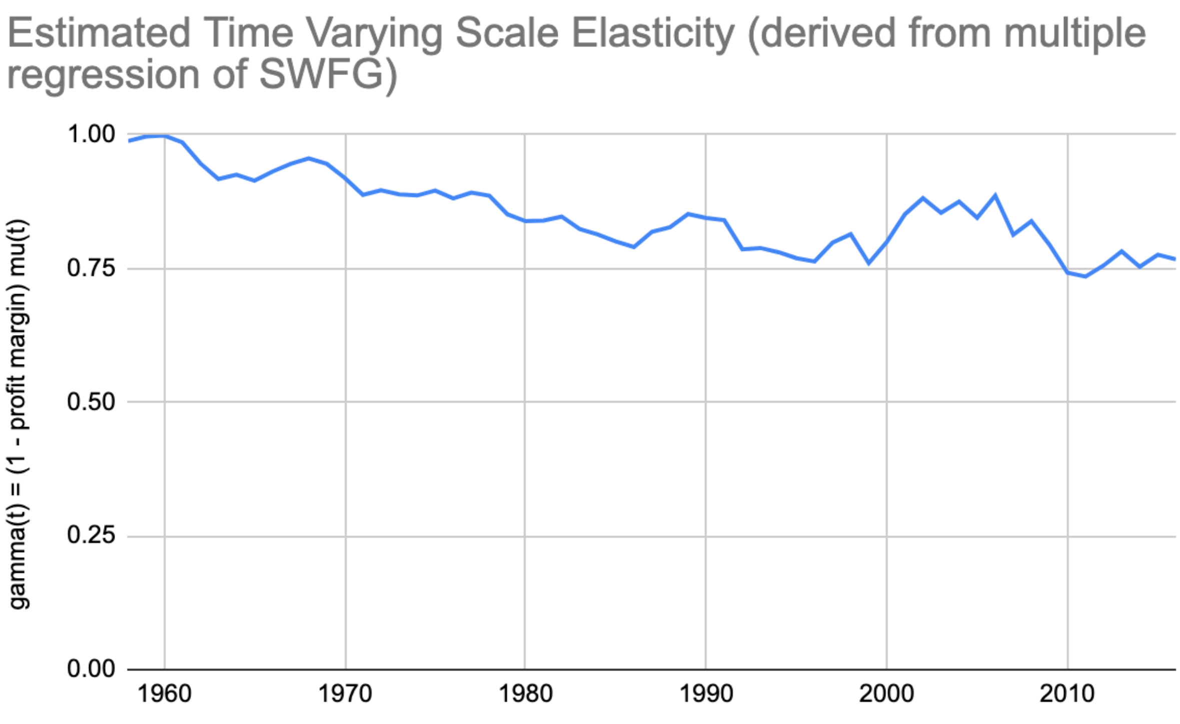


Figure 14 shows how markup varies over time. We see that the time-dependent version of the markup equation is decreasing over the period. This makes sense because competition would have increased due to firms entering the industry. Therefore, firms' market power would be reduced and they would be forced to compete with other manufacturers. The average markup was calculated from our regression of SWFG onto the growth rate of output. The average markup over the period was calculated to be 1.1279. To imagine this on a graph imagine a horizontal line at markup equals 1.1279.

The following research was found at data.census.gov. We spent hours searching for historical data on the census website and found very little information. What we did find was that 68.8% of the revenue in the battery storage market was earned by the top four firms, in 2012. The top eight, top twenty, and top fifty earned 81%, 93%, and 99% respectively. Knowing that the top fifty manufacturers earned 99% of the revenue in 2012 gives us a good idea of the number of firms in the industry. Unfortunately, the data starts in 2012 and does not contain the same charts for 2016. As a result, we can not see how the number of firms in the industry changed.

