Assessing China's Role in the Decline of U.S. Manufacturing Employment

Ya-Wen Yu and David L. Kleykamp*

Abstract

China's expanding trade in manufactured goods has been suspected of causing a massive fall in manufacturing employment in the U.S. and other advanced economies since the early 2000s. An alternative view to this is that slower demand growth for manufactured goods, relative to services, coupled with relatively strong growth in labor productivity is to blame for the decline. This paper presents China's role in the loss of U.S. manufacturing employment since 1992 by decomposing manufacturing employment growth into growth in manufacturing demand, productivity, and trade. The growth in overall trade is then split into trade between the U.S. and China and trade between the U.S. and the rest of the world excluding China. For value-added output, findings show that China was directly responsible for a loss of 571,000 jobs or 10.1% of total U.S. manufacturing job losses from all sources during 1992-2000, a loss of 1,269,000 jobs or 23.1% of all losses during 2002-2007, and finally a loss of 118,000 jobs or 13.5% of total losses during 2011-2018. In addition, the decomposition indicates that about 75% of job losses in U.S. manufacturing over the periods 1992-2000 and 2002-2007 were due to growth in productivity. By contrast, weak to negative growth in productivity and moderate growth in demand were responsible for a rise in U.S. manufacturing employment of over 1 million jobs during 2011-2018.

Keywords: Manufacturing, Employment, Productivity, China Shock, Trade Deficit

JEL Classification: F14, F15, J01, J23, P23

* Corresponding authors: Ya-Wen Yu, Associate Professor in the Graduate Institute of International Security, National Defense University, No. 1000, Xingfeng Rd., Bade Dist., Taoyuan City 334301, Taiwan, R.O.C., Tel.: 886-3-3657891, E-mail: yawenyu1@gmail.com. David L. Kleykamp, Research Consultant of the ASEAN Studies Center, Tamkang University, No. 151, Yingzhuan Rd., Tamsui Dist., New Taipei City 251301, Taiwan, R.O.C., Tel.: 886-2-26215656 ext. 3615, E-mail: davidkleykamp@gmail.com. The authors are very grateful to two anonymous referees for their helpful comments and suggestions.

Received March 24, 2021; revised July 27, 2021; accepted January 5, 2022.

經濟研究 (Taipei Economic Inquiry), 59:1 (2023), 69-110。
臺北大學經濟學系出版

1. Introduction

From January 2000 to December 2009 employment in U.S. manufacturing contracted by 5.8 million jobs. This amounted to a 33.6% fall in employment in manufacturing. The impact on Americans was profound and shocking. The political backlash was swift and punishing. Research initiatives previously tasked with studying the effect of North American Free Trade Agreement (NAFTA) on U.S. manufacturing naturally pivoted to analyzing the impact of China's massive surge in imports to the U.S. Over time this topic grew in both significance and controversy. It continues to be an important topic in business, the media, politics, and academia throughout the world.

In this article, we endeavor to accurately assess the direct role played by China's unbalanced trade in causing losses in U.S. manufacturing employment. The methodology used here weighs China's impact against other important factors such as U.S. demand for manufactured goods, growth in manufacturing labor productivity, and growth in U.S. manufacturing trade with the rest of the world excluding China. One particular strength of this research is that it utilizes a simple but comprehensive accounting of many of the important facets being discussed on the subject both in academia and with the public at large regarding the important period 1992-2018. The methodology is a formalization, generalization, and extension of that used by Bivens (2004). It is a logical decomposition of the factors affecting employment that inescapably follow from the definition of productivity and from the assumption of continuous market clearing of manufacturing output over the span of a year. The decomposition neatly separates growth in manufacturing employment into the following identity

$$\begin{array}{c}\text{Growth in}\\ \text{Manufacturing}\\ \text{Employment}\end{array} \equiv \begin{array}{c}\text{Growth in}\\ \text{Domestic}\\ \text{Demand}\end{array} - \begin{array}{c}\text{Growth in}\\ \text{Manufacturing}\\ \text{Productivity}\end{array} + \begin{array}{c}\text{Growth in}\\ \text{Trade}\\ \text{Factor}\end{array}$$

where the trade factor is equal to the ratio of domestic manufacturing output to domestic manufacturing demand. In the next section a formal discussion of the methodology shows that this trade factor is a monotonic function of net manufacturing imports to manufacturing output and thus the trade factor may be thought of as a net import shock to the industry. The equation above will hold identically with respect to time if there is continuous market clearing in manufactures and if the average labor hours per worker in manufacturing are constant. After decomposing according to the equation above we further decompose the trade factor growth into that due to China and that of all other countries excluding China. This final decomposition allows us to evaluate the employment losses in manufacturing as a result of the manufacturing trade deficit with China and compare that to the losses in employment from all causes combined. In this sense, we seek to segregate the channels according to their proximate effects on manufacturing employment and judge their relative strengths.

For reasons that will become clear later, our analysis divides the entire period 1992-2018 into three non-overlapping periods (excluding recessionary periods). Our findings show that for value-added output, the period 1992-2000 witnessed approximately 571,000 jobs in U.S. manufacturing lost to Chinese unbalanced trade in manufactures with the U.S.. Over the period 2002-2007 roughly 1,269,000 U.S. manufacturing jobs were lost due to the China trade shock. And, during the final span 2011-2018, when actual U.S. manufacturing employment was rising and the China shock was growing at a mere 0.5% per year, China’s unbalanced trade was still calculated to be responsible for the loss of 118,000 U.S. manufacturing jobs.[1]

---

1 The so-called China shock is defined here as the ratio of China’s trade surplus with the U.S. in manufactures per unit of value-added U.S. manufacturing output. This ratio grew about 310% over the period 1992-2000, 170% during 2002-2007, but a mere 4% in 2011-2018. This shows that China has already been facing significant diminishing returns for a decade in expanding its share of the manufacturing market in the U.S. It’s scale is nevertheless enormous, even as it grows very slowly now. One may say that since 2011 the China shock has essentially plateaued and is no

Table 1 (see Section 6) contains an abbreviated list of some China trade researchers and their estimates of the impact of the so-called China import shock on employment in the U.S. One early study that drew significant recognition and acceptance was Autor et al. (2013). In this work Autor estimated that over the period 2000-2007 almost 1 million Americans lost their manufacturing jobs due to China's import penetration. Over the earlier period of 1990-2000 Autor found that nearly 600,000 persons lost their jobs to China. These are surprisingly close to our findings. Additional research, like that of Autor's, adopted micro-based models and looked at local effects on employment and wages for hundreds of industries and within hundreds of commuting zones (CZ) that cover large areas of the United States (see Autor et al., 2016; Acemoglu et al., 2016; Feenstra et al., 2017; Feenstra and Sashara, 2018). These studies had findings that roughly accorded with the original work of Autor et al. (2013).

A more strident portfolio of research led by Robert E. Scott looked at the effect of the U.S. trade deficit with China on U.S. employment (see Scott, 2012; Scott, 2013; Kimball and Scott, 2014; Scott, 2017; Scott and Mokhiber, 2018 and Scott and Mokhiber, 2020). The most recent of these studies shows that over the period 2001-2018 the trade deficit with China resulted in a loss of 3.7 million jobs throughout the economy. The same study additionally found that 2.8 million manufacturing jobs were lost during the same period due to the impact of the trade deficit with China.

Some economists have emphasized the effect of rising productivity on job losses in U.S. manufacturing. Lawrence (2017) has bluntly stated that "faster productivity growth interacting with unresponsive demand has been the dominant force behind the declining share of employment in manufacturing in the United States and other industrial economies".

longer contributing much to changes in U.S. manufacturing employment. We calculate a mere 14,750 jobs per year were lost to China's unbalanced trade during 2011-2018 compared to 211,000 jobs per year during the inter-recessionary period 2002-2007 and 63,444 jobs per year during the earlier period 1992-2000.

Table 1 Summary of Results on U.S. Job Losses by Various Authors and Shocks

Researchers	Year	Period Concerned	General Job Losses	Job Losses Manufacturing	Type of Shock
Autor et al.	2013	1990-2000	-	0.59 m	China imports
Autor et al.	2013	2000-2007	-	0.98 m	China imports
Feenstra et al.	2017	1999-2011	nil by offsets	0.40 m	China imps – all exps
Feenstra and Sasahara	2018	1995-2011	1.8-2.0 m	-	China imps
Feenstra and Sasahara	2018	1995-2011	gain 4.50 m	-	China imps – all exps
Acemoglu et al.	2016	1999-2013	2.0-2.4 m	0.56 m	China imports[1]
				1.00 m	China imports[2]
				2.40 m	China imports[2]
Asquith et al.	2019	1992-2007	nil by offsets	2.10 m	China imps exposed
Caliendo et al.	2019	2000-2007	NA	0.55 m	CGE model
Scott and Mokhiber	2020	2001-2018	3.70 m	2.80 m	China (imps – exps)
Hicks and Devaraj	2017	2000-2010	1.60 m	0.75 m	General Trade

Note: [1] China imports studied alone, [2] China imports studied with upstream/downstream effects, [3] China imports studied with upstream/downstream effects and with aggregate demand changes. CGE model refers to a Computable General Equilibrium model. China (imps – exps) means China's net imports to the U.S. General trade means U.S. trade with all the world and not just China. China imps – all exps means China's imports to the U.S. minus total U.S. Manufacturing exports to all countries. China imps exposed refers to all U.S. industries which are exposed to Chinese imports.

