Understanding the Role of China in the "Decline" of US Manufacturing*

Avraham Ebenstein
Hebrew University of Jerusalem

Margaret McMillan
Tufts University

Yaohui Zhao
Peking University

Chanchuan Zhang
Peking University

November 2011

Abstract: This paper examines China's role in declining US manufacturing employment and increasing productivity. We present a set of empirical facts using micro-census data from 1990 and 2005 that suggest that rapid increases in trade between the two countries has been underestimated as an explanation for these trends. First, Chinese employment growth has been largest in industries with US employment declines, suggesting substitution between US and Chinese workers. Second, during the sample period, while the share of workers performing routine occupations in the US declined, the share increased in China, and these changes were correlated across industries. We also find correlated increases in the manager to worker ratio in the US and declines in this ratio in China, implying that more routine tasks of the production process are being sent overseas. Third, we document that Chinese employment growth by industry is highly correlated with declining unit labor costs and productivity growth in the US, suggesting that the rapid US productivity growth is directly related to trade with China. We then examine the association between Chinese employment growth and profits and wages among US firms and workers. We find that within manufacturing, Chinese employment growth is correlated with corporate profit growth and increasing wage inequality among the remaining US manufacturing workers. Our results suggest that the role of technological progress (e.g. automation) may be overstated relative to trade-based explanations for recent trends in productivity growth and employment decline in US manufacturing.

---

*Corresponding author: ebenstein@mscc.huji.acil.. Excellent research assistance was provided by Michael Freedman, Jacob Levine, Hillel Levin, and Susan Schwartz. Special thanks to Dani Rodrik and Robert Lawrence for helpful conversations, and David Autor and David Dorn for providing data critical to our analysis

I. Introduction

Between 1960 and 1990, the American manufacturing industry employed roughly 18 million workers. Jobs in this sector provided workers relatively high wages and generous benefits packages. While manufacturing declined as a share of the US economy during this period, it retained importance by keeping local economies viable in many cities, providing opportunities for less skilled workers to enter the middle class. However, the last two decades have been far less kind. Employment declined modestly in the 1990s, as import competition reduced domestic employment in textiles and other labor intensive industries. But since communication technology improvements (e.g. internet) of the late 1990s, the decline has been precipitous in domestic employment. Since 1999, firms have shed nearly 7 million domestic workers, leading to higher unemployment in local labor markets (Autor et al. 2011).

Conventional wisdom is that automation and the rapid adoption of computer-aided production processes are responsible for the decline in manufacturing employment. In this view, new technology is largely responsible for the accelerating job loss, as this period has coincided with rapid increases in labor productivity as measured by the Bureau of Labor Statistics (BLS). Edwards and Lawrence (2011) articulate this view in a recent paper, which argues that the secular decline in manufacturing's share of the economy has been accelerated by technical change and that imports have played only a small role in the demise of the US manufacturing worker. They argue that rapid technological advance in the manufacturing sector, like the agricultural sector in the previous century, simple does not need as many workers to produce enough to meet the needs of the consumer. However, an alternative hypothesis is gaining traction among economists that technology is *not* in fact responsible for the demise of the American manufacturing worker. Rather, a "new trade" in tasks is seen as responsible for the trends in manufacturing, where workers are given orders from US managers, and companies can relocate almost any task overseas (Antras et al. 2006). This has led to fundamental re-organization of the global supply chain, with detrimental effects on domestic manufacturing workers and surging corporate profits.

In this paper, we will argue that the increase in the growth rate of American productivity is most likely the *result* of trade, rather than a competing explanation for the decline in domestic labor demand in manufacturing. We present several pieces of evidence in favor of our hypothesis, such as showing that the uptick in productivity growth in US manufacturing coincides in a striking way with the increase in timing of offshoring to China. The productivity growth is also concentrated in industries that have expanded in China.

Trade can induce productivity growth through three primary channels: increased productivity of existing firms; the forced exit of less productive firms (Melitz 2003); or a "batting average effect", whereby the more labor-intensive tasks are performed more cheaply overseas, and the remaining workers in the US are on average more productive. This effect, if large, implies that the productivity increase is to some extent an artifact of the accounting method by which productivity is recorded, and does not reflect any *new* technology being employed (Houseman 2007).[1] We will present evidence in favor of this third hypothesis.