(Figure 15)



This estimation of the scale elasticity, which takes into account mu varying over time, still shows a pattern similar to the point-estimate scale elasticity estimation. The point estimate was derived from a regression of one of Hall’s equations. The point estimate for elasticity was 0.869. The time varying elasticity estimation with the multiple regression starts at a higher level (closer to one) and ends at a lower value (closer to 0.75). It is as if the original graph was stretched between the interval from 0.75 to 1. Assuming that the time-variant estimate of mu(t) is accurate, then this makes the estimation of elasticity more accurate as it reflects the more minute changes over the period. Since gamma(t) has decreased over time, firms have moved to a portion of the long run cost curve where there are decreasing returns. This correlates to the evolution of industry concentration because as the number of firms in this industry increases, the scale elasticity of output for each firm decreases.

This graph should be evaluated with some skepticism. We still must consider the possibility that mu(t) is not a more accurate predictor of mu given that the p-value on (t x SWFG) did not yield adequate results within a 95% confidence interval. The coefficient had a p-value of 0.59, therefore we must be skeptical of concluding that the calculations derived from the initial equation are more accurate. Another reason for concern is that our calculation of gamma was less than one at every point in the interval. Under imperfect competition, gamma is typically greater than one. Perfect competition may have been satisfied for the entire period. The condition of perfect competition is not impossible, but it is unlikely and merits skepticism.

Interpreting Estimates of TFP

(Figure 16)

