Productivity Drops and Labor Decline

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Econ 4930 – Fall 2024

Contents

1 Abstract

I estimate the direct effects of a drop in labor productivity on employment in subsequent years, holding constant effects of compensation and raw output. Using panel data from the Bureau of Labor Statistics across 162 NAICS industries and over 35 years, I find that, if a specific industry's labor productivity is more than a standard deviation below average productivity for a specific year, employment experiences about a 7 percentage point over the next year, with employment not fully recovering until about seven years after productivity returns to within a standard deviation of the mean. Thus, there exists a direct connection between a productivity drop and employment decline.

2 Introduction

"Productivity isn't everything, but in the long run it is almost everything" Paul Krugman opens with in his book The Age of Diminished Expectations. The next sentence further explains that he means. "A country's ability to improve it's standard of living over time depends almost entirely on its ability to raise output per worker."

This study provides a model to measure the effects of heterogeneity among industry-level productivity values. Specifically, when a certain industry lags in productivity relative to the rest of the economy, we expect its profits to decline and thus its employment to decline as well. Using fixed effects, it is possible to isolate the result of a drop in productivity without endogeneity concerns. The study looks at how employment reacts to a drop in productivity over the coming years. I find that, when productivity is more than a standard deviation below the mean, employment experiences a 5.411 percentage point drop immediately and another 2.282 percentage points in the next year, bottoming out at a 7.693 percentage point drop. This effect then becomes statistically insignificant after seven years.

The historical empirical data confirms Krugman's hypothesis that productivity drives the standard of living. For example, [Battisti, Del Gatto, and Parmeter, 2018] find that technological growth is the main factor in driving productivity, [Hornbeck and Moretti, 2024] find that increases from technological growth spreads from productivity and then trickles down to wage growth, as local workers' wages benefit from increases in productivity, and [Baumol, 1986] argues that a persistent lag in productivity growth may not affect most macroeconomic trade trends, but it will diminish average standards of living.

But while the economy benefits from productivity growth in general, how ubiquitous are the benefits? In other words, there exists a concentration within productivity growth that is focused specifically on productivity, wage growth, and employment in subsets of the economy. [Autor and Salomons, 2017] suggest that industries that lead in productivity growth tend to shrink in employment as a consequence of being able to generate more output per worker, thus necessitating fewer workers.

But does that then mean that industries that lag in productivity growth end up hiring more workers? It seems to be a logical consequence from [Autor and Salomons, 2017] that lagging firms need more workers to generate the same relative output. This issue is the topic of this paper. In other words, how connected are productivity decline and employment?

[Baumol, 1967] provides a framework for thinking about productivity decline that will be referred subsequently as the Baumol Effect. The thesis of Baumol's paper is that unbalanced growth can still lead to almost balanced wages due to cross-elasticity for labor demand. Put into simpler terms through an example, if you work at a firm experiencing average productivity growth, and we assume wages are tied to productivity, your wages will increase at an average rate. But if you see that a competing firm is growing quicker than average, employee wages will also be growing quicker than average, thus offering a financial incentive for labor demand of that firm to increase. Therefore, the firm experiencing average productivity growth still has to maintain competitive wages with the market, leading to a pronounced decoupling of wages from productivity, empirically confirmed by [Schwellnus, Kappeler, and Pionnier, 2017] and [Standbury and Summers, 2017].

These relative productivity drops mean that, although wages may remain relatively constant, those constant wages begin to cut into profits. I am explicit here in my assumption that productivity growth drives profit; Consequently less productive firms and industries, in theory, will have lower profit margins than more productive firms and industries, holding all else fixed.

When profits decline because productivity declines, the business has four main options, 1) accept the lower profits, 2) reduce number of workers, 3) give workers fewer benefits, or 4) make a structural change to once again increase productivity.

I hypothesize that the first three reasons, those which do not involve once again increasing productivity, lead to reducing employment. First, I assume that with lower profits, the firm is unable to make key investments in capital or labor. Hence, they are unable to sustain future growth and, in a competitive labor market, their average variable costs rise, rendering them unable to sell goods or services at the same price as competitors, lowering sales and eventually ending in a cycle of decline.

