Research

The Impact of U.S. Imports on Manufacturing Employment

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Executive Summary

- The effect of trade on the U.S. labor market is a highly debated topic, with most critics pointing to job losses in the manufacturing sector following China's entrance to the World Trade Organization in 2001.
- It is likely, however, that the labor-market impact of imports changed since the "China Shock" ended in 2010, as global trade flows fully adjusted.
- This analysis estimates the relationship between imports and manufacturing jobs from 2010 to 2016, finding that a 1 percent increase in imports leads to a 0.07 percent increase in jobs.
- Based on these results, over one quarter of total manufacturing jobs created between 2010 and 2016 – roughly 220,000 jobs – can be directly attributed to increases in imports.

Introduction

The link between international trade and U.S. employment is a fraught subject in public debate. Today, 74 percent of the public agree that trade provides considerable benefits to the economy, and more than half believe it has a positive impact on U.S. workers. At the same time, President Trump's trade policy – which has centered around levying significant new tariffs on our trade partners – contradicts this public sentiment. Likewise, most Democratic candidates in the 2020 presidential cycle argued in favor of trade barriers to protect U.S. workers from international competition.

This dichotomy is not new. While most agree that trade provides considerable benefits to consumers, considerable disagreement exists over its impact on workers. This debate surged in the wake of China's ascension to the World Trade Organization (WTO) in 2001, an event referred to as "the China Shock." In the decade following China's WTO entrance, China's exports to the rest of the world nearly doubled in real terms. This trade liberalization caused major changes to global trade flows and significant shifts in local labor markets, causing observers to question the benefits of trade liberalization.

This paper uses empirical analysis to contribute to this debate by estimating the impact of imports on the U.S. manufacturing labor force.

Background

Most of the research surrounding the China Shock has studied its negative impact on the U.S. labor market in highly tradable sectors such as manufacturing. One of the most prominent studies was authored by David H. Autor, David Dorn, and Gordon H. Hanson. By analyzing the impact of rising imports from China on U.S. manufacturing employment from 1990 to 2007, they found that a $1,000 per-worker increase in import exposure was predicted to reduce manufacturing employment by 0.6 percentage points per working-age population – results that explained 44 percent of the decline in manufacturing employment over the time frame.

Alternatively, other research suggests that China's admittance to the WTO produced considerable benefits for U.S. consumers. One study estimated that, after the China Shock, 97 percent of Americans experienced increases in their real income due to lower-cost Chinese goods, while another found that consumer prices in the United States fell 2 percent as a direct result of the China Shock.

Evidence about the overall labor-market impacts of increased trade with China points in a number of directions. According to one study, nearly 36 million U.S. jobs were related to total U.S. trade in 2016, with approximately 7,000 jobs overall directly supported by trade with China. The Federal Reserve has also found that, while imports from China led to the loss of about 800,000 manufacturing jobs from 2000 to 2007, lower-cost goods from China – many of which are used in domestic production – created a similar number of jobs in other sectors of the economy. When also considering the jobs lost, the new jobs that trade with China created provided a net benefit to consumers' incomes.

There is no shortage of research on the labor market implications of imports, especially surrounding the China Shock. Most agree, however, that the China Shock ended in the late 2000s: Real U.S. import growth from China slowed from an average annual rate of 15 percent from 2002 to 2010 to 5 percent after 2010. Furthermore, rising wages in China, due to both demographic challenges and institutional reforms, have weakened it as a source of underpriced labor. Given the evidence that global trade has adjusted to a new norm, experts believe that the China shock ended in aggregate by 2010.

Taking these factors into consideration, the following analysis examines the impact of imports on manufacturing employment after the United States had fully adjusted to the China shock in 2010. To get a full picture of the impact, it examines the relationship between total U.S. imports and manufacturing employment, as opposed to limiting the scope to U.S.-China trade.