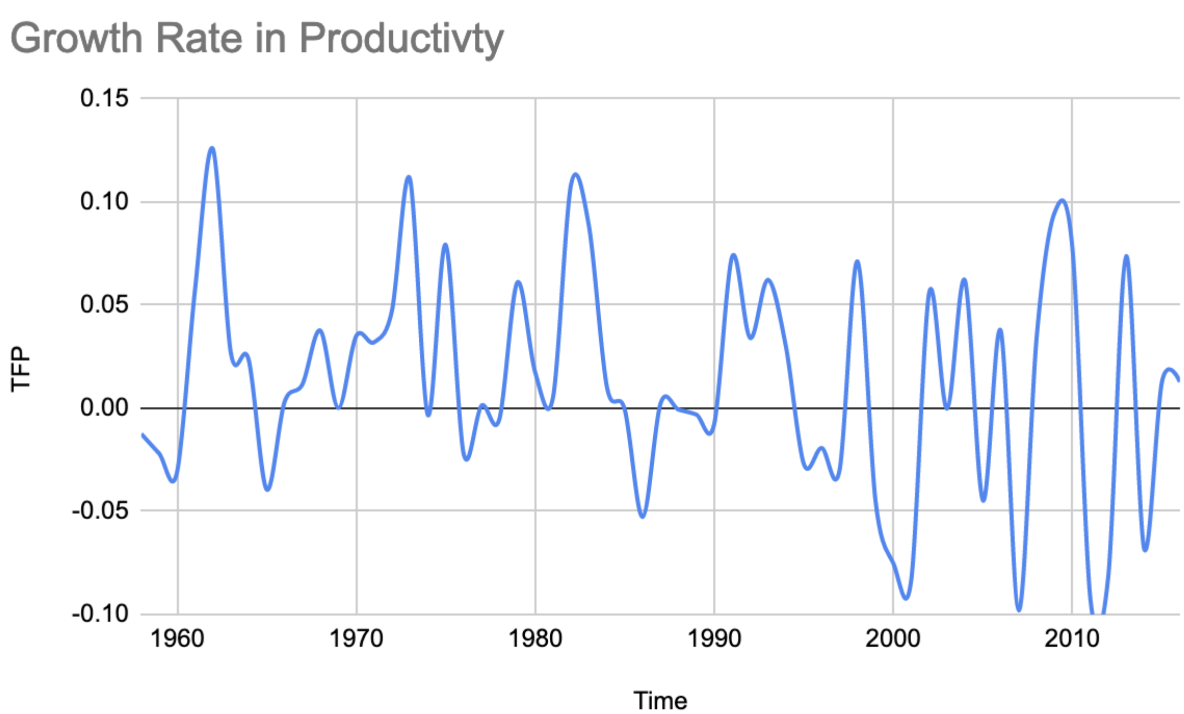


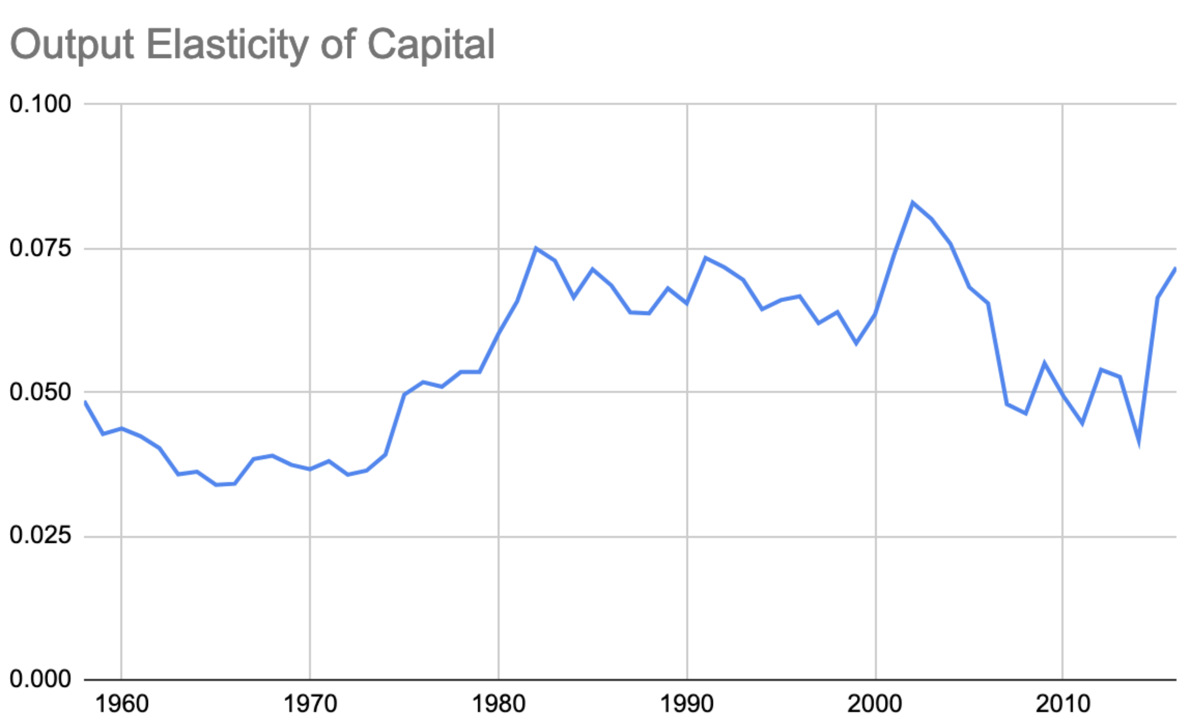
Figure 16 shows the total factor productivity over time. This graph helps to highlight the decreasing returns to scale that we see in this industry over this interval. Input factors are less efficient, meaning that the same amount of inputs would produce more output in 1958 than in 2016. TFP is a complex subject because the underlying concept is a mathematical catch-all. It is used to explain changes in output that cannot be explained by capital, labor, and intermediate inputs. TFP has time-dependent properties. Since we included time-dependent analysis for how mu and gamma change over time, we have to think about how that impacts TFP. The figure above calculated TFP by regressing dV and a time-variant version of mu multiplied by the SWFG onto dQ. We were able to calculate the TFP by adding the constant to the error at every interval. See equation 4.

$$dQ = dV + mu(t) \times SWFG + e \qquad \text{(equation 4)}$$

As a result of equation 4, we made Figure 16 and it clearly shows TFP is decreasing. TFP has a mean of approximately zero from 2000 to 2016, but the variance appears to have doubled. The change in the mean and variance most likely symbolize that battery production has entered a period of increasing research and development. That would explain why the variance has approximately doubled.