This view has been conditionally supported by Fort et al. (2018) who claim, “The combination of relatively steady and then declining employment, and rising output, indicates that, over the long term, labor productivity has risen faster in the manufacturing sector than in the broader economy”. Hicks and Devaraj (2017) considered a breakdown of manufacturing employment changes into those attributable to growth in demand, productivity, and trade. Their main conclusion was that nearly 88% of employment losses in recent years (2000-2010) could be attributed to growth in productivity. Trade was responsible for about 13% of employment losses. These authors did not consider China, per se.[2]

---

2 Other research projects dealing with trade and the labor market during the first two decades of the 21st century have been broad and thought-provoking without always specifically quantifying manufacturing job losses. Autor et al. (2015) concluded that Chinese import competition has reduced manufacturing employment especially among non-college workers while expanding employment in non-manufacturing firms. Autor has claimed this is a natural polarization of labor markets due to technical advance. Bernard et al. (2017) found using microeconomic data that some firms simply switched their identity from manufacturing to non-manufacturing, thus biasing the measured employment losses upwards.

Charles et al. (2018) state that the fall in manufacturing employment led to substantial unemployment of unskilled labor in other industries in the local area and even led to a rise in drug addiction. By contrast, Bloom et al. (2019) found that most of the losses in manufacturing employment were experienced by large import firms that in turn contributed to job gains in the non-manufacturing sector. Eriksson et al. (2019) demonstrate that the impact of trade penetration in manufacturing employment depends on the current stage of the life cycle of the products and technologies, with cutting-edge technology firms having greatest resistance to competitive trade while late-stage firms tending to move and relocate to lower skilled areas. Much attention has been placed on possible offsetting job gains in manufacturing firms (and elsewhere) due to the low cost Chinese intermediate inputs.

Asquith et al. (2019) also used microeconomic modelling but concentrated on comparing how job losses were distributed between reductions in plants (internal margins) and reduction in firms (external margins). In their modeling, plants represented only a part of firms and thus allowed a comparison of local versus national job losses. They found that there were significant job losses at the internal margin, but such losses were generally offset by employment elsewhere in the firms. Clearly, offsetting changes to employment within firms are important to the debate.

It should be noted that Autor et al. (2013), Autor et al. (2016), and Acemoglu et al. (2016), as well as several other authors employ industry level and micro-based analyses that aim at measuring employment losses and changes in wages at what they call the CZ level. They did this in order to specifically study how local U.S. labor markets adjusted to China's import shock. However, there are numerous issues arising from their methodology, despite the fact that these works have been well received in the profession. The macro-based decomposition method we employ, while far from perfect, avoids many of these issues, including such things as the lack of clear and comprehensive productivity and domestic demand variables; the lack of exports to China and other countries from the CZs; the reliance on nominal values rather than real values, or in some studies, an exclusive use of the Personal Consumption Expenditure index to deflate nominal values; the exclusive reliance on value of shipments which include intermediate transactions that can distort the contribution of manufacturing alone; the problematic projection or apportionment of national level Chinese imports onto the micro CZs based on the fraction of CZ industry employment to national industry employment; clear and serious changes in the structure of trade with China between the years 1992-2000 that can be seen in the 4-digit HS trade data, the assumption of perfect labor immobility, not to mention

---

Some authors have even claimed that the manufacturing employment losses have been completely offset to such an extent that employment in manufacturing was raised by China trade, see Magyari (2017). This of course would imply 100% of job losses were due to productivity growth. Lin et al. (2017) used an extended input-output model to measure the direct and indirect impact of exports on employment and found that Chinese exports to the U.S. raised employment by a small amount, 77,000 in 2007. A less optimistic view is expressed by Ebenstein et al. (2012) who uses micro-based Census data from 1990 to 2005 to study correlations with various Chinese manufacturing phenomena and U.S. manufacturing. They infer that Chinese trade has fundamentally altered U.S. manufacturing, quite apart from changes in U.S. productivity. Kollmeyer (2009) has claimed, for the 18 the Organization for Economic Cooperation and Development (OECD) countries considered over the period 1970-2003, all three channels affect manufacturing employment, but the major impact on falling employment has been the dramatic shift from goods to services in consumers' budgets as the public has become more affluent.

the usual statistical issues of possible measurement errors, functional form errors, sampling errors, missing variable and use of dubious proxies, and problems with the instruments used to deal with simultaneous equations bias. These statistical and modeling issues are not found in the decomposition method, so long as it is understood that losses computed are attributed to proximate (not ultimate) causes and that actual total losses always requires the combination of all three sources. The decomposition losses are notional or latent losses and provide an indication of the relative strengths of the three sources of employment changes – demand, productivity, and trade after all equilibrating changes have occurred. Note however, that the decomposition method cannot speak to the question of microeconomic labor market adjustments. Even so, the manufacturing unemployment rate (as well as the general unemployment rate) surprisingly fell during the important period 2002-2007 as the China shock reached its zenith. To suppose poor mobility of labor for the U.S. manufacturing labor market seems a dubious assumption at best.

Our results compare well with the findings of authors such as Autor et al. (2013), Acemoglu et al. (2016), and Asquith et al. (2019), even though we utilize a quite different methodology and definition of China shock. In general, our results are well within the range of all estimates contained in Table 1. An obvious strength of the decomposition analysis here is that by definition it includes all factors influencing manufacturing employment, such as productivity growth, growth in demand for manufactures, trade with China, and trade with the rest of the world excluding China. If there is something that affects manufacturing employment, it must have exerted its influence on these variables. The decomposition uses final equilibrating growth values of the variables after all forces have had their effect. These variables display the relative strengths based on these final growth values.

Our contribution to the literature includes new and separate macro-based numbers for China's impact on U.S. manufacturing employment over the period 1992-2018 (excluding recessionary periods), which has not been done using this specific method, according to our understanding. In addition, our analysis focuses on the impact of China's net imports per unit output, rather than looking at imports alone or some other definition of shock such as that used by the authors in Table 1. The analysis shows, among other things, that China's unbalanced trade was itself responsible for over 23% of job losses from all sources during the important period 2002-2007, which is a new finding. Furthermore, our study documents the decline in impact of unbalanced trade from the ROW countries during the period 2002-2007, some of whom were rerouting supply lines through China. It also completely captures the roles of aggregate demand and productivity, which is missing in many of the other works. The model is an important extension of the decomposition tool to the analysis of net trade for a single country, something we believe is both new and useful. It is our view that, despite a large body of research, the question of China's role in the decline of U.S. manufacturing employment has not been settled and remains in controversy. Our analysis helps by bringing a higher degree of unity and clarity to the subject.

2. Methodology

The basic method of decomposition employed in this paper was used by Bivens (2004) in analyzing the extent that demand, productivity, and trade affects employment in U.S. manufacturing.[3] His work was limited to a comparison of only a few observations and was restricted to overall manufacturing trade without singling out a particular country. The decomposition can be motivated by using two relations assumed to hold identically with respect to time. These are

3 For purposes of comparison and to remain true to the spirit of his original analysis, we have replicated the results of Bivens (2004) to the best of our ability considering that much of the data has been altered through changes in definitions and updating. The results of the replication are quite close except for more modern times which differ because of the updating of data. The methodology we employ in the paper is an extension of his analysis.

$$y \equiv \frac{Y}{L}, \tag{1}$$

and

$$Y_D \equiv Y + (M\text{-}X), \tag{2}$$

where y=real average output per worker in manufacturing; Y=real output manufacturing; L=number of workers employed in manufacturing, M=real imports of manufactured goods; X=real exports of manufactured goods; and Y_D=domestic demand for real manufactured output. As Bivens correctly noted in his paper, growth in the variable y found in equation (1) can be associated with growth in average labor productivity, if average hours worked in manufacturing are sufficiently stable. Later we will show that this assumption holds true statistically, provided we divide the total time frame into three distinct periods. As Bivens also noted in his original exposition, equation (2) assumes continuous market clearing and that the levels of inventories are kept low and stable, thus making them inconsequential. This will likely hold if the periods we consider do not experience serious recessions or strong expansions. Setting $\mu = (M\text{-}X)/Y$ and $d = 1/(1+\mu)$, we may combine (1) and (2) to get

$$L \equiv \frac{dY_D}{y}, \tag{3}$$

where it must be true that at most only three of the variables can be independent of each other. We will find that there are at least three different definitions of output that can be used in the analysis and these outputs differ in both their economic meaning and their magnitudes. Yet another problem besides the issue of the best definition for output stems from a lack of an "ideal" deflator that can reduce nominal manufacturing values to real manufacturing values. Again, we will employ three different deflators, which show considerable variance amongst themselves over the different periods. Each of these deflators share characteristics of some types of manufacturing output. We believe that the difficulties surrounding outputs and deflators are mitigated to a large degree by calculating the results under different assumptions and then comparing the outcomes for changes in magnitudes and general structure.