Data and Methodology

To estimate the relationship between imports and manufacturing employment, this analysis employs a fixed-effects regression with a balanced panel of data on all 50 states from 2010 to 2016. During that time, import levels increased on average 22 percent across all states (adjusted for inflation), ranging from a 47 percent decrease in Wyoming to an 85 percent increase in Nevada.

Data on U.S. manufacturing employment by state come from the U.S. Bureau of Labor Statistics (BLS), and state-level imports are from the U.S. Census Bureau. To maintain consistency, all nominal dollars are transformed to real 2012 dollars using Bureau of Economic Analysis (BEA) end-use import price indices, obtained from BLS.

The dependent variable is the natural log of manufacturing employment in each state. The first independent variable of interest is the natural log of real imports by state.

An equally important consideration is interstate trade. Imports do not necessarily remain in their state of original destination after entering the country, but sometimes travel to other states to be used in production or sold to consumers. Therefore, the second independent variable of interest is regional import levels, calculated by summing imports across geographically adjacent states.

To get a clear picture of the relationship between imports and manufacturing employment, this analysis uses two separate models. The first model is the simplest; it estimates the direct relationship between imports and manufacturing jobs using only state fixed effects and year effects. The second model replicates the first model while also including additional controls, i.e., factors besides imports that, as they change over time, influence manufacturing employment. Controlling for these confounding variables is necessary to isolate the specific relationship between imports and manufacturing jobs.

The largest confounding variable is the state of the economy, which has a direct impact on both import and employment levels. This analysis employs three state-level variables to control for general economic conditions: personal consumption expenditures per capita, house prices, and claims of unemployment insurance (referred to as jobless claims).

Automation also has a clear impact on the manufacturing labor force. As manufacturing firms become more reliant on capital and relatively less reliant on labor, they can sustain (or even increase) production with fewer workers. This phenomenon helps to explain why manufacturing employment has been falling for decades even as manufacturing output has continued to rise. To account for this impact, the second model includes an instrumental variable for automation. The instrument – an "automation dummy" – is equal to one if a state's manufacturing labor share (the share of manufacturing income given to labor) is less than the national average and zero otherwise.

The appendix contains a more thorough explanation of the second model.

Results

Model 1

The first, simplest model finds no relationship between imports and manufacturing employment. Table 1 displays the full regression results. Without controlling for any other factors, this analysis finds that the impact of state-level imports and regional level imports on state-level manufacturing employment is not significantly different than zero.

Model 1 Regression Results with Respect to Log Manufacturing Jobs; No Controls Included

Regressor	**Coefficient (P value)**
Log Imports	0.025 (0.313)
Log Regional Imports	0.086 (0.132)
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$	

Model 2

The second model, which controls for the impacts of automation and economic conditions, finds a positive relationship between imports and manufacturing employment. Table 2 displays the results. As in the first model, model 2 finds that the impact of state-level imports on state-level manufacturing jobs is not significantly different than zero. Regional imports, however, were estimated to have a positive impact on manufacturing employment.

The model indicates that a 1 percent increase in regional imports increases state-level manufacturing jobs by .07 percent.

The economic control variables included in model 2 each had a statistically significant impact on manufacturing jobs, suggesting that their inclusion improved the explanatory power of the model. Furthermore, the newfound significance of regional import provides evidence that the confounding economic controls are related to both import levels and manufacturing jobs and should be included in the model.

Model 2’s full regression results, along with robustness checks, can be found in the appendix.

Model 2 Regression Results with Respect to Log Manufacturing Jobs; Controls Included

Regressor	**Coefficient (P value)**
Log Imports	-0.007 (0.802)
Log Regional Imports	0.074** (0.022)
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$	

Based on these results, approximately 220,000 manufacturing jobs created between 2010 and 2016 nationwide – just over one quarter of the 800,000 total manufacturing jobs created during this period – can be attributed to increases in imports. This calculation is explained further in the appendix.