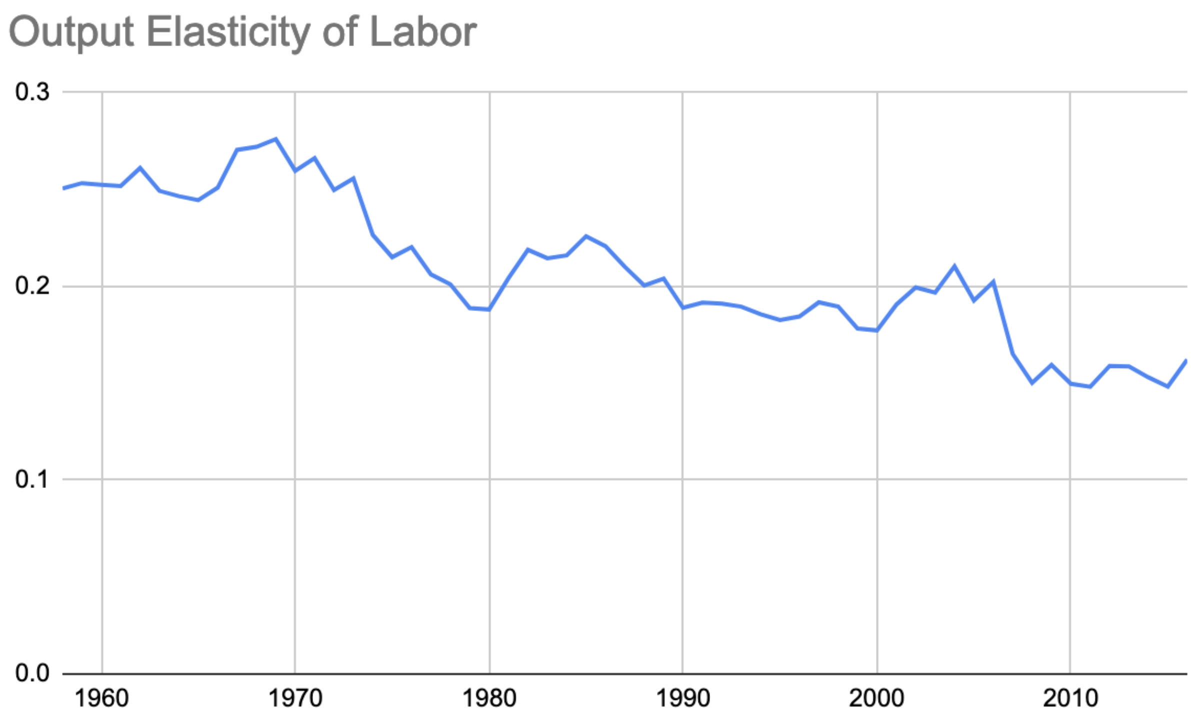
The growth rate of productivity can also be explained by our level of ignorance.This approach has mathematical support because TFP is simply the difference between the change in output and the change in inputs. Calculating TFP is a simple calculation and has a tremendous amount of utility and provides the basis for an entire section of economics. We can dive into the intangible aspects behind innovation, but that is far too advanced for our purposes.

Interpreting the Output Elasticities with Respect to Factor Inputs
(Figure 17)