In this paper, using detailed microdata on workers and firms in the United States and China, we examine how the structure of both countries' economies have evolved in the wake of globalization and the role these shifts have played in US employment and productivity in manufacturing. We document large declines in employment in the US in certain sectors of manufacturing, and a correlated increase in employment in China. Furthermore, we find that

[1] This point was first made by Houseman (2007), who argues that productivity statistics in manufacturing should be interpreted with caution in light of the sensitivity of productivity calculations to accounting for cheaper inputs.

routine tasks employment has *grown* as a share of the manufacturing labor force in China, suggesting that it is not simply technical change that has replaced the American manufacturing worker. Rather, US workers are occupying a higher link in the value chain and ceding these lower skill tasks to Chinese workers. This hypothesis is further supported by the rising manager-worker ratio in the US, and a fall in this ratio in China that is highly correlated across industries.

We examine the performance of US manufacturing firms in the wake of trade with China. Trade is anticipated to lead to lower prices, as firms pass the benefit of productivity increases or lower costs of production on to consumers. However, we will show that firms have been able to absorb the cost savings as increased profits at least in part. During the window of increased offshoring to China, US manufacturing firms experienced robust growth in profits. Many successful American firms, such as Apple Co., have successfully relocated their production processes to non-unionized plants in China. Not only does our period of analysis coincided with robust profit growth among US firms, but this windfall is also largest in industries with the largest expansion of employment in China. Our results suggest that the trade differentially benefited domestic US manufacturing firms, with benefits to workers or consumers being more modest. This is also consistent with a recent analysis of China's Special Economic Zones that local wages only rose modestly during the period, allowing firms to capture much of the windfall from globalization (Ebenstein 2011). The data also highlight the disparity between public perception of an American manufacturing sector in decline, and the reality of firms' terrific financial performance.

Our results also suggest that trade may have played a considerable role in increasing wage inequality in the US. We examine the relationship between within-industry wage inequality and Chinese employment, and find a robust association – which is perhaps unsurprising, since it is generally “middle skill” production workers who are relocated, leaving industries with managers and lower skill clerical workers in place. While we do not explicitly examine the fate of workers who are displaced from manufacturing in this paper, these workers generally experience large wage losses (Ebenstein et al. 2009), and so the evidence here of trade-induced employment shifts suggests that rising US wage inequality may be intimately connected with the offshoring phenomenon. We argue that the skill-biased technical change argument for explaining rising wage inequality may be worth revisiting, as trade-induced employment declines in production would have a similar effect on the wage distribution and could explain polarization of the occupational distribution (Autor, Katz, and Kearney 2008; Firpo, Fortin, Lemieux 2011).

The rest of the paper is laid out as follows. In the second section, we present background information on trade between China and the US, and briefly summarize the existing literature on identifying trade’s role in the changing structure of the US economy. Section 3 summarizes the theoretical predictions relevant to our analysis. In Section 4, we present our empirical results and in Section 5, we conclude.

II. Background

In the last 60 years, the world economy has becoming increasingly globalized. In the wake of World War II, formal barriers to trade have been lowered and the flow of capital across national boundaries has increased rapidly. Institutions in support of free trade have been established, such as the World Trade Organization (WTO), which allow countries to commit to low tariffs in return for reciprocity from other member states. Developing countries’ exports, once consisting of mainly natural resources and agricultural products, have now expanded into labor-intensive and lower value-added manufactured goods (Spence 2011). China’s accession to the WTO in 2001 represented a watershed event, highlighting the country's increasing integration into the world economy. China's integration has coincided with rapid job losses in manufacturing in developed countries such as the United States, which has generated a heated scholarly and political debate regarding the welfare implications of the new global economy.

Many economists take a sanguine view of trade's potential to harm workers, and argue that the decline of US manufacturing was unavoidable. Edwards and Lawrence (2011) champion this view in their influential paper. They point to what happened in the agricultural sector for a guide to what is now happening in the manufacturing sector. "Faster productivity growth allowed the US to meet its growing need for food (and that of many foreigners) while at the same time redeploying workers to other parts of the economy. The same is now true for manufactured goods." They posit that the particular combination of relative productivity and demand growth is responsible for the steady decrease in American manufacturing employment. Davis et al. (1992) support this view, finding that most job creation and destruction in manufacturing plants resulted from individual plant-specific shocks such as implementation of new technology, firm reorganization, new strategies, and domestic outsourcing. However, in recent years, following the rapid advance in information technology and the declining costs of communication overseas; economists have become more sympathetic to the possibility that "task trade" represents a fundamental shift in the importance of trade for explaining US employment shifts (Grossman and Rossi-Hansberg 2008). Spence (2011) suggests that this new reality allows firms to produce sub-components of almost *any* manufactured good in developed countries, even while keeping more complex tasks within the US, such as product design and management.