Option two results in reducing workers and is trivially true. Option three is an attempt to get around the Baumol effect by lowering the overall package of a employee without necessarily reducing their take-home pay. I argue that, in theory, an employee takes benefits into account in determining their overall wages, and fewer benefits provides the incentive that Baumol describes to move to a more productive firm, decreasing employment.Thus, in theory, productivity decline should result in employment decline in the long-run.

[Sarangi, 2023] makes an attempt to measure this hypothesis by tracking the effects of less productive industries specifically across manufacturing subsectors; [Hartwig and Krämer, 2023] argue that the consequences of the Baumol effect can also be transferred to the service economy as well. Thus, a test of the entire United States economy will be able to include both the manufacturing and the service parts of the economy.

In conclusion, my hypothesis follows this structure:

1) A drop in productivity leads to a drop in profits, where productivity and profits are relative to the rest of the economy.

2) A relative drop in profits necessitates cutting costs through accepting lower profits, laying off workers, or reducing investment in human capital, causing incentives for employees to leave.

3) Employees are rational and thus will respond to incentives to leave, lowering employment.

Conclusion: Therefore, a drop in productivity leads to lower employment.

3 Data and Methods

[Sarangi, 2023] uses manufacturing subsector data, defined as 2-digit North American Industry Classification System (NAICS) codes, to measure changes in relative labor share. For reference, NAICS codes are given numbers according to the type of economic activity, with more digits meaning a more specific subset of firms. By including a more precise subset (like 4-digit NAICS codes), we are able to further measure the intricate effects and use extra observations for statistical robustness. Hence, I use data taken from the Bureau of Labor Statistics (BLS), looking at 162 non-farm industries, defined as having 4-digit NAICS classifications. There are 5747 observations in total.

As for the time aspect, BLS has industry-wide data yearly from 1987-2023. In working with data in Stata, I first calculate yearly changes and use data from 1988 onward, ensuring that every industry has percentage growth for each statistic. Below is a description of variables used, with definitions given by the BLS:

Labor Productivity The efficiency with which goods and services are produced via labor hours; often referred to as output per hour.

Real Sectoral Output The amount of goods and services produced by an industry for delivery to consumers outside that industry.

Hours Worked The number of labor hours worked by all workers in the production of goods and services.

Unit Labor Costs The payments for labor services used to produce each unit of goods and services.

Hourly Compensation The sum of wage and benefits paid per hour of work.

Labor Compensation Payments to labor to produce goods and services, including wages, benefits and other monetary or non-monetary payments.

Employment The number of jobs in a given sector. An individual who works multiple jobs has each of their jobs counted in the employment measure, as this measure is a count of jobs, not persons.

There exists a large necessity to clean up data, and the first 70 lines of my Stata code are simply sorting data. When first downloaded, many observations began as simply having "measure" and "unit" with every variable listed in one column. I first separated the variables, giving each measure their own column. For example, the labor productivity percent and the labor productivity index both had their own columns after the cleanup process. I then dropped every observation tied to a NAICS number that was not 4 digits.

After the above clean-up process, I then generated an average and standard deviation measure for productivity growth (as a percentage) in each year. Figure 1 shows the mean productivity as an index and Figure 2 shows mean productivity as a percentage, which I believe is a more helpful graph when looking at long-term trends. I chose to base the values off of each year as opposed to each NAICS number to more accurately observe industries who are falling behind the average productivity growth of the United States. Thus, we need not control for recessions or shocks where productivity temporarily drops for all NAICS codes.

I first generate a variable indicating if productivity growth dropped more than one standard deviation below the yearly average. Thus, about 16% or 900 observations are flagged as having this quality. I then make a leading variable to account for future changes in employment as a result of the productivity drop. This allows the model to account for what happens 1-7 years after productivity drops, which as we will later conclude, is very statistically significant.

I add the caveat here that this model fails to account for small but consistent changes in relative productivity decline or accentuate major declines. Giving productivity decline a dummy variable simplifies the model consistently, allowing us to measure the effects of relative productivity drop easier, but also means that the industry with the highest drop in productivity is coded the same way as the industry with productivity growth just slightly below one standard deviation below the mean.