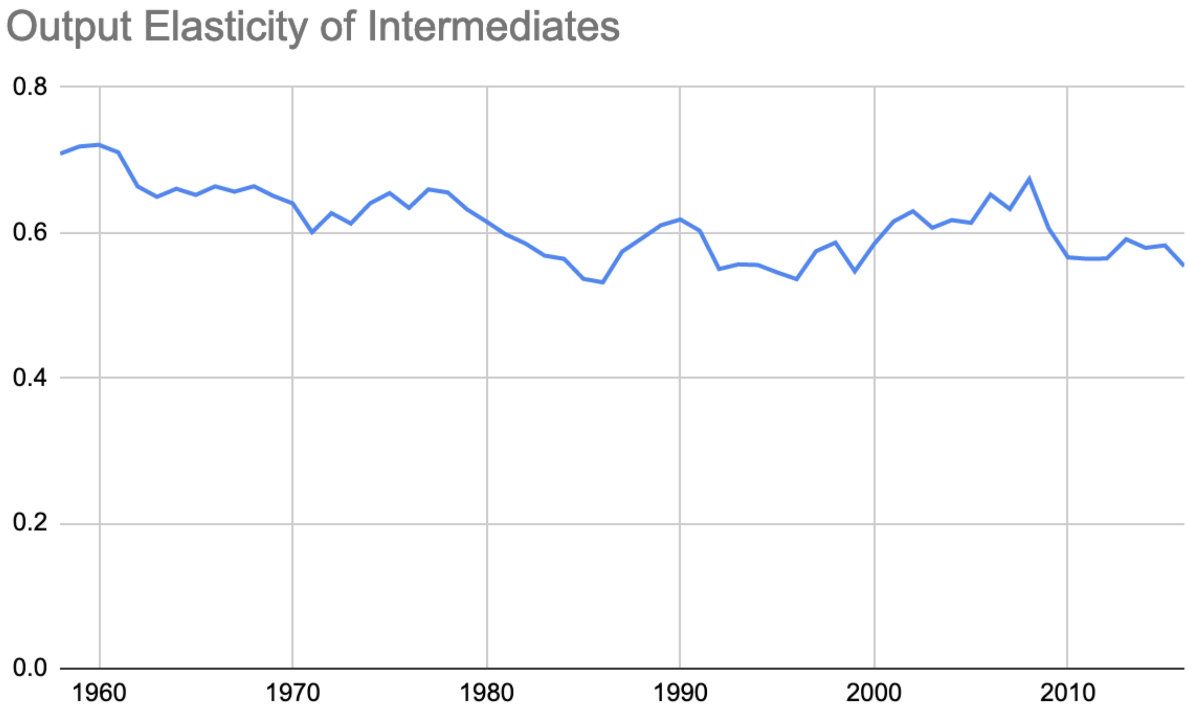
Output elasticity of capital varies over the time period with a slight upward trend, ranging from about 0.035 to 0.08. This level of elasticity indicates that as capital inputs increase by 1%, output increases by between 0.035 and 0.08. Compared to other inputs, a 1% increase in capital inputs yields a much lower increase in output than intermediate inputs and labor. This tells us that intermediate inputs and labor are much more important factors of production when hoping to increase output. The fluctuations in output elasticity of capital can be attributed to the life cycle of capital goods while the slight upward trend can come from improvements to technology.

(Figure 18)



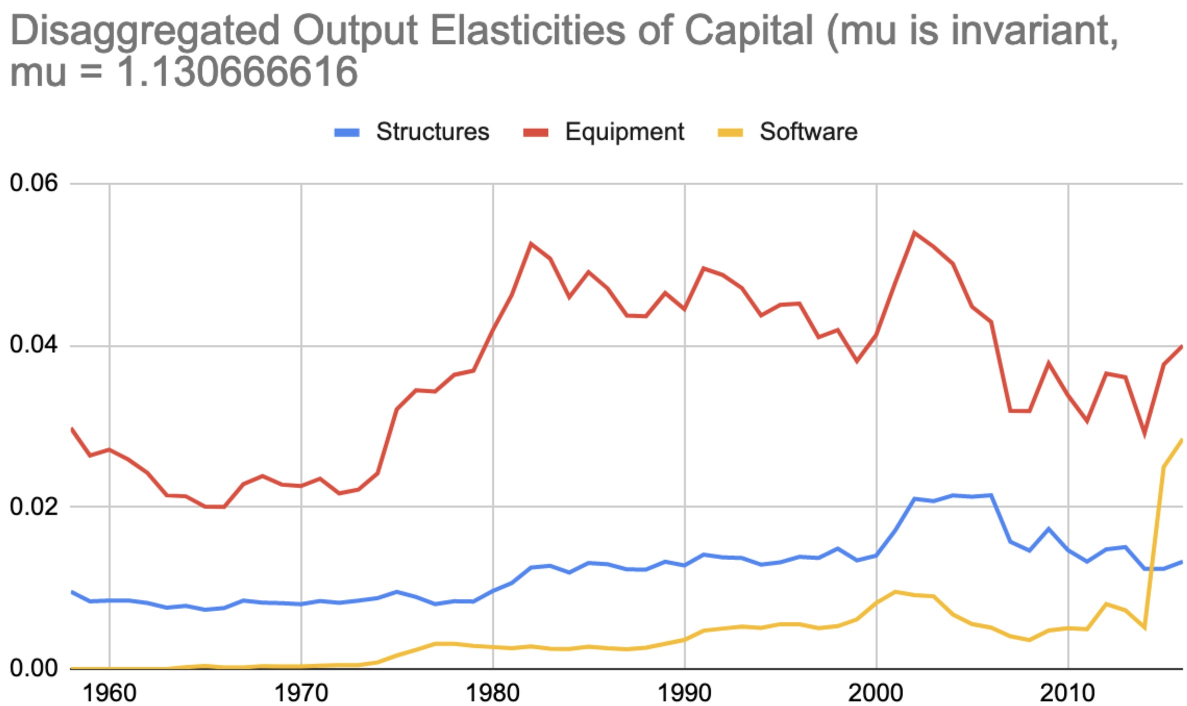
Output elasticity of labor varies with a slight downward trend, varying from 0.28 down to 0.15. This downward trend suggests that labor in this industry has become less efficient over time. Compared to other inputs, labor falls between the increase in output per 1% increase in capital inputs and intermediate inputs. Its effect on output is much more pronounced than that of capital inputs, however.