Next, since (1) and (2) are assumed to hold identically over time, (3) will also be an identity and hence we may logarithmically difference it to obtain,

$$\frac{\Delta L}{L} \equiv \left(\frac{\Delta Y_D}{Y_D} - \frac{\Delta y}{y} + \frac{\Delta d}{d} \right) + R \equiv S + R, \tag{4}$$

where S is the linear combination in braces and where the non-constant remainder term R in each period is whatever is needed to produce exact equality in (4). It will be useful to distribute this small and varying residue R equally and proportionately over the three growth rates on the right-hand side of (4) by multiplying each growth rate by $(1+R/S)$. If the ratio R/S is not large, then the effect of this action will be both harmless and useful, and we will be able to write (using corrected rates of growth)

$$\frac{\Delta L}{L} \equiv \left(\frac{\Delta Y_D}{Y_D} \right)^* - \left(\frac{\Delta y}{y} \right)^* + \left(\frac{\Delta d}{d} \right)^*, \tag{5}$$

where the corrected growth rates are defined as $(\Delta x/x)^* = (1+R/S)(\Delta x/x)$.

Since we have annual data on Y, L, M and X, both Y_D and y can be easily computed and we can therefore proceed to measure the contribution of each of the right-hand side variables in (5) to the left-hand side total. Bivens calls the first two variables on the right side of (5) the domestic factors.[4] Obviously, a rise in growth of domestic demand for manufacturing output $(\Delta Y_D / Y_D)^*$ will increase the demand for labor needed to produce that additional output given fixed productivity and trade. By contrast, a rise in the productivity of labor $(\Delta y / y)^*$ will reduce the need for labor employed. The effect of growth in d on

4 Alternatively, one can group domestic demand and trade penetration together as a demand side force and allow productivity to represent the supply side of the economy.

employment is not immediately obvious but remembering $d = 1/(1+\mu)$ where $\mu =$ the ratio of *net* manufacturing imports to manufacturing output, a rise in imports will drive up μ, and thus d will fall. This fall in d will therefore be associated with a fall in employment, so that d must be inversely related to the net import penetration of foreign suppliers, μ. It follows at that if $(\Delta d/d)^{*}>0$, then this will raise employment.

We refer to d as the trade factor. It will figure prominently in our analysis of the impact of China trade on U.S. manufacturing employment. The term d can be written

$$d \equiv \frac{1}{1+\mu} \equiv \frac{Y}{Y+M-X} \equiv \frac{Y}{Y_D}.$$

It is therefore the ratio of manufacturing output to realized manufacturing domestic demand. Note that it can only be affected by net imports per unit manufactured output. We therefore recognize its dependence on trade and simply call d the “trade factor”. The residue of manufacturing output not exported must be combined with imported manufactures to satisfy domestic demand for manufactures. Naturally, we assume there is continuous market clearing in order to ensure $Y+M-X \equiv Y_D$.

It is important to emphasize what may seem obvious. Namely, that $\Delta L/L$ in (5) above is a resultant of the three right-hand side growth factors. This means that it may be true that millions of jobs are notionally lost due to the element of greater productivity growth, but at the same time many millions of jobs may be notionally created by the element of rising demand. Some of these gains and losses involve the same jobs, which experience offsetting notional gains and losses; that is, the jobs remain unchanged. The actual change in total employment will always be determined by the interplay of all three terms in (5).

To express the jobs gained or lost using (5) above we obtain the average annual growth rates for Y_D, y, and d over the period concerned. Next, we express (3) in terms of growth in the following manner

$$L(N) = \frac{d(N)Y_D(N)}{y(N)} = \frac{d(0)(1+g_d)^N Y_D(0)(1+g_{YD})^N}{y(0)(1+g_y)^N} \equiv L(0)(1+g_L)^N,$$

and thus,

$$L(N) - L(0) = L(0)[(1+g_L)^N - 1] \approx L(0)Ng_L.$$

By the same reasoning,

$$\frac{L(N)-L(0)}{L(0)} = Ng_L = Ng_{YD} - Ng_y + Ng_d, \tag{6}$$

for the total change in employment over the period consisting of N years.[5] In this case, we employ the arithmetic averages of the growth rates g_L, g_{YD}, g_y, g_d, and the initial level of actual manufacturing employment, $L(0)$.[6]

Once the overall decomposition of manufacturing employment has been accomplished, it will be possible to divide the job gains/losses specifically from trade (*d*) into those that are explicitly due to China trade (*c*) and those due to the rest of the world (*ROW*). This can be done as follows.

$$d \equiv \frac{1}{1+\mu} \qquad \text{or} \qquad d(1+\mu) \equiv 1,$$

and differencing this we can write

$$(1+\mu)\Delta d + d\Delta\mu + \Delta d\Delta\mu \equiv 0.$$

The first and last terms on the left-hand side can be combined, resulting in

$$\frac{\Delta d}{d_0} \equiv \frac{\Delta\mu}{\mu_0} \cdot \frac{-\mu_0}{(1+\mu_1)}.$$

---

5 We have used the approximation $[(1+g_{YD})(1+g_d)/(1+g_y)]^N \approx 1 + N(g_{YD} - g_y + g_d)$ to arrive at this representation.

6 This can be done if the period N is not too long. In our case, for Period I, N=9, Period II, N=6, and Period III, N=8, See Section 3 for how these periods are decided.

where the subscript 0 refers to previous period and 1 refers to current period. Next, recognizing the term $\mu \equiv (M - X)/Y \equiv (M_C - X_C)/Y + (M_{ROW} - X_{ROW})/Y \equiv \mu_C + \mu_{ROW}$, the above equation can be rewritten as

$$\frac{\Delta d}{d_0} \equiv \left(\frac{\Delta \mu_C}{\mu_C^0}\right) \times \left[\frac{-\mu_C^0}{(1+\mu_C^1+\mu_{ROW}^1)}\right] + \left(\frac{\Delta \mu_{ROW}}{\mu_{ROW}^0}\right) \times \left[\frac{-\mu_{ROW}^0}{(1+\mu_C^1+\mu_{ROW}^1)}\right].$$

Defining $\Psi_C \equiv (\Delta\mu_C / \mu_C^0) \times \left[-\mu_C^0/(1+\mu_C^1+\mu_{ROW}^1)\right]$ and $\Psi_{ROW} \equiv (\Delta\mu_{ROW} / \mu_{ROW}^0) \times \left[-\mu_{ROW}^0/(1+\mu_C^1+\mu_{ROW}^1)\right]$, we can write the above decomposition in compact form as follows

$$\frac{\Delta d}{d} \equiv \Psi_C + \Psi_{ROW}. \tag{7}$$

Note that (7) is not a weighted average of the separate growths rates of μ_C and μ_{ROW}, but is the exact contributions to growth in d from China and from ROW. Equation (7) is the tool we can use to obtain information on China's impact alone. In this sense, we are extending Bivens original analysis to consider the impact of a single country on manufacturing employment. A rise in μ_C leads to a decrease in d and hence a fall in employment. This is what we would intuitively expect as China's trade penetration increases.

To obtain the changes in employment due to China and ROW, we multiply the respective growths in (7) by the initial year's employment and by the number of years in the period. Adding these two changes together equals the total change in manufacturing employment due to the growth in trade penetration, by construction. If China's unbalanced trade has been responsible for a sizeable loss of U.S. manufacturing jobs during the periods considered, the decomposition in (7) should reveal this. This also requires that the data and the periods of observation be chosen with great care and without bias.

3. Choice of Periods and Data Issues

The decomposition above requires average work hours per employee in manufacturing remain relatively stable. This is because we are interested in assessing the role that growth in labor productivity has in determining growth in employment. If average hours worked per person are stable or statistically constant, growth in productivity is equal to growth in the average product of labor.

3.1 Three Periods of Stable Average Work Hours

In selecting the periods over which to apply the above analysis, several considerations were made.

First, the length of the data, particularly for output data, went back as far as 1988. Any attempts to push the date back further were unsuccessful since the data did not exist in a coherent and consistent form, definitions ceased to match over time, or the data was updated far too much for us to place any faith in its consistency. Attempts were made to use one consistent source per variable rather than to combine multiple sources. We took 2018 as the endpoint of our data set. The data from 1988 to 1992 proved to be somewhat unreliable, again since they were taken from multiple sources in order to complete the data set. Relatively consistent data were available for most of the data from 1992-2018. Another reason for starting the analysis with 1992 was the problem of recession in 1991 that tended to bias the data with a large drop in aggregate demand.

Second, the periods 2001 and 2008-2010 were dropped from the data set, again because of the distortion caused by dramatic falls in aggregate demand and the subsequent quick recovery in 2010. Manufacturing output and thus manufacturing employment fell hard during these two periods. Inventories were subject to unusually large changes and this made continuous market clearing doubtful. In addition, average hours worked were not constant due to the recessions.

Third, the three periods 1992-2000, 2002-2007, and 2011-2018 were chosen because average hours worked in manufacturing were relatively constant. An F test on the equality of the means over the three periods was undertaken and a common zero mean could not be rejected. The results of this test are included in Table 2 contained in Section 6. The test is applied using data over the whole span 1992-2018. Dummy variables were constructed for the excluded years 2001, 2008, 2009, and 2010. Using these dummies is equivalent to excluding data from these years from the regression. The null of zero change in average hours worked cannot be rejected even at the 10% level of confidence. meaning that within all three periods there is no statistically significant growth of average hours worked in manufacturing and hence, growth in output per worker is statistically equivalent to growth of average labor productivity. The regression was checked by alternatively using a standard one-way analysis of variance (ANOVA) test of zero means and the results agreed exactly.