Thus, the regression run in this study analyzes the percentage effects of employment, where other BLS data categories are used as independent variables to prevent against omitted variable bias, as shown in Equation 1.

Equation 1:

$$E_{it} = \beta_0 + \beta_1 P_{it} + \sum_{k=0}^{7} \beta_{2+k} \text{lag}_{it,k} + \beta_{10} \text{O}_{it} + \beta_{11} W_{it} + \beta_{12} Lcost_{it} + \\ \beta_{13} Hcomp_{it} + \beta_{14} Lcomp_{it} + \beta_{15} EMP + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Where E_{it} is log(employment); P is a productivity index; $\text{lag}_{it,k}$ represents the effect of each subsequent year after productivity is more than one standard deviation below the mean (in other words, k=0 is the first year that productivity is well below average and the model estimates until year k=7). This notation is based on [Autor and Salomons, 2017]; O represents a percentage increase in real sectoral output, W represents an index for hours worked; 'Lcost' represents a percentage increase in labor costs; 'Hcomp' represents a percentage increase in hourly compensation; 'Lcomp' represents a percentage increase in labor compensation; EMP represents a percentage change in employment; μ_i represents a fixed effect for each NAICS unit i; λ represents a fixed effect for each year t; and ε is an error term. $2 \leq k \leq 7$ are the object of the study and $8 \leq k \leq 15$ merely serve to guard against omitted variable bias.

4 Results

The results of the regression are shown in Table 1 and the statistical effects of $\hat{\beta}_k$ where $2 \leq k \leq 7$ are shown in Figure 3. k=0 is the first year in which productivity growth is more than one standard deviation below the mean productivity growth for that specific year. The lines represent 95 percent confidence intervals. Note that each effect is in a regression, and is thus independent of the other effects. Therefore, we conclude from the graph that, after the productivity drop, employment drops by an estimated 5.411 percentage points immediately and another 2.282 percentage points in the next year, down to $\hat{\beta}_3$'s value of a 7.693 percentage point drop. In subsequent year, employment rebounds if there are no further shocks, becoming statistically insignificant in year 7. Thus the model predicts that a lack of productivity growth in year k=0 will continue to negatively affect employment until year k=6.

These effects are also isolated such that, if productivity growth in an industry drops below one standard deviation below the mean in two subsequent years, both years will affect employment. For example, during the second year of relative productivity decline, productivity will drop 2.282 percentage points due to the effects of the first year's productivity and 5.411 percentage points due to the effects of the second year's productivity. In essence, effects combine.

5 Conclusion

Restating the main findings of Equation 1, an industry being more than a standard below average in terms of productivity causes a 5.411 percentage point decrease in productivity immediately and a 2.282 percentage point decrease in productivity during the next year, with the industry taking about 6 years to recover in terms of employment. Thus the data further confirms the hypothesis put forth in the introduction, the a drop in industry productivity leads to a drop in industry employment, especially over the next few years. The sample contains both manufacturing and service industries over 35 years.

The implications of this findings further add to the literature on industry cyclicity. In a scenario where one industry acts as a substitute replaces another industry, a result of the natural process of innovation, the replaced industry is then likely to reduce in employment, setting the stage for industry decline and a leaving of workers for better prospects. It seems, therefore, that the research presented in this paper simply models the rate of decline of that less-competitive industry.

Further research is needed to determine the effects varying across regions, specifically with region-wide or state-wide fixed effects, the effects of buyer/supplier power in determining the rates of layoffs versus quits in employment decline, and more specific measurements to determine the effect from firm-to-firm, as opposed to the aggregate values of the industry.

6 References

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[3] Baumol, W. J. (1967). Macroeconomics of unbalanced growth: The anatomy of urban crisis. *The American Economic Review*, 57(3), 415–426. https://www.jstor.org/stable/1812111

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[6] Hornbeck, R., & Moretti, E. (2022). Estimating who benefits from productivity growth: Local and distant effects of city productivity growth on wages, rents, and inequality. *The Review of Economics and Statistics*, 1–49.

[7] Krugman, P. R. (1998). *The age of diminished expectations: U.S. economic policy in the 1990s*. MIT Press.