The debate regarding trade's impact on US employment also has relevance for a longstanding argument within the literature attempting to explain rising US wage inequality during the 1980s and 1990s. A popular explanation for this trend is skill-biased technological change, in which higher-skill workers were able to capitalize on the computer but lower-skill workers performing routine tasks found themselves replaced by technology (Autor et al. 2003). In this view, rising US wage inequality was inevitable, and other factors such as declining real minimum wages (Lee 1999) or de-unionization (Dinardo et al. 1995) are less critical. However, in our empirical results section, we present evidence that (to some extent) US production workers performing routine tasks were not replaced by machines but rather by Chinese workers, suggesting that at least to some extent US workers were forced to compete with cheaper Chinese workers. This may be a partial explanation for *why* the US experienced declines in real minimum wages and unionization rates, as foreign wage pressure required states and workers to adjust to the new global economy. As we will show in our empirical results, the patterns observed in our manufacturing employment data, where US declines are followed by growth in China, are difficult to reconcile with a fully technology-based explanation for the job loss, and represents an important alternative explanation for rising US wage inequality.

III. Theoretical Predictions

In the wake of globalization, a rich theoretical literature has developed to explain the changes observed in both developed and developing countries. Trade theory that examines the expected impact of China's entry into global markets often begin with the standard insight of the Heckscher-Ohlin (H-O) model, which predicts that countries will specialize in goods that require a resource-abundant input good. In China, cheap unskilled labor is a relatively abundant resource and developed economies, such as the United States, have a greater supply of other resources, such as capital and high-skilled labor. As predicted by the H-O model, in the wake of China's liberalized trade policy, the US data reflect a decline in employment in industries that employ workers who perform “routine” tasks, and a concurrent increase in imports in these industries (Ebenstein et al. 2009). Insofar as foreign workers can perform routine tasks easily and multinational parent corporations can easily monitor them (Grossman and Rossi-Hansberg 2008), these tasks will be the first to be sent overseas.

Antras et al. (2006) consider a 1 sector, 2 country model in which large declines in communications costs enable the formation of North-South teams. They argue that the “globalization” equilibrium, wherein Northern workers can team up with Southern workers at no additional expense, will lead to international teams in which Northern managers supervise teams of Southern workers. They predict in their model that wage inequality will be higher in the South following these changes: “Globalization improves the quality of managers with whom Southern workers are matched, thus raising the productivity of these workers, and thereby leading to an increase in the return to skill. This effect is reinforced by an occupational choice effect: more agents become workers, hence increasing the range of abilities in the worker distribution”. This paper explains how globalization may lead to increasing wage inequality, as US managers are able to more profitably capitalize on their talent but force US production workers into competition with their lower wage Chinese counterparts. As we will demonstrate, this model matches a set of empirical facts that are observed in US and Chinese census data, including a shift away from routine tasks in the US and a shift *towards* these tasks as a share of manufacturing employment in China.

III. Data and Summary Statistics

A. Data Description

Our sample of US workers is taken from the Integrated Public Use Microdata Series (IPUMS) for 1990 (5% sample), 2000 (5% sample), 2005 (1% sample), and 2009 (1% sample). These samples provide data for millions of workers who are assigned a consistent classification of their industry and occupation, and provide information on wages, employment status, and basic demographic characteristics. Our sample of Chinese workers is taken from the Chinese national census for 1990 (1% sample), 2000 (0.1% sample), and 2005 (0.2% sample). These samples provide data on industry classification and occupation. We supplement these data with the Urban Household Survey, which provides wage data and employment status.

Our labor productivity data are produced by the US Bureau of Labor Statistics, and is available for the years 1950-2010. In addition, these data provide annual data on the number of US workers in manufacturing. These employment data are complemented by employment data provided by COMPUSTAT for 1980-2010. We rely on the COMPUSTAT North American firm database, which provides annual data on employment, profits, and other financial outcomes for all publicly traded firms. Note that in the COMPUSTAT data, firms report both domestic and foreign employment, and profits are recorded for global operations.