Table 2 Regression-Based Test of Equality of Zero Means for Growth of Average Weekly Hours of Production and Nonsupervisory Employees, U.S. Manufacturing 1992-2018

Coefficient	Estimate	t-statistic	p-value
β_1	0.043	0.228	0.822
β_2	0.357	1.325	0.200
β_3	0.296	1.271	0.218
γ_1	-2.123	-3.220	0.004
γ_2	-1.051	-1.590	0.128
γ_3	-2.288	-3.470	0.024
γ_4	3.179	4.820	0.0001

$Obs. = 27,\quad H_0 : \beta_1 = 0,\ \beta_2 = 0,$ and $\beta_3 = 0 \quad F(3,20) = 1.54,\ DW = 2.15,\ Adj.\ R^2 = 0.61$

Note: 1. $\hat{G}_H(t) = \beta_1 D_1(t) + \beta_2 D_2(t) + \beta_3 D_3(t) + \gamma_1 D_{2001} + \gamma_2 D_{2008} + \gamma_3 D_{2009} + \gamma_4 D_{2010} + \varepsilon_t$.

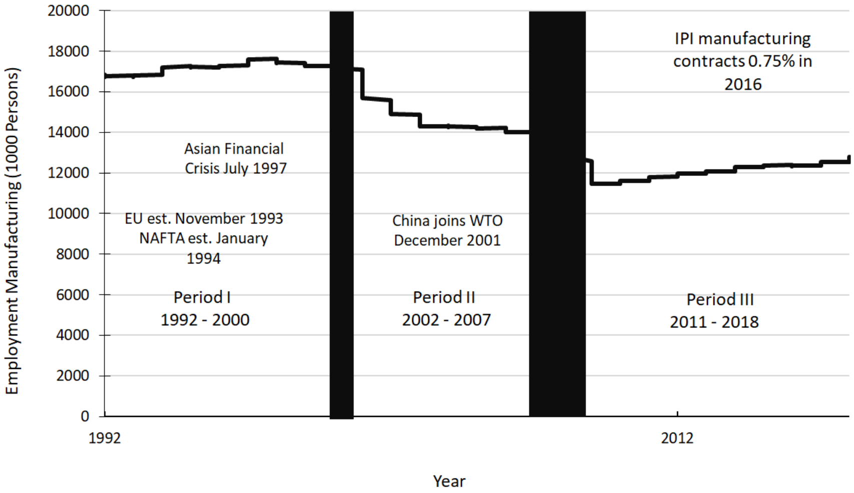
2. The dependent variable is annual growth in Average Weekly Hours of Production and Nonsupervisory Employees, U.S. Manufacturing. *Di*=dummy forperiod *i*=I, II, or III defined in the article, or year of excluded observations *i*=2001, 2008, 2009, 2010. The intercept is excluded to avoid perfect multicollinearity. The statistical F test establishes that this growth in average weekly hours per person is constant over the three periods. The fact that the three *βs* are jointly zero shows that output per worker is equal to average labor productivity within the three periods I, II, and III.

Having set out the three periods over which our analysis will be viewed, we now turn to the behavior of manufacturing employment during these three periods. Data on manufacturing employment in the U.S. (both all and production employment) are published monthly.[7] Thus, despite being lagged indicators of the economy's overall health, such employment variables are high-frequency, closely watched, and certainly worthy of scrutiny. Figure 1 shows the time series behavior of U.S. manufacturing employment.

Manufacturing jobs are highly prized since they are generally well paid and are incubators of human capital. Many manufacturing jobs in America are associated with large and important multinational corporations in the U.S. that have long histories and good reputations. According to the Bureau of Labor Statistics (BLS) statistics in 2020, 55% of U.S. manufacturing employment is in firms having 250 or more employees (large firms) and this rate has been slowly rising from 50% since 1993, see https://www.bls.gov/web/cewbd/table_f.txt.

---

[7] To avoid any confusion that might arise with respect to our definition of employment, we have chosen the standard definition used by the Bureau of Labor Statistics (BLS) (1997) Handbook of Methods, "all employees" that includes anyone on the payroll (i.e., paying unemployment insurance premiums) receiving pay by the 12th of the month. This includes a large group of people including those directly involved in the production process, whether full-time or part-time, as well as people having service jobs within the company, such as clerical workers, janitors, accountants, and even management (see the online BLS Handbook of Methods). It excludes individuals that are employed by another company, who are contracted to do work in the plants, factories, etc. Another BLS definition of employment is limited to "production employees". These are non-supervisory individuals who are directly involved in the production process of the firm. Time series data on all employees (*L*) and production employees (*P*) display an extremely high sample correlation. Importantly, quarterly growth rates for the two series from February1990 to April 2019 had a sample correlation of 0.98. The ratio *P/L* was very stable over the period ranging from a minimum of 0.70 (April 2019) to a maximum of 0.73 (February 1995). We chose the definition "all employees" over "production employees" because it is the one that is typically used by media, academia, and the government when discussing possible employment effects of trade, etc. Note however, the statistical test (see Table 2, Section 6) for constant average workweek hours uses manufacturing "production employees", since data on average workweek hours for manufacturing "all employees" in the U.S. begins in 2006 and does not cover earlier years.



Note: 1. Blackened areas are U.S. recessions as determined by the NBER Business Cycle Dating Committee.
2. Employment is defined as all employees of manufacturing firms. Average Hours worked per employee are relatively constant during the periods. The IPI is the U.S. industrial production index for manufacturing.

Figure 1 U.S. Manufacturing Employment

Figure 1 shows the three separate non-overlapping periods, each characterized by constant average work hours per laborer, which we will constantly refer to during our empirical analysis. In January 1992, U.S. employment in manufacturing stood at about 16.8 million persons. This number was considerably down (-14%) from its historic high of 19.55 million persons registered in June 1979. Thus, falling employment levels in manufacturing dates to at least the early 1980s, well before China trade expanded. In fact, Rowthorn and Ramaswamy (1997) estimated 60% of the fall in manufacturing employment in total employment throughout the developed world could be attributed to productivity growth. Starting in 1992 manufacturing employment rose a respectable 5% to a local high of 17.64 million persons in April 1998. It then began falling after April 1998, approximately four years and four months after the signing of NAFTA, reaching 17.2 million (or 2.5% lower than April 1998) in December 2000. The change in jobs was net positive from December

1991 to December 2000, but this rise was less than 250,000 jobs. We call 1992-2000 Period I and note that average hours worked are relatively constant throughout this period.

As Figure 1 indicates Period I was characterized by some important political-economic shocks including the establishment of the European Union (EU) and the establishment of NAFTA, both of which were expected at the time to have major effects on U.S. trade flows for the 1990s. However, actual employment in manufacturing surprisingly did not change by much. The Asian financial crisis that began in 1997 was also expected to have a major effect on trade, but again actual manufacturing employment in the U.S. did not suffer because of this. Instead Taiwanese and Japanese companies began investments in China, effectively rerouting their value chains through China which accelerated with China's accession to the World Trade Organization (WTO) in 2001.[8] Ostensibly, trade in Period I had little effect on employment, but later our decomposition shows that China alone was responsible for over half a million jobs lost during this time, while the ROW countries were responsible for nearly double this number of jobs lost.[9] Actual employment in manufacturing rose a small amount because of the tremendous increase in the demand for manufacturing that outpaced the losses due to productivity and trade.

According to the NBER business cycle dating committee a short but dramatic recession occurred beginning in March 2001 ending in November 2001. This coincided with the bursting of the dotcom bubble

---

8 According to Ministry of Economic Affairs (MOEA) statistics, Taiwan companies approved investment in China in 1996 was about 1.2 billion USD. This rose 108% to 2.5 billion USD in 2001 and again 168% to 6.7 billion USD in 2006; see Statistical Yearbook of the Republic of China 2019. Lanvin et al. (2003) claims that over half of Japan's 1 trillion USD manufacturing value moved to mainland China over the decade 1992-2002.

9 This is seen from Table 4 Panel I, Panel II, and Panel III for the period 1992-2000. For example in Panel I for value-added output, using the PPI-manufacturing deflator, the loss of jobs due to China was 603,000 while the loss due to ROW countries collectively was 1,103,000. The loss due to China is very close to the estimate of Autor et al. (2013) for roughly the same period.

in the stock market. The impact on manufacturing employment was staggering with employment dropping 1.1 million persons from March to November of 2001.