[8] Sarangi, S. (2023). `https://economics.utah.edu/research/publications/2023-07.pdf`

[9] Schwellnus, C., Kappeler, A., & Pionnier, P. (2017). Decoupling of wages from productivity: Macro-level facts. OECD Economics Department Working Papers, No. 1373, *OECD Publishing*, Paris.

[10] Stansbury, A. M., & Summers, L. H. (2017, December 1). Productivity and pay: Is the link broken? *National Bureau of Economic Research.* `https://www.nber.org/papers/w24165`

[11] U.S. Bureau of Labor Statistics. (n.d.). `https://www.bls.gov/productivity/tables/home.htm`

7 Graphs and Stata Code

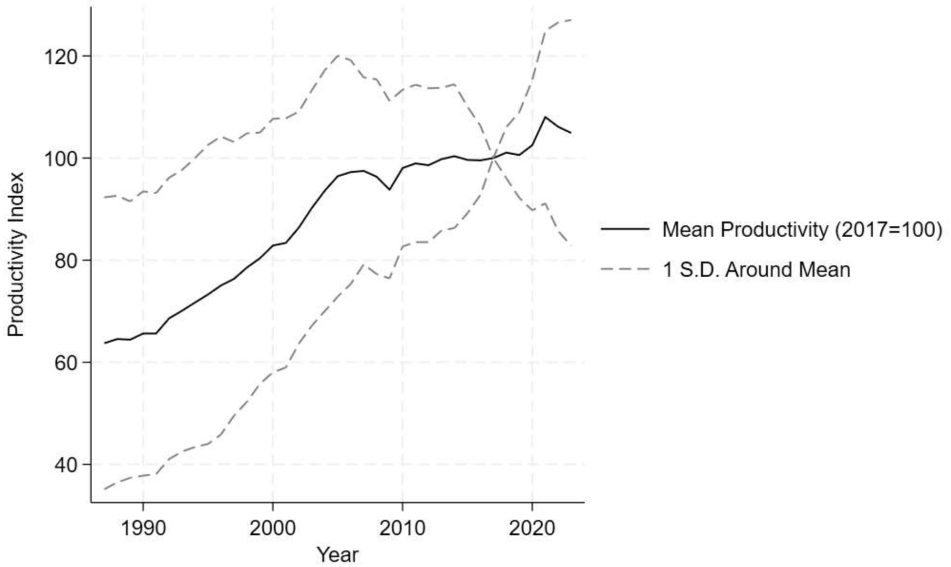

Figure 1: Average productivity values as an index with dashed lines one standard deviation around the mean; year 2017 = 100 for all NAICS codes

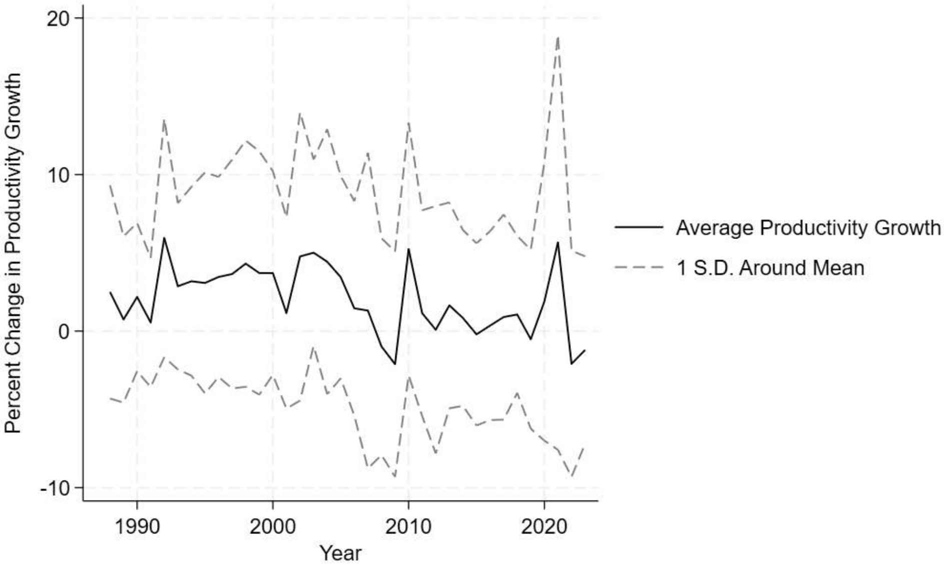

Figure 2: Average productivity growth as a percentage with dashed lines one standard deviation around the mean