In our empirical analysis, we divide the US and Chinese economies into 64 sectors, and use a set of concordances to create consistent industry categories across year and country (see Appendix Table 1). Following Dorn (2007), we also divide workers into one of 14 consistent occupation categories (see Appendix Table 2).[2] Following Autor et al. (2003), we examine the task content of occupations using Standard Occupation Classification (SOC) definitions. We aggregate their five different measures of the routine-ness of tasks into a single index for each occupation *k*. Two indicators measure how routine manual and cognitive tasks are (Routine

[2] Special thanks to David Autor and David Dorn for extreme generosity in sharing these data with the authors for the US.

Manual$_i$ and Routine Cognitive$_i$, ranging from 1 for not routine to 10 for fully routine). The index of routine-ness by worker education level, industry, and year is given by:

$$Routine_k = \frac{Routine\,Cognitive_k + Routine\,Manual_k}{Routine\,Cognitive_k + Routine\,Manual_k + DCP_k + EFH_k + Math_k}.$$

The index ranges from 0 to 1.[3] The input tasks include routine cognitive and routine manual, non-routine analytic, non-routine interactive, and non-routine manual. The last three terms refer to cognitive tasks that are higher order in their complexity, and presumably are associated with larger costs of performing outside of a firm's central location.

B. Summary Stats

Table 1 provides summary stats on the employment structures of the US and Chinese economies. We exclude from our sample people who report being out of the labor force in both countries, and exclude the unemployed in China due to inconsistency in this variable across the Chinese samples. We divide the economy into five sectors: agriculture, manufacturing, construction, services, and unemployed. Several structural trends are evident. Manufacturing employment has dropped in the US from about 18% of the workforce in 1990 to 11% in 2009, which translates into about 5 million lost jobs. Services employment has increased in the US by 3 percentage points, which translates into about 25 million additional jobs, presumably driven in part by absorption of the manufacturing workers. For the US, we observe an increase in the unemployed by roughly 3% of the labor force, translating into 8 million lost jobs.

While the number of manufacturing jobs has decreased steadily in the US, the employment numbers in China indicate a steady increase in manufacturing jobs. As shown in Table 1, Chinese workers have been leaving agriculture in massive numbers, and concurrent

[3] See Autor et al. (2003) for a thorough description of these variables. Our calculation of routine is the sum of routine manual tasks (Finger Dexterity) and routine non-manual (Set Limits, Tolerances or Standards), as a share of those tasks and non-routine manual (Eye, Hand, Foot), non-routine analytic (General Educational Development, Mathematics), and non-routine interactive (Direction, Control and Planning) tasks. See also the data appendix.

increases in manufacturing and service employment. China's manufacturing sector increased by 3 percentage points of the economy from 1990 to 2005, translating into 25 million additional jobs.

Table 2 provides summary statistics for the wage levels and wage inequality in the US and China. Several empirical facts are noteworthy. First, manufacturing jobs pay better in the US on average, implying a potential loss in average wages simply by the changing composition of the workforce. In 2005, the mean salary in manufacturing was $3,903 monthly while the mean salary in services was $3,446, a 13% difference. However, in China the striking change is the movement in manufacturing and services, which are both characterized by higher wages than agriculture. In 2005, the mean salary in agriculture in China was $98 monthly, while the mean salary in manufacturing was $274 monthly, almost a 400% increase. Third, American firms have a large incentive to replace American workers with Chinese workers. The mean monthly salary for a US manufacturing worker in 2005 of $3,903 is about fifteen times the amount for a Chinese, adjusted for Purchasing Power Parity.[4] While many American policymakers decry China's weak Yuan policy, the table provides suggestive evidence that a stronger *Yuan* would increase the dollar-denominated labor costs of Chinese labor but only represent an inframarginal change for many firms making plant-location decisions. A third striking pattern in the wage data is increased wage inequality in both the US and China. While data limitations in our Chinese data prevent rigorous analysis of explanations for the increase in wage inequality in China, the data indicate China's experience of rising inequality mirrors the US experience. Also note that Chinese wage inequality is also partly attributed to shifting towards more service sector employment, which interestingly provides *higher* monthly wages than manufacturing.

[4] Exchange rates during the period between China and the US indicate 1 ¥=$0.125. We employ a PPP index where ¥1=$0.25.

IV. Empirical Strategy and Results

A. Empirical Strategy

In our empirical analysis, the primary unit of analysis is the industry. Consider the following relation that can be estimated in our data:

$$S^{US}_{j,2005} - S^{US