In January 2002, after the dot com recession has subsided, manufacturing employment stood at 15.6 million or 9% lower than it was in December 2000. As can be seen in Figure 1, employment continued to fall precipitously reaching 14.3 million by February 2004. This occurred even though the economy had recovered from the recession with manufacturing output rising. The rise in output coupled with a fall in employment led some observers to claim that the long term trend in productivity, along with reduced real exports in 2002-2003 due to a strong dollar, were responsible for much of the non-recessionary loss in jobs; see Fort et al. (2018), Lawrence and Edwards (2013), and Mankiw (2003). From February 2004 to July of 2006 there was surprisingly little change in employment. In July of 2006 employment was 14.2 million, or about 0.6% below its level over two years earlier. However, after July 2006 hemorrhaging of jobs continued with employment falling to 13.3 million in December 2007. The total fall in employment from December 2001 to December 2007 was all of 2.5 million workers, an extraordinary reduction since this was a period of recovery in the economy and a time where real manufacturing output grew over 15% (or 2.4% per year over 6 years).[10]

[10] This is something that Atkinson et al. (2012), Houseman (2018), and others have claimed is misunderstood, since they assert real manufacturing productivity has been distorted upward by unusually high productivity in the computer and electronic products sector, thus creating a significant outlier. According to them, the growth productivity in manufacturing has been due to billowing growth in productivity in the computers sector and hence the enormous loss in jobs only appears to be caused by this rise in productivity. We looked at: (1) the Industrial Production Index (IPI) excluding computers and peripherals; and (2) manufacturing employment excluding employment in the computers and peripherals sector. Average growth in the ratio of these two variables which approximates manufacturing labor productivity was 2.3% in Period I, 4.16% in Period II, and −0.50% in Period III. Note that the IPI includes mining, electric and gas, which are not considered manufacturing. Growth in productivity in mining and electric and gas was −4.6% in Period I, 2.7% in Period II, and -1.3% in Period III. Thus, considering the influence of including mining, electric and

From January 2008 to June of 2009 the Great Recession took its toll on the manufacturing sector as the U.S. shed 1.6 million jobs. Manufacturing employment in June 2009, the date the NBER says that the recession formally ended, was 11.7 million. One would have to go back to 1946 to find manufacturing employment so low, and at that time the civilian labor force was only 38% of its size in 2009. The dotcom recession resulted in a loss of 1.1 million workers, whereas the Great Recession of 2008 resulted in a loss of 1.6 million. It is interesting to note that the interim period between the two recessions saw a loss of slightly more manufacturing jobs than the two recessions combined. The notion that trade was suddenly and largely responsible for this interim fall in employment is difficult to believe and hard to justify empirically. This is even more so if one limits oneself to China's role in the employment fall. For example, Mankiw (2003) found that China's rising exports to the U.S. were more than offset by the fall in other Asian exports to the U.S. This is especially important since the micro-based studies do not typically include competing and complementary imports from other countries.

The final period, where average hours worked were roughly constant, begins in 2011. Period III had very weak or negative productivity (i.e. output per worker) growth, unlike periods I and II. The China shock (i.e. the ratio of the U.S. manufacturing trade deficit with China to U.S. manufacturing output) peaked at 0.20 in 2015. The growth in domestic demand for manufactures was sufficient to overcome the depressing force of an unfavorable balance of trade and drove employment up in U.S. manufacturing. Employment bottomed at 11.5 million in January of 2010 and by January of 2011 it had risen to 11.6 million. After this start in 2011, employment steadily rose to a high of 12.8 million in December 2018. This was an amazing addition of 1.2 million employees or a 10.3% increase.

---

natural gas on the IPI, growth in manufacturing labor productivity after excluding computers and peripherals looks to be quite close to the typical value-added figures; see Table 3 in Section 6. below for the value-added productivity averages over the three periods. Our use of different deflators to arrive at VA manufacturing output indicates at most that past estimates of productivity's effect on employment is off roughly 9% to 10%.

3.2 Data Definitions, Sources, and Transformations

Data used in the analysis are all publicly available from a variety of sources. All data pertain specifically to manufacturing. We have decided to compare the results of the analysis using different definitions of output and different price indexes to deflate nominal values to real (e.g. imports and exports of manufactured goods). The three different output definitions are (1) value-added (VA) output from manufacturing; (2) gross output (GO) from manufacturing; and (3) final user (FS) output from manufacturing.[11]

VA manufacturing output needs little explanation; its real value comes in the form of a growth index (2012) and is published by BLS in the U.S. covering 1987-2019. Nominal VA output was collected from the Bureau of Economic Analysis (BEA) for the period 1988-2017. We identified nominal and real as equal for 2012 and have used the BLS real index to construct real output from this. One additional point to be made is that we create a price deflator, which we call the value-added manufacturing deflator, by dividing the nominal VA output series by its corresponding real series. This deflator along with two other deflators are used in Table 3 in Section 6.

The second choice we have for output is GO manufacturing output that includes all intermediate sales and is a nominal figure. The BEA is the source for this data. BEA describes the series as a measure of manufacturing sales or receipts, which can include sales to final users in the economy (GDP) or sales to other industries (intermediate inputs). Because it includes intermediate sales, it is significantly larger than the corresponding VA series. The nominal GO series is roughly 2.8 times the

---

11 Most definitions of single factor labor productivity use value-added output to avoid double counting intermediate inputs. However, as Schreyer (2001) has explained, the process of outsourcing, which has become so prevalent and controversial in manufacturing, will normally reduce the measured labor input while leaving gross output the same. This raises output per worker, and in our case productivity. By contrast, value-added output will decline with outsourcing and hence this attenuates the rise in productivity using VA output. It will therefore be useful to view the decomposition using both VA and GO output measures.

size of the nominal VA series and deviations range at most ±15% relative to this multiple over the entire period 1988-2018. Both FS output and GO output show similar behavior relative to VA output. Note that other studies of employment losses that use microeconomic-based analyses typically take factory shipment values as the nominal output variable and apply the personal consumption expenditure (PCE) deflator to get real values. These shipments obviously include intermediate values and are not value-added figures. The use of the PCE index to deflate is also problematic since shipments to other manufacturing plants should employ something like the producer price index for manufacturing as the deflator. Clearly, the problems of choosing an appropriate deflator are not solved even if we use micro-based or factory level data.

The third type of output considered is what we call FS (final user) manufacturing output. This output is nominal and is constructed from data taken from BEA I/O Use of Commodities by Industries tables showing manufacturing output sold to final users including private consumption (F010), private investment (F020), change in inventories (F030), government spending (F100), and exports (F040). The growth rates of FS and GO outputs have a sample correlation over the period 1989-2018 equal to 0.96. Thus, their behavior are very similar. We will focus our attention on VA output since it is the measure that most economists prefer to use.

Export and import data consist of total U.S. manufacturing exports and imports and U.S. exports and imports of manufactures from China, with all data obtained from the orld Integrated Trade Solution (WITS) online data tool at the World Bank. The World Bank states these trade data correspond to the sum of Standard International Trade Classification (SITC) Revision 3 two digit codes 50-89, excluding code number 68. We independently checked this by reproducing the data directly from the UN Comtrade database. For data covering China-U.S. trade we consistently use the same definition and the UN Comtrade (U.S. reporting country, China partner country) and sum the categories of manufactured products for each year in the relevant observation period. Note that both the total manufacturing trade series and that pertaining specifically to U.S.-China trade are taken from UN Comtrade using the same definition. These are nominal series and are therefore reduced to real values by the three deflators mentioned above to arrive at real net manufacturing imports used in the decomposition. No separate U.S.-China trade price indexes exist over the whole period of 1992-2018. The rest of the world (ROW) data are constructed by subtracting China trade from total manufacturing trade.

The remaining variable is y or average labor productivity, which is equal to output per employee in manufacturing since average working hours are constant. These data can be constructed from the real output and employment data collected above, so long as we restrict ourselves to the three periods defined as having relatively constant average hours worked.

4. Analysis of Decomposition Results

4.1 Analysis of Factors in Overall Job Losses and Gains

This sub-section discusses the empirical performance of growth in demand, productivity, and trade as they act collectively to determine the actual job gains or losses in U.S. manufacturing during the three periods of observation we have chosen.

The arithmetic averages of the growth rates in equation (5) assuming VA output are given in Table 3 below. To arrive at the actual growth (i.e., the resultant of the gains and losses) one takes the jobs created through growth in the demand for manufacturing goods, adds the job losses (generally negative for U.S.) due to average labor productivity growth in manufacturing, and then further adds the jobs lost (generally negative for U.S.) due to growth in manufacturing trade penetration; what we have called the trade factor, *d*.

Table 3 Variables Affecting Average Annual Growth and Absolute Change in U.S. Manufacturing Employment

Annual Growth Rates in Employment, Demand, Productivity, and Trade Factor (%)					
	Period	Employment	Demand	Productivity	Trade Factor
I	1992-2000	0.13	3.85	2.61	-1.11
II	2002-2007	-2.75	1.85	3.50	-1.10
III	2011-2018	1.21	2.32	0.48	-0.63
Changes in Employment, Demand, Productivity, and Trade Factor (thousands of persons)					
	Period	Employment	Demand	Productivity	Trade Factor
I	1992-2000	204	5,917	-4,007	-1,706
II	2002-2007	-2,716	1,817	-3,448	-1,085
III	2011-2018	1,113	2,138	-440	-585

Note: Decomposition of growth and change of Employment with respect to Demand, Productivity, and Trade Factor is based on equation (5) in the text. Real manufacturing output is defined as nominal value-added manufacturing output deflated by the manufacturing PPI. Period I is defined as 1992-2000, Period II is defined as 2002-2007, and Period III corresponds to 2011-2018. The trade factor d is identical to the ratio of manufacturing output to realized manufacturing domestic demand.

For simplicity of presentation, Table 3 focuses on VA manufacturing as the definition of output with the manufacturing PPI alone being used to deflate nominal to real output. The actual change in employment in Period I, shown in the lower panel column (2) of Table 3, was positive, amounting in total to a rise of 204,000 workers for the nine year period. The table shows that this actual change in employment in U.S. manufacturing occurred because of the interaction of the three main factors. The total number of jobs lost to trade in Table 3 for Period I was notionally 1,706,000 or roughly 190,000 per year on average. Over the 9 year period this enormous loss of potential jobs was offset by the concomitant rise in the domestic demand for manufacturing output, notionally raising employment 5,917,000 over the same nine-year period, while productivity growth notionally eliminated 4,007,000 employees. Thus, demand and productivity growth together created a net positive growth of 212,222 jobs per year on average. Period I was a time of great expansion in the U.S. economy; productivity naturally followed this growth pro-cyclically as it had done on previous occasions. It is clear from Table 3 during Period I that job losses due to trade in general (not just China) as a percentage of total job losses in the period was 29.9% (computed as 1,706,000/(1,706,000+4,007,000)) while 71.1% of manufacturing employment losses was due to productivity growth, correctly interpreted here as anything that raised output per worker during the period.