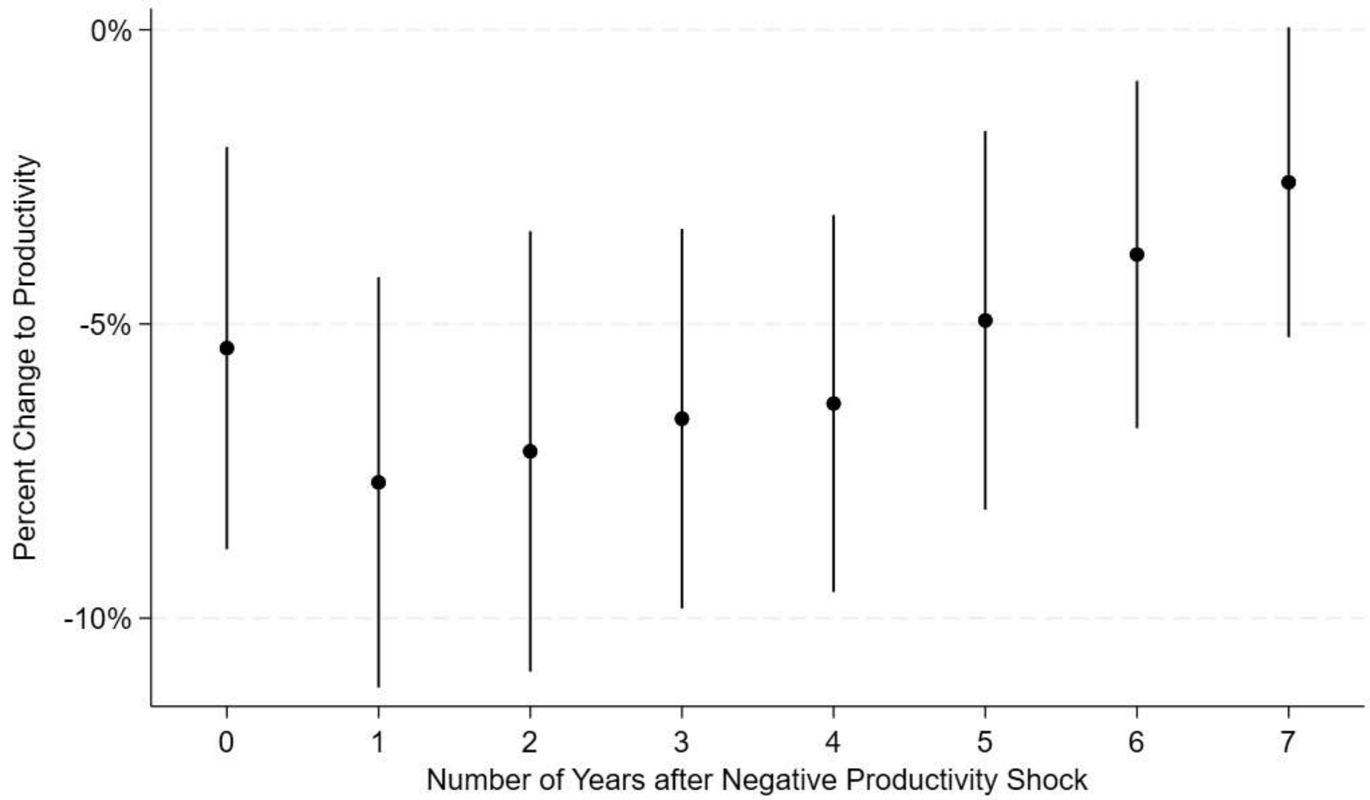

Figure 3: Estimates of the number of years after a negative productivity shock on the percent change in productivity, with 95% confidence bars