Conclusion

This study uses empirical analysis to determine the impact of imports on the manufacturing labor force. The results show that international trade, and specifically imports, are job creators. Conceptually, this finding reflects global supply-chain integration in the modern economy. For example, over 60 percent of imports to the United States are used by U.S. firms in the production of final goods. By providing U.S. businesses with access to lower-priced raw materials, imports reduce the cost of domestic manufacturing and enable those businesses to increase their activity and hire more workers. These results suggest that, post-China Shock, the use of imports through continued U.S. trade liberalization is a net benefit to the manufacturing labor force.

Appendix

Models

This analysis utilizes standard fixed-effects models to predict the level of manufacturing jobs in each state dependent on import levels and controlling for other factors. The model specification is expressed below.

In the above equation, is the natural log of manufacturing jobs by state, is a vector of regressors and their slope estimates (including year-specific dummy variables), and is the unobservable error, assumed to be uncorrelated with the regressors and have a mean of zero. is a vector of random variables – factors that are constant over time but vary by state – to capture unobserved heterogeneity across states that could impact manufacturing employment. As an example, a state with a vibrant manufacturing history due to geographic advantages or a business-friendly policy environment may draw more investment and greater manufacturing employment than other states. To account for this heterogeneity, state-specific effects are controlled for.

The reported standard errors for both specifications are robust to heteroskedasticity and serial correlation. This is to account for likely heterogeneity in across states and across time. For instance, the variation in import levels is likely higher in wealthier states and during periods of economic prosperity than in poorer states and during periods of economic stagnation. Import levels are also correlated across time, resulting in serial correlation. Because of these issues, panel robust standard errors are used to obtain valid test statistics for hypothesis testing.

The response variable is the natural log of manufacturing employment in each state. The main regressors of interest are the natural log of real imports by state and the natural log of real imports by region. The regional import variable is especially important because import data by state does not account for inter-state trade. It is possible that imports to one state may have a direct impact on manufacturing employment in another state, either because the state of original import destination is not the same as the state of final use, or if two state economies are unusually linked.

To account for this possibility, the regional variable was created by summing the imports of the directly adjacent states for each observation. For instance, the value corresponding to Alabama's import levels in 2010 would be the 2010 import levels of Alabama, Florida, Georgia, Tennessee, and Mississippi. While it is certainly possible for imported goods to travel across numerous states after entering the country, survey data show that roughly 75 percent of all commodities, including imports, travel less than 500 miles from their location of origin. Therefore, including a variable that sums imports over neighboring states will likely control for most inter-state shipments.

In model 1, consists of the two main regressors of interest only: state-level imports and regional-level imports. Model 2 replicates model 1 while also including additional control variables, explained in detail below.

Model 2 Control Variables

The first control variable is included to hold the impact of automation constant. Automation is measured by labor's share of manufacturing income, which is defined as the share of national output given to workers as compensation. It should be expected to fall as manufacturers shift away from labor and toward capital. The labor share control variable is calculated by dividing nominal manufacturing output per state by nominal compensation to manufacturing employees per state (both obtained by BEA).

Measuring automation in this way, however, results in the methodological issue of reverse causality. Just as labor share is expected to influence manufacturing employment, manufacturing employment should also be expected to impact the share of manufacturing income given to labor. To account for this issue, labor share is instrumented with a binary variable (called the automation dummy) equal to one if a state's manufacturing labor share is less than the national average and zero otherwise.

Another factor that may explain the variation in manufacturing employment is the general state of the economy. Three economic controls are included: the Freddie Mac House Price Index (HPI), jobless claims, and personal consumption expenditures per capita. Personal consumption expenditures per capita is calculated by transforming nominal personal consumption expenditures into 2012 dollars using the consumer price index, dividing it by the population of each state, and taking the natural log. Jobless claims are included as a proxy for labor market conditions, taken from the BLS. Like with automation, however, manufacturing employment and jobless claims suffer from reverse causality. Therefore, the jobless-claims variable is calculated by taking the natural log of jobless claims and lagging it one year. Finally, HPI is included to measure inflation in home prices, a commonly used control for the state of the economy in the years surrounding the Great Recession.

Summary statistics for all regressors can be found in Table 1 below. Table 2 transforms the log summary statistics into levels for context.