(Figure 19)



Output elasticity of intermediate inputs ranges from 0.58 to 0.72, decreasing over time. Being an elasticity closer to 1, as intermediate inputs increase by 1%, the percent of output changes by approximately 0.65%. This shows that increasing intermediate inputs is the most effective way to increase output. It is important to note, however, that a firm could not only increase intermediate inputs and have long run increases in output. It is critical that all inputs increase by some level in the long run to create a long lasting effect on overall output. Additionally, over this time interval, we observed the costs of intermediate inputs rising over time, potentially hindering their ability to contribute proportionately the same amount to output.

(Figure 20)



From this graph we see that equipment contributes most significantly to increases in output from increases in capital inputs. This suggests that durable goods like machinery play an important role in the storage battery manufacturing industry, more so than software or structures. However, we see a huge leap in the output elasticity of software around 2014. This jump is due to the introduction of a “battery design software suite” in the electric vehicle industry that decreased the cost and time needed to create a battery (Howell, 2014). This is an interesting consideration and shows how innovation in the industry disperses quickly and can increase output immediately after implementation.

(Figure 21)

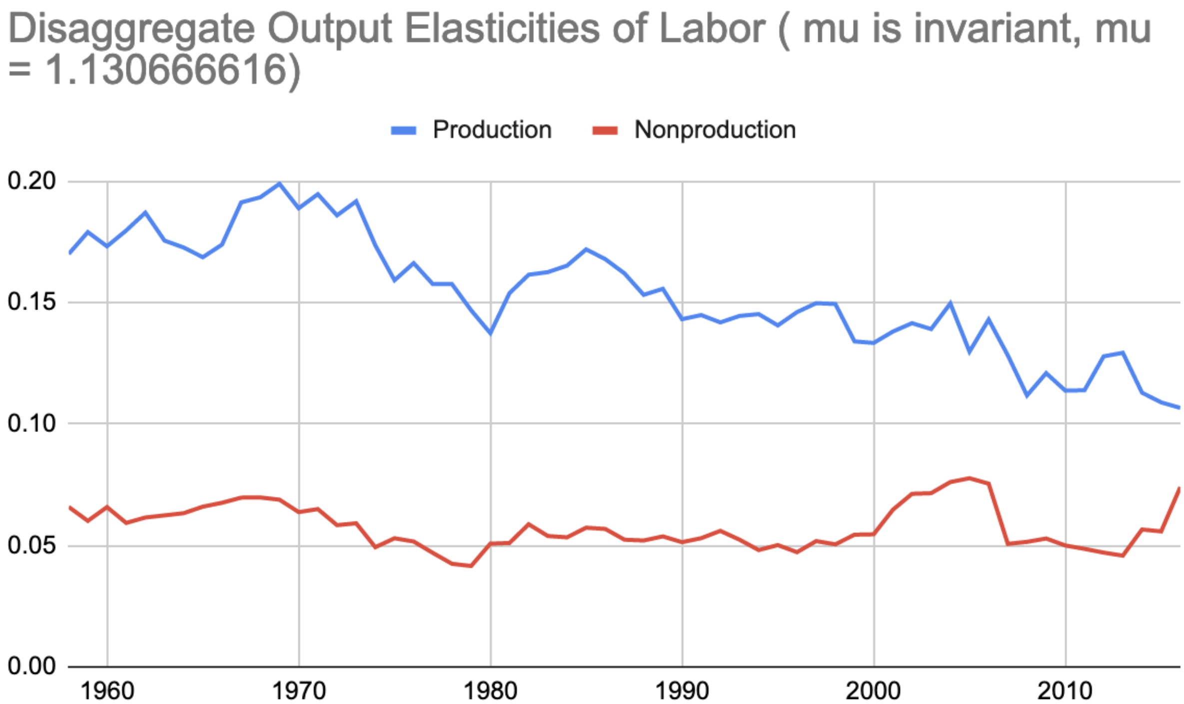


Figure 21 shows the disaggregation of labor into production and nonproduction labor, and how both types affect output. We observe that a 1% increase in production labor is more effective in increasing output than a 1% increase in nonproduction labor. The output elasticity of nonproduction labor stays relatively constant over time, whereas production labor becomes less efficient over time. This can contribute to the decline in the graph of aggregate output elasticity of labor.

(Figure 22)