Table 1: Estimation of Equation 1

Variables	(1) Estimation
(mean) Productivity Index	0.00182
	(0.00139)
Below 1 S.D.	-0.0541***
	(0.0173)
1 Year Lead Below 1 S.D.	-0.0769***
	(0.0177)
2 Year Lead Below 1 S.D.	-0.0716***
	(0.0190)
3 Year Lead Below 1 S.D.	-0.0661***
	(0.0163)
4 Year Lead Below 1 S.D.	-0.0635***
	(0.0162)
5 Year Lead Below 1 S.D.	-0.0494***
	(0.0163)
6 Year Lead Below 1 S.D.	-0.0382**
	(0.0149)
7 Year Lead Below 1 S.D.	-0.0259*
	(0.0133)
Real Sectoral Output (%)	-0.0133
	(0.0113)
Hours Worked (%)	-0.0478***
	(0.0130)
Unit Labor Costs (%)	-0.0116
	(0.0105)
Hourly Compensation (%)	-0.0449***
	(0.0123)
Labor Compensation (%)	0.0573***
	(0.0151)
Employment (%)	0.00850***
	(0.00164)
Constant	5.176***
	(0.112)
Observations	4,604
R-squared	0.971

Robust standard errors in parentheses. Dependent variable is (log)employment. Includes fixed effects for the year and NAICS codes.
*** p<0.01, ** p<0.05, * p<0.1

```
use "C:\Users\tommy\OneDrive\Desktop\School\2024 Fall\Labor Economics\Final Paper\Data\BLS Data.dta"

*Cleaning up data
replace NAICS = "44" if NAICS == "44,45"
replace NAICS = "6221" if NAICS == "6221,3"
replace NAICS = "722613" if NAICS == "722513,4,5"
destring NAICS, replace
keep if NAICS > 999 & NAICS <10000

gstats sum Value if Units=="% Change from previous year" & Value<=0
egen type = group(Units)
encode Units, gen(type2)
drop Units
drop type
drop Basis
drop if Measure == "Output per worker" | Measure == "Sectoral output" | Measure == "Sectoral output price deflator"


gen productivity_index = Value if type2 == 2 & Measure == "Labor productivity"
gen productivity_percent = Value if type2 == 1 & Measure == "Labor productivity"
preserve
bysort Year: egen mean_productivity = mean(productivity_index)
bysort Year: egen sd_productivity = sd(productivity_index)
gen above_mean = mean_productivity + sd_productivity
gen below_mean = mean_productivity - sd_productivity
collapse (mean) mean_productivity (first) above_mean (first) below_mean, by(Year)
*Figure 1 (figures are listed out of order and are for personal reference only)
twoway (line mean_productivity Year) (line above_mean Year) (line below_mean Year)
restore

preserve
bysort Year: egen mean_productivity = mean(productivity_percent)
bysort Year: egen sd_productivity = sd(productivity_percent)
gen above_mean = mean_productivity + sd_productivity
gen below_mean = mean_productivity - sd_productivity
collapse (mean) mean_productivity (first) above_mean (first) below_mean, by(Year)
*Figure 3
twoway (line mean_productivity Year) (line above_mean Year) (line below_mean Year)
restore

*Sorting Data
gen real_sectoral_output_percent = Value if type2 == 1 & Measure == "Real sectoral output"
gen real_sectoral_output_index = Value if type2 == 2 & Measure == "Real sectoral output"
gen hours_worked_percent = Value if type2 == 1 & Measure == "Hours worked"
gen hours_worked_index = Value if type2 == 2 & Measure == "Hours worked"
gen hours_worked_hours = Value if type2 == 4 & Measure == "Hours worked"
gen unit_labor_costs_percent = Value if type2 == 1 & Measure == "Unit labor costs"
gen unit_labor_costs_index = Value if type2 == 2 & Measure == "Unit labor costs"
gen hourly_compensation_percent = Value if type2 == 1 & Measure == "Hourly compensation"
gen hourly_compensation_index = Value if type2 == 2 & Measure == "Hourly compensation"
gen labor_compensation_percent = Value if type2 == 1 & Measure == "Labor compensation"
gen labor_compensation_index = Value if type2 == 2 & Measure == "Labor compensation"
gen labor_compensation_dollars = Value if type2 == 3 & Measure == "Labor compensation"
gen employment_percent = Value if type2 == 1 & Measure == "Employment"