Period II of Table 3 summarizes the important span between the 2001 recession and the 2008-2009 recession. Period II is especially interesting since this is a time that saw a dramatic and unprecedented fall in manufacturing employment. In total, there were 2,716,000 jobs lost during Period II, much greater than Period I or III. Table 3 accounting indicates that domestic demand for manufactured goods expanded an anemic 1.85% on average in Period II (much less than the 3.85% growth per year of Period I). Productivity growth averaged about 3.5% per year and was clearly stronger than Period I productivity growth. Period II was thus a time of marked slower manufacturing do1estic demand growth and higher manufacturing productivity growth. Average growth in the manufacturing trade factor d was -1.10% per year in Period II, almost identical to the -1.11% per annum in Period I. Notional losses from total U.S. global trade imbalances stood at 1,085,000 in Period II.

In Table 3 productivity growth for Period III was dramatically lower than the previous two periods averaging a mere 0.48% per year. Productivity ceased being a major job killer in U.S. manufacturing during this eight year span. Notional losses due to productivity growth were a meager 440,000 (or 55,000 per year on average), while domestic demand growth rose to 2.3% generating 2,138,000 notional jobs. There was a loss of 585,000 jobs due to overall unbalanced trade of the U.S. with its global trading partners. The total effect of combined demand, productivity, and general trade resulted in a measured rise of 1,113,000 jobs during the eight years of 2011-2018. This represented the first sustained growth in manufacturing employment in the U.S. since the period 1993-1998. The increase in actual employment was the result of a substantial drop in productivity growth coupled with a medium growth in the demand for manufactures. Because of the weak and sometimes negative growth in productivity in 2011-2018, unbalanced trade with all countries including China was responsible for 57% of all notional job losses in Period III. Meaning that weak productivity growth was responsible for only 43% of notional job losses in manufacturing, a surprising reduction.

According to Table 3, trade with all countries in Period II was responsible for about 24% of all manufacturing jobs notionally lost, or roughly 1,085,000 jobs. This can be compared with 76% of notional job losses, or 3,448,000 jobs, that can be attributed to productivity growth during the same six year period. This figure is well below the 88% calculated by Hicks and Devaraj (2017) for losses in manufacturing employment due to productivity gains. Using instead the Manufacturing deflator or alternatively the Personal Consumption deflator on nominal value-added output in Table 3 shows that Period II productivity (trade) growth explains 81.8% (18.2%) and 78.7% (21.3%) of job losses, respectively. The averages across the three different deflators are 78.8% for productivity and 21.2% for trade. The bulk of notional job losses for Period II were still manifestly due to the growth of productivity. Our use of different deflators suggests that the overestimation of productivity gains, which Houseman (2018) has persuasively asserted exists, may be responsible for an upward bias of productivity's trade's impact on employment of no more than about 9-10 percentage points (e.g. Hicks and Devaraj (2017)'s 88% versus our average of 78.8%).

For value-added output, the behavior of labor productivity growth in manufacturing has been difficult to explain. Generally speaking productivity growth was relatively high during the 1990s and up to 2003, see Fernald and Wang (2015). After 2003 productivity tended to fall secularly and throughout the Great Recession of 2008-2009. Following the sharp rebound in 2010, labor productivity stagnated and actually contracted after 2014. It has since failed to recover the high productivity growth of Period I and Period II.

In general, Fernald and Wang (2015) claim that the use of information technology was what generated the high productivity gains in Period I and Period II. Houseman (2007) has claimed that outsourcing and offshoring activities of manufacturing firms artificially raised the measurement of productivity. For example, business services previously done in-house with employees of the manufacturing firm, are outsourced to an outside firm, so that output remains the same, but employment is reduced. This raises labor productivity for the firm. However, the stagnation of productivity in Period III cannot be fully explained by vertical integration and reshoring. The movement towards reshoring and reversing the trend in outsourcing is only beginning to gain momentum.

Economists have identified a number of different possible causes of the slowdown in productivity after the Great Recession. These would include: (1) re-acquisition of laid off workers naturally beginning with the most productive workers before turning to ever- increasingly less productive workers; (2) early returning workers gaining from early large increases in capacity utilization thus making them more productive than later acquired workers; (3) Summers (2015) who emphasizes the likelihood of a 1% mis-measurement problem with productivity growth and Gordon (2016) who asserts severe diminishing returns associated with the exhaustion of inventions and new ideas; (4) Bergeaud et al. (2019) who state that low real rates of interest allow poorly run manufacturing firms better opportunities to avoid bankruptcy, leading to poor investment and continued slow or falling productivity of their workers; and (5) greater health and environmental regulations forcing firms to reorient production and employ more workers who do not directly contribute to the production of output. All of these are possible reasons for the productivity slowdown in manufacturing during Period III. Some explanations have generated better acceptance than others, but the profession has not reached a consensus on exactly why productivity growth began falling in Period II and remained unusually low in Period III.

4.2 Analysis of China's Impact on U.S. Manufacturing Job Losses and Gains

Table 4 below provides the results of the decomposition of the trade factor into China (*c*) and the rest of the world (*ROW*). The results shown are for VA output only to save on space and narrow the focus. We have also averaged across the three manufacturing price deflators for nominal USD trade figures. Table 4 decomposition reveals the extent to which China trade affected manufacturing employment relative to total losses of employment due to trade only for the three periods

Table 4 The Impact of Trade Factor Growth on U.S. Manufacturing Employment from China (Ψ_C) and ROW (Ψ_{ROW})

	Period	Total Trade Factor Growth $\Delta d/d$	Ψ_C	Ψ_{ROW}	Total Employment Effect	China (*c*)	*ROW*
I	1992-2000	-1.04	-0.37	-0.67	-1,706	-603	-1,103
II	2002-2007	-1.15	-1.29	0.14	-1,085	-1,264	-179
III	2011-2018	-0.66	-0.13	-0.53	-585	-124	-461

Note: Trade factor growth ($\Delta d/d$) is an average annual percentage growth of net import penetration over the period and is divided into growth due to China (Ψ_C) and growth due to ROW (Ψ_{ROW}) as shown in equation (7). Corresponding employment effects for Total, China, and ROW are measured as the total change over the period measured in thousands of workers. Figures have been averaged across the three different manufacturing deflators.

For Table 4 in Period I, the overall trade growth factor $\Delta d/d$ is –1.04% which can be exactly divided between *c* (-0.37%) and *ROW* (-0.67%). Notional job losses for the period, are 603,000 (*c*) and 1,103,000 (*ROW*). Thus, China's unbalanced trade effect with the U.S.

was on average roughly 35.4% of the total trade effect due to all other countries combined for the period 1992-2000. In Period I, over a third of manufacturing employment losses, due exclusively to trade, were attributable to Chinese net penetration of the U.S. market. Note that this does not consider losses due to productivity which are discussed in Table 5.

Table 5 Measuring the Effect of the China Shock's on Employment

Value-Added (VA) Output	Average China Shock Losses	% of Total Losses
Period I 1992-2000	571,000	10.1
Period 2 2002-2007	1,269,000	23.1
Period 3 2011-2018	118,000	13.5
Final User (FS) Output	**Average China Shock Losses**	**% of Total Losses**
Period I 1992-2000	253,000	2.7
Period 2 2002-2007	474,000	7.8
Period 3 2011-2018	46,000	8.8
Gross Output (GO)	**Average China Shock Losses**	**% of Total Losses**
Period I 1992-2000	219,000	3.4
Period 2 2002-2007	452,000	8.4
Period 3 2011-2018	106,000	25.9

Note: Average China Shock losses refers to the average of losses for the three different types of price deflators given the particular definition of manufacturing output used. The % of Losses refers to the China shock losses relative to all trade based losses plus any losses due to productivity growth. Losses are not net of job gains due to growth in manufacturing domestic demand or any other positive change in jobs.

One important thing to note in Table 4 is that during Period II, the rest of the world had a positive impact on employment. This is true across all deflators and output types in the more detailed tables suppressed here to save space. Indeed, this is true, despite the fact that the rest of the world outside of China collectively ran significant surpluses with the

U.S. in manufacturing trade. This seemingly paradoxical fact is understood once the definition of Ψ_{ROW} is considered. The impact term Ψ_{ROW} is defined in equation (7) in Section 2 above. It is dominated by the percentage change in the net imports to output ratio. The ROW experienced rapidly falling surpluses in manufactures with the U.S. in Period II, just the opposite of China which experienced rising surpluses with the U.S. It is the falling surpluses that caused the employment impact of ROW in Table 4 to turn positive on average. In other words, China was acquiring a growing share of an expanding market in the U.S. manufacturing sector during Period II at the expense of ROW countries. In Table 4 China is clearly responsible for all of the job losses from unbalanced trade in manufactures during 2002-2007 since the impact on employment from ROW countries taken together as a group was positive due to collective declining surpluses with the U.S.[12] Focusing on value-added output, Table 4 shows that the total net losses during this time due to unbalanced trade were 1,085,000. During this period, China was responsible for 1,264,000 notional jobs lost while ROW countries were collectively responsible for offsetting average notional gains of 179,000 during Period II.