Table 1: Summary Statistics

Variable	Mean	SD	Minimum	Maximum	N
Log Manufacturing Jobs	11.83	1.18	9.07	14.09	350

Log Imports	23.68	1.37	20.47	26.90	350
Log Regional Imports	25.7	1.20	21.13	27.08	350
Log Jobless Claims (Lagged)	8.38	1.09	5.65	11.22	350
Log PCE per Capita	10.76	0.13	10.50	11.05	350
HPI	139.90	26.21	73.23	260.08	350
Labor Share (instrumented)	0.51	0.09	0.22	0.82	350
Automation Dummy (instrument)	0.19	0.40	0	1	350

Table 2: Summary Statistics for Select Variables in Levels

Variable	**Mean**	**SD**	**Minimum**	**Maximum**	**N**
Manufacturing Jobs (Thousands)	239.71	243.22	8.70	1309.60	350
Imports (Billions)	$46.10	$74.00	$0.01	$482.80	350
Regional Imports (Billions)	$232.22	$154.61	$1.50	$576.5	350
Jobless Claims (Lagged, Thousands)	7.72	10.09	0.28	74.60	350
PCE Per Capita (Thousands)	$47.46	$6.19	$36.21	$62.72	350

Table 3 displays the full regressions results for model 2. The analysis finds no relationship between state-level imports and state-level manufacturing employment. Alternatively, a 1 percent increase in import levels increases the predicted number of manufacturing jobs by 0.07 percent, a result that is statistically significant at the 95 percent confidence level. Several controls have statistically significant impacts on predicted manufacturing employment: HPI, the natural log of jobless claims (lagged), and the natural log of personal consumption expenditures per capita. Of these, the personal consumption expenditures had the greatest impact on manufacturing jobs – the elasticity of manufacturing jobs with respect to personal consumption expenditures is 0.43. Year effects were also significant.

Table 3: Regression Results with Respect to Log Manufacturing Jobs, Control

Regressor	Coefficient (P value)
Log Imports	-0.008 (0.756)
Log Regional Imports	0.074** (0.021)
HPI	0.001*** (0.000)
Log Jobless Claims (lagged)	-0.104*** (0.001)
Log PCE per capita	0.428** (0.014)
Labor's Share of Manufacturing Income (instrumented)	-0.039 (0.800)
****p* < 0.01, ***p* < 0.05, *p < 0.10	

Test for Weak Identification

An instrumental variable is weak if it has little correlation to the problematic endogenous variable, which is in this case labor's share of manufacturing income. If a weak instrument is used, the slope estimates obtained by the regression would be inconsistent and thus could not be used for statistical inference. Therefore, to test if the automaton dummy is a weak instrument for labor share, the Kleibergen-Paap rk statistic is estimated with cluster-robust standard errors to be 33.0. Using the Stock-Yogo critical value of 16.4 – which reflects an acceptable bias level of 10 percent relative to ordinary least squares – we can reject the null hypothesis that the automation dummy is a weak instrument for labor share.

Test for Redundancy

The second robustness check is a test for redundancy, which assesses whether the inclusion of the instrumental variable improves the asymptotic efficiency of the model. In a test for redundancy, the chi-squared test statistic is estimated to be 15.9. With a p-value of 0.0, we can reject the null hypothesis that the automation dummy instrument is redundant, and instead conclude that the instrument does indeed improve the model's asymptotic efficiency.

<u>Application of Results</u>

These results can be used to estimate how many of the manufacturing jobs created between 2010 and 2016 were a direct result of increases in imports. The predicted growth in manufacturing jobs for each state is calculated by multiplying the observed growth in regional import levels by the slope coefficient 0.074. That growth rate is then applied to the number of manufacturing jobs per state in 2010 to estimate predicted manufacturing job creation due to increases in imports. The number of jobs created is summed across all states to find the nationwide job creation attributable to imports, estimated to be 220,678.

The full calculation can be found in an Excel file here.