gen employment_jobs = Value if type2 == 6 & Measure == "Employment"

drop Measure
drop Value
drop type2
drop Sector
drop Industry
drop Digit

collapse productivity_index productivity_percent real_sectoral_output_percent real_sectoral_output_index hours_worked_percent hours_worked_index hours_worked_hours unit_labor_costs_percent unit_labor_costs_index hourly_compensation_percent
```

```
hourly_compensation_index labor_compensation_percent labor_compensation_index labor_compensation_dollars employment_percent employment_jobs , by(Year NAICS)

sort NAICS Year
drop if Year==1987
drop if missing(productivity_index) | missing(employment_jobs)

*Cleaning up Data Complete
*Goal now: Find NAICS codes that have lagged behind in productivity

*Declare panel data
xtset NAICS Year
sort NAICS Year
xtdescribe

*Create Variable that makes a flag if productivity is below 1 SD below the mean 3 years in a row
bysort Year: egen mean_prod = mean(productivity_percent)
bysort Year: egen sd_prod = sd(productivity_percent)

gen below_1sd = (productivity_percent < (mean_prod - sd_prod))
sum below_1sd
bysort NAICS (Year): gen count_below_1sd = sum(below_1sd)
bysort NAICS (Year): gen lag_below_1sd = L1.below_1sd
bysort NAICS (Year): gen lead_below_1sd = F1.below_1sd
gen three_consecutive = (below_1sd == 1 & lag_below_1sd == 1 & lead_below_1sd == 1)
*There are 25 situations where productivity is below 1 SD below the mean 3 years in a row. This is not enough observations to accurately depict a trend, and the effect is also statistically insignificant. This will not be mentioned in the final paper.


*below done with Fr. Esparza
gen log_employment = log(employment_jobs)
reg log_employment productivity_index below_1sd i.NAICS
reghdfe log_employment productivity_index below_1sd, absorb(NAICS)
reghdfe log_employment productivity_index below_1sd, absorb(NAICS Year) cluster(NAICS)


*Huge because leading productivity drop is super statistically significant. Let's generate previous years and see if the run-up matters at all. Based on the below regression, it matters a lot, with the peak effect 2-3 years before the drop.
reghdfe log_employment productivity_index below_1sd lead_below_1sd real_sectoral_output_percent hours_worked_percent unit_labor_costs_percent hourly_compensation_percent labor_compensation_percent employment_percent, absorb(NAICS Year) cluster(NAICS)

bysort NAICS (Year): gen two_lead_below_1sd = F1.lead_below_1sd
bysort NAICS (Year): gen three_lead_below_1sd = F1.two_lead_below_1sd
bysort NAICS (Year): gen four_lead_below_1sd = F1.three_lead_below_1sd
bysort NAICS (Year): gen five_lead_below_1sd = F1.four_lead_below_1sd
bysort NAICS (Year): gen six_lead_below_1sd = F1.five_lead_below_1sd
bysort NAICS (Year): gen seven_lead_below_1sd = F1.six_lead_below_1sd

reghdfe log_employment productivity_index below_1sd lead_below_1sd two_lead_below_1sd three_lead_below_1sd four_lead_below_1sd five_lead_below_1sd six_lead_below_1sd seven_lead_below_1sd real_sectoral_output_percent hours_worked_percent unit_labor_costs_percent hourly_compensation_percent labor_compensation_percent employment_percent, absorb(NAICS Year) cluster(NAICS)

 outreg2 using myreg.doc, replace label ctitle(Model 1) title(Table 1: Estimation of Equation 1)

*95% Confidence Intervals - Figure 3
estimates store model1
coefplot model1, vertical drop(_cons) ci(95) keep( below_1sd lead_below_1sd two_lead_below_1sd three_lead_below_1sd four_lead_below_1sd five_lead_below_1sd six_lead_below_1sd seven_lead_below_1sd)
*68% Confidence Intervals
 coefplot model1, vertical drop(_cons) ci(95) keep( below_1sd lead_below_1sd two_lead_below_1sd three_lead_below_1sd four_lead_below_1sd five_lead_below_1sd six_lead_below_1sd seven_lead_below_1sd)
```