Table 5 makes use of more detailed versions of Tables 3 and 4 (available from the authors on request) to construct an average loss for each type of output across deflators and determine the percentage of total job losses from all sources that can be apportioned exclusively to China. The losses under VA output are of particular interest since many observers feel value-added output is the most appropriate type of output to be used in macro-based studies. Comparison of the job losses in Table 5 with the job losses estimated by other authors contained in Table 1 can

12 Not every country in the ROW set of countries had declining surpluses to output ratios with the U.S. and therefore China was not the only country responsible for reducing U.S. employment. The EU and Mexico both had net imports to output that experienced positive growth on average during Period II but were many orders of magnitude smaller than China. The comparison above that attributes 100% responsibility to China is the direct result of comparing China with the ROW collectively and not its individual members.

then be attempted. One problem with such comparisons is that the observation periods may not perfectly align. Another problem with direct comparisons is that causes for the losses vary across research works. In some cases, the cause is China import penetration, in other works the cause consists of U.S. net imports from China. While it is certainly true that exact comparisons cannot be made, such contrasts are nevertheless suggestive and provide a measure of support for many of the works in Table 1, especially as regards the important period 2000-2007.

We focus our attention on the results in Table 5 corresponding to VA output. For Period I the losses due to China, averaged across the three different deflators, was 571,000 jobs. This early period shows China had an impact on employment, but this impact still only represented 10.1% of total losses from all sources, including productivity growth and ROW trade. Productivity growth was by far the most important factor driving job losses. Actual employment in manufacturing rose slightly during this period due to an extraordinary increase in domestic demand for manufacturing. Our calculation of 571,000 jobs lost in Table 5 is surprisingly close to Autor et al. (2013) who estimated 590,000 losses during 1990-2000 using a different definition of China shock.

If we consider Period II figures in Table 5 for the case of VA output, job losses due to China on average across the three deflators was 1,269,000 or 23.1% of total losses from all sources, including productivity growth. This is about 30% higher than Autor et al. (2013) who estimated losses of 980,000 over the period 2000-2007. As we have commented above, some may find it surprising that during Period II, This is not so unexpected since Period II was a time when East Asian supply lines were being re-routed through China and thus ROW trade naturally acted as a compensatory offset to the negative China shock. This was especially true during 2005-2007 when ROW collective surpluses with the U.S. relative to manufacturing output fell. In any event, productivity growth was especially strong during this time and was overwhelmingly responsible for the bulk of job losses (nearly 80%). Both Feenstra et al. (2017) and Caliendo et al. (2019) found lower levels of losses during

Period II at 400,000 and 550,000, respectively, which were roughly 1/2 to 1/3 of our losses, respectively. Acemoglu et al. (2016) found losses over a slightly longer period of about 560,000, again roughly half of our calculated losses. However, they also modified their model to account for upstream and downstream interactions with China and found about 1 million jobs lost altogether. This is close to our finding of 1,269,000. Asquith et al. (2019) found losses of 2,100,000 over the period 1992–2007 and by adding our Period I and Period II results for VA output we get about 1.8 million which is again reasonably close to their estimated losses. It should be emphasized that the observation periods do not perfectly align and that the definition of China trade shock is often different in many of these works. Overall, several of the results we obtain over the three periods are reasonably close to those that other researchers have found. Some of our results however show a larger impact from China net trade imbalances. We attribute this to their lack of consideration of demand growth minus productivity growth which would force trade to have a larger effect. On the whole, there is reasonable coherence with the results taken from multiple works in Table 1, despite the use of different methods, data sets, causes, and nonidentical observation periods. China’s impact on U.S. manufacturing employment was noteworthy, especially in Period II, but productivity growth, broadly defined, was clearly the major job destroyer.

Table 5 figures show that the China shock was already affecting U.S. manufacturing employment in the 1990s, although it was relatively small when compared with the combined trade shocks from ROW countries taken together and the effect of massive productivity growth. This is true regardless of the deflator used to reduce nominal values to real values. The China shock became more concentrated in Period II but moderated late in the period by offsets from trade with the rest of the world. Productivity growth and not trade was the major reason for the fall in employment in Period II.

Period III saw a dramatic fall in productivity growth coupled with moderate growth in demand; this intensified the impact from the China shock on job losses. Note that Acemoglu and Restrepo (2019) claim over the last three decades there has been a strong displacement effects of automation for workers in manufacturing but a steady weaking of productivity growth. We do not believe that automation has been a significant force in reducing the number of jobs in manufacturing during Period III. Instead we feel that this unusual result of increased automation and low productivity growth is explained by discrepancy between well run firms that have automated and much more numerous poorly run firms that have not automated. The productivity gains of the best firms have been more than offset by the worst firms – hence we have automation with near zero productivity growth. The alternative explanation to this is that productivity has been horribly mis-measured. Overall employment in manufacturing rose during this time and productivity barely grew at all.

For the whole period 1992-2018, China was responsible for a weighted average of 14.7% of total job losses assuming value-added output. However, during Period III these losses were greatly offset by growth in domestic demand for manufactures and slow or even falling productivity growth which required the employment of more labor to produce sufficient output to satisfy growing demand. Indeed, Period III experienced an actual gain of over 1.1 million net manufacturing jobs in the U.S.

The structure of this narrative is the same regardless of the type of output or deflator one uses. The decomposition we have used sidesteps the issue of how the key variables adjust with each other intra-period. The model's strength is that it shows how the key variables end up after all such contemporaneous equilibrating adjustments and positioning have occurred and the collected employment losses then combine to produce actual job losses. Beyond this, the model is silent and will remain so without extending the analysis using detailed, high frequency data on all variables involved in the equilibrating process, combined in a suitably dynamic way. In the future, with higher frequency data, a structural VAR model might be able to more precisely estimate the extent that the China shock influenced employment in U.S. manufacturing.

5. Conclusions

Over the past two decades enormous efforts have been made to ascertain the extent to which unbalanced trade in U.S. manufacturing (and with China, in particular) has affected U.S. manufacturing employment. This topic has weighed heavily on the collective mind of the U.S. public and has influenced elections and public policy. The jarring loss of over five and a half million U.S. manufacturing jobs after 1998, with China's concomitant ascendancy in manufacturing, has led some to conclude that the bulk of these employment losses can be directly attributed to China's steady encroachment on U.S. markets.

Using a simple model that accounts for employment in manufacturing by the logical combination of the definition of productivity and the assumption of continuous clearing of product markets, it is possible to decompose manufacturing employment growth into growth in domestic demand for manufactures, productivity in manufacturing, and net imports of manufactures per dollar real output in manufacturing.

Dividing the observed data into three separate periods corresponding to spans where average hourly workweeks in manufacturing are relatively constant and focusing on a value-added definition of manufacturing output, it is shown that for the period 1992-2000 approximately 571,000 jobs in U.S. manufacturing were lost to Chinese unbalanced trade in manufactures with the U.S. Over the period 2002-2007 roughly 1,269,000 U.S. manufacturing jobs were lost due to the China shock. The final span of 2011-2018 had China's unbalanced trade causing the loss of 118,000 U.S. manufacturing jobs. These job losses should be considered notional since rising demand and productivity, along with growth in trade with the rest of the world, also generated notional changes in jobs that when combined produced the observed or actual data on losses or gains.

The calculation of job losses from all sources allows an evaluation of the importance of China to overall changes in U.S. manufacturing unemployment. Again, focusing on value-added output, the losses due to

China's unbalanced trade with the U.S. in manufacturing relative to all losses were 10.1%, 23.1%, and 13.5% during the periods 1992-2000, 2002-2007, and 2011-2018, respectively. China was seen to have played a significant role in job losses in America, but the data clearly indicates that for the first two periods, growth in productivity was far and away the most impactful variable generating around 75% of all job losses in U.S. manufacturing. Moreover, during the final period 2011-2018 slowing and possibly even falling labor productivity was sufficient to contribute to a rise in manufacturing employment. The results of the present study are reasonably coherent with the estimates from numerous other well-known works published over the past decade and adds to a growing literature showing roughly consistent outcomes. The structure (but not the magnitude) of losses remains roughly constant across three different output measures. And the use of three different deflators mitigates against possible bias from over emphasizing productivity gains due to changes in the computer and electronic equipment industry.

References

Acemoglu, D., D. Autor, D. Dorn, D. Hanson, and B. Price (2016), "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34:1, 141-198.

Acemoglu, D. and P. Restrepo (2019), "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 33:2, 3-30.

Asquith, B., S. Goswami, D. Neumark, and A. Rodriguez-Lopez (2019), "U.S. Job Flows and the China Shock," *Journal of International Economics*, 118, 123-137.

Atkinson, R. D., L. A. Stewart, S. M. Andes, and S. Ezell (2012), *Worse Than the Great Depression: What Experts Are Missing about American Manufacturing Decline*, Washington, D.C.: The Information Technology & Innovation Foundation.

Autor, D. H., D. Dorn, and G. H. Hanson (2013), "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103: 6, 2121-2168.

Autor, D. H., D. Dorn, and G. H. Hanson (2015), "Untangling Trade and Technology: Evidence from Local Labour Markets," *The Economic Journal*, 125:584, 621-646.