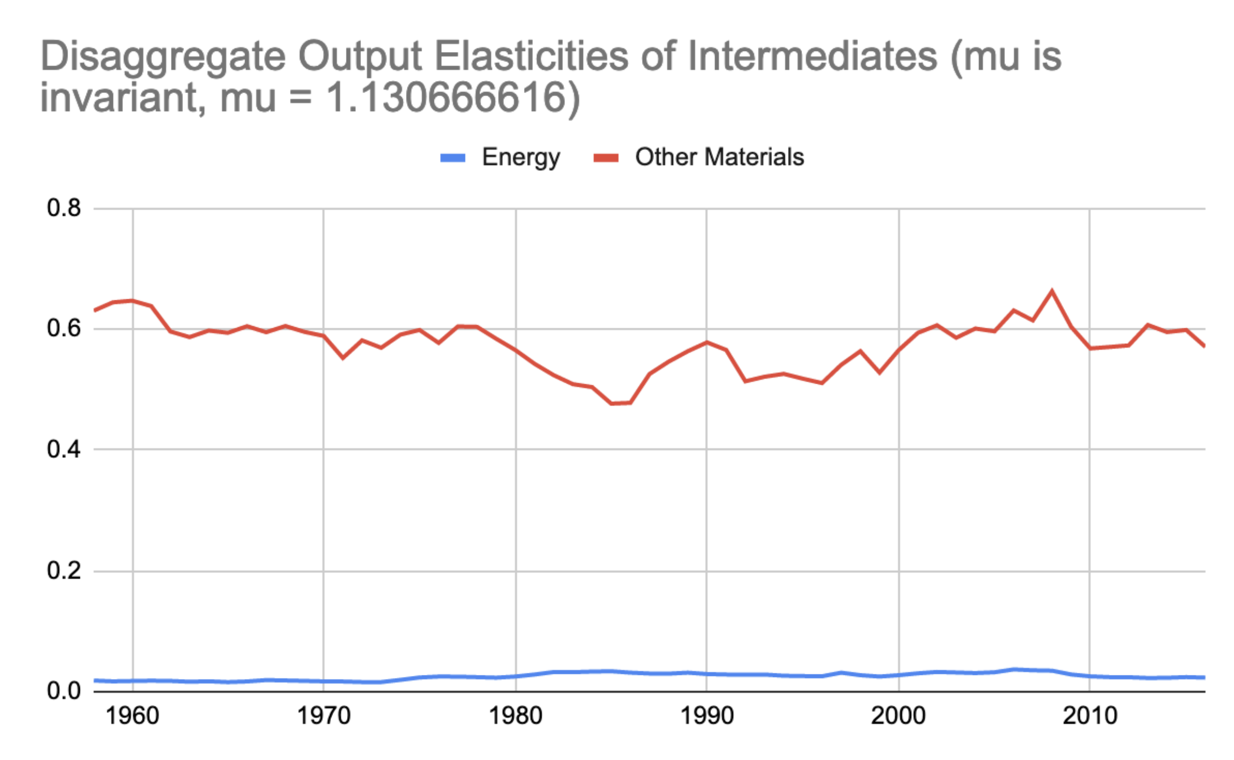


Figure 22 tells us that the effect of an increase in energy input does not greatly affect overall output in the storage battery manufacturing industry. However, the input of other materials has a pronounced effect on output. The output elasticity of other material inputs hovers around 0.6 over the time period. This is not surprising since the batteries are composed of rare and expensive chemicals. Firms would have to compete over finite supplies of lithium, manganese, and other chemicals. Gathering these inputs is costly because they have to be mined or recovered. Establishing power in the market for these inputs is extremely difficult, especially in a world where consumers want to be more eco-friendly. The surge of electrification, especially of vehicles, is likely to tense these negotiations even further.

Merits and Limitations

There are several merits and limitations to our research here. We will start with the merits. One merit is the completeness of the analysis using the available data about the storage battery manufacturing industry. Our charts and graphs show a wide range of the available data and clearly outline the importance of the factors they depict. Another is that analyzing huge datasets, like the one from FRB, in this way makes the information much more easily digestible, albeit a complicated analysis.

There are three main types of limitations to this research. The limitations we outline here are in addition to those described in the final part of this assignment. The first type of limitation is model-imposed limitations. Hall's model is limiting because output can depend on more than the aggregate or disaggregate factors on which his model is based. The aggregate version only takes capital, labor, intermediate inputs, and technology into account. The disaggregate version takes structures, equipment, software, production labor, nonproduction labor, energy, other materials, and technology into account. It is important to remember, however, that there are other factors that can play a role here, including social factors that cannot be explained by a model like this. This of course is the case for much economic study. Additionally, the technology index in Hall's model is quite obscure. His method only explains markup and output elasticity given inputs and does not explain consumer behavior or competition fully. There also is an underlying assumption that the government plays a role in the economy either. These limitations simplify Hall's model but restrict the conclusions we can draw from it.

We also experienced data limitations in this research. Macroeconomic data does not give us great insight into how firms act in various situations. Much of our data comes from a period before computers, so sometimes the data is miscopied or otherwise inaccurate. The storage battery manufacturing industry also had limited data on the US Census website, especially about concentration ratios. We also had trouble finding exact numbers for the number of firms in the industry over time as it seems that varying sources give varying estimates.

The final limitation type is the limitations of the estimation method used in this research. Regression of time variant calculation of mu has a high p-value, meaning that there is not enough information to propose that a correlation exists between variables. Additionally, switching between time series and cross-sectional methods can muddy the data and conclusions from such data.

References

"CES Manufacturing Industry Database." NBER, 2016, https://www.nber.org/research/data/nber-ces-manufacturing-industry-database

Federal Reserve. "Board of Governors of the Federal Reserve System." *The Fed - Industrial Production and Capacity Utilization - G.17*, United States Federal Reserve, 2018, https://www.federalreserve.gov/releases/g17/.

Howell, David. "Overview of the DOE Advanced Battery R&D Program - Energy." *Vehicle Technologies Office*, US Department of Technology, 2014, https://www.energy.gov/sites/prod/files/2014/09/f18/battery_rd_amr_plenary_june_2014_final.pdf.

US Census. "335911: Storage Battery Manufacturing." *Explore Census Data*, 2022, https://data.census.gov/cedsci/profile?n=335911&g=0100000US.

US Census. "Storage Battery Manufacturing 1997 Economic Census: Manufacturing." 1997, https://doi.org/https://www2.census.gov/library/publications/economic-census/1997/manufacturing-reports/97m3359a.pdf.