Autor, D. H., D. Dorn, and G. H. Hanson (2016), "The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade," *Annual Review of Economics*, 8, 205-240.

Bergeaud, A., G. Cette, and R. Lecat (2019), "The Circular Relationship Between Productivity Growth and Real Interest Rates," Banque de France Working Paper No. 734.

Bernard, A. B., V. Smeets, and F. Warzynski (2017), "Rethinking

Deindustrialization," *Economic Policy*, 32:89, 5-38.

Bivens, J. (2004). "Shifting Blame for Manufacturing Job Loss: Effect of Rising Trade Deficit Shouldn't Be Ignored," Economic Policy Institute Briefing Paper No. 149.

Bloom, N., K. Handley, A. Kurman, and P. Luck (2019), "The Impact of Chinese Trade on U.S. Employment: The Good, The Bad, and The Debatable," Society for Economic Dynamics, 2019 Meeting Papers 1433, https://economicdynamics.org/meetpapers/2019/paper_1433.pdf. (accessed January 23, 2022)

Caliendo, L. and M. Dvorkin, and F. Parro (2019), "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica*, 87:3, 741-835.

Charles, K. K., E. Hurst, and M. Schwartz (2018), "The Transformation of Manufacturing and the Decline in U.S. Employment," NBER Working Paper No. 24468.

Ebenstein, A., M. McMillan, Y. Zhao, and C. Zhang (2012), "Understanding the Role of China in the "Decline" of U.S. Manufacturing," *Unpublished Manuscript*, https://pdfs.semanticscholar.org/8ea5/3d80c1ac75f705a 061fd78acf91a3984fcdc.pdf. (accessed January 23, 2022)

Eriksson, K., K. Russ, J. C. Shambaugh, and M. Xu (2019), "Trade Shocks and the Shifting Landscape of U.S. Manufacturing," NBER Working Paper No. 25646.

Feenstra, R. C., H. Ma, and Y. Xu (2017), "U.S. Exports and Employment," NBER Working Paper No. 20456.

Feenstra, R. C. and A. Sasahara (2018), "The 'China Shock', Exports and U.S. Employment: A Global Input-Output Analysis," NBER Working Paper No. 24022.

Fernald, J. and B. Wang (2015), "The Recent Rise and Fall of Rapid Productivity Growth," FRBSF Economic Letter, Federal Reserve Bank of San Francisco, https://www.frbsf.org/wp-content/uploads/sites/4/el2015-04.pdf.

Fort, T. C., J. R. Pierce, and P. K. Schott (2018), "New Perspectives on the Decline of US Manufacturing Employment," *Journal of Economic Perspectives*, 32:2, 47-72.

Gordon, R. J. (2016), *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*, Princeton and Oxford: Princeton University Press.

Hicks, M. J. and S. Devaraj (2017), "The Myth and the Reality of Manufacturing in America," Ball State University Center for Business and Economic Research, April 2017, https://conexus.cberdata.org/files/MfgReality.pdf. (accessed January 23, 2022)

Houseman, S. N. (2007), "Outsourcing, Offshoring, and Productivity Measurement in U.S. Manufacturing," *International Labour Review*, 146:1-2, 61-80.

Houseman, S. N. (2018), "Understanding the Decline of U.S. Manufacturing Employment," Upjohn Institute Working Paper No.18-287.

Kimball, W. and R. E. Scott (2014), "China Trade, Outsourcing and Jobs: Growing U.S. Trade Deficit with China Cost 3.2 Million Jobs between 2001 and 2013, with Job Losses in Every State," Economic Policy Institute Briefing Paper No. 385.

Kollmeyer, C. (2009), "Explaining Deindustrialization: How Affluence, Productivity Growth, and Globalization Diminish Manufacturing Employment," *American Journal of Sociology*, 114:6, 1644-1674.

Lanvin, B., P. C. M. Mar, Christine Zhen-Wei Qiang, and F. Jürgen-Richter (2003), "Born Global: The Impact of the WTO Process on China's ICT Competitiveness," in *The Global Information Technology Report 2002-2003: Readiness for the Networked World*, ed., Soumitra D., B. Lanvin, and F. Paua, 162-177, New York: Oxford University Press.

Lawrence, R. Z. and L. Edwards (2013), "U.S. Employment Deindustrialization: Insights from History and the International Experience," Peterson Institute for International Economics, Policy Brief No. PB13-27.

Lawrence, R. Z. (2017), "Recent US Manufacturing Employment: The Exception that Proves the Rule," Peterson Institute for International Economics Working Paper No. 17-12.

Lin, G., F. Wang, and J. Pei (2017), "Global Value Chain Perspective of US–China Trade and Employment," *The World Economy*, 41:8, 1941-1964.

Magyari, I. (2017), "Firm Reorganization, Chinese Imports, and US Manufacturing Employment," CES Working Paper No. 17-58.

Mankiw, N. G. (2003), "China's Trade and U.S. Manufacturing Jobs," in *Testimony Before the House Committee on Ways and Means*, Washington, D.C.: Council of Economic Advisers, https://georgewbush-whitehouse.archives.gov/cea/mankiw_testimony_house_ways_and_means_oct_30.html.

Rowthorn, R. and R. Ramaswamy (1997), "Deindustrialization: Causes and Implications," IMF Working Paper No. WP/97/42.

Schreyer, P. (2001), "The OECD Productivity Manual: A Guide to the Measurement of Industry-Level and Aggregate Productivity," *International Productivity Monitor*, 2, 37-51.

Scott, R. E. (2012), "The China Toll: Growing U.S. Trade Deficit with China Cost More Than 2.7 Million Jobs between 2001 and 2011, with Job Losses in Every State," Economic Policy Institute Briefing Paper No. 345.

Scott, R. E. (2013), "Trading Away the Manufacturing Advantage: China Trade Drives Down U.S. Wages and Benefits and Eliminates Good Jobs for U.S. Workers," Economic Policy Institute Briefing Paper No. 367.

Scott, R. E. (2017), "Growth in U.S.–China Trade Deficit between 2001 and

2015 Cost 3.4 Million Jobs: Here's How to Rebalance Trade and Rebuild American Manufacturing," Economic Policy Institute, Washington, D.C., https://files.epi.org/pdf/114752.pdf. (accessed January 23, 2022)

Scott, R. E. and Z. Mokhiber (2018), "The China Toll Deepens: Growth in the Bilateral Trade Deficit between 2001 and 2017 Cost 3.4 Million U.S. Jobs, with Losses in Every State and Congressional District," Economic Policy Institute, Washington, D.C., https://files.epi.org/pdf/156645.pdf. (accessed January 23, 2022)

Scott, R. E. and Z. Mokhiber (2020), "Growing China Trade Deficit Cost 3.7 Million American Jobs between 2001 and 2018," Economic Policy Institute, Washington D.C., https://files.epi.org/pdf/181374.pdf. (accessed January 23, 2022)

Summers, H. L. (2015). "Keynote Address: Reflections on the Productivity Slowdown," in the Conference on Making Sense of the Productivity Slowdown, November 16, 2015, Peterson Institute for International Economics, Washington, D.C..

評估中國貿易對美國製造業之就業的影響

游雅雯、柯大衛*

摘　要

自 2000 年起，中國的擴大貿易被懷疑是導致美國和其他地區製造業就業人數下降的原因。另一種觀點則指出，相對於製造業的需求，對服務業的需求有所上升，加上勞動生產力的持續增長，才是導致製造業就業機會流失的原因。本文旨在計算自 1992年起中國貿易對於美國製造業工作機會流失的影響。本文將製造業就業增長分解為製造業需求增長、生產力增長和貿易增長。其次，本文將整體貿易的增長區分為美國和中國之間的貿易，以及美國與中國以外的其他地區之間的貿易。就附加價值的產出而言，本研究發現在 1992 年至 2000 年期間，中國直接造成了 571,000 個工作機會的流失，佔全美所有來源的製造業工作機會流失總數的 10.1%。在 2002 年至 2007 年期間，中國造成了 1,269,000 個製造業工作機會流失，佔製造業就業流失總數的 23.1%。在 2011 年至 2018 年期間，中國則造成了 118,000 製造業工作機會的流失，佔製造業工作人數流失總數的 13.5%。此外，本研究的分解結果發現，在 1992 年至 2000 年和 2002 年至 2007 年期間，美國製造業中約 75% 的製造業工作機會的流失是由於生產力增長所導致的。相比之下，在 2011 年至 2018 年期間，由於生產力的下降以及市場需求的增加，反而造成美國製造業增加了 100 萬個以上的工作機會。

關鍵詞：製造業、就業、生產力、中國衝擊、貿易赤字
JEL 分類代號：F14, F15, J01, J23, P23

* 兩位作者分別為聯繫作者：游雅雯，國防大學國際安全研究所副教授，334301 桃園市八德區興豐路 1000 號，電話：03-3657891，E-mail: yawenyu1@gmail.com；柯大衛，淡江大學東協研究中心學術研究顧問，251301 新北市淡水區英專路 151 號，電話：02-26215656 轉 3615，E-mail: davidkleykamp@gmail.com。
作者由衷感謝兩位匿名審查委員對本文的寶貴意見與建議，文責由作者自負。

投稿日期：110 年 3 月 24 日；修訂日期：民國 110 年 7 月 27 日；
接受日期：111 年 1 月 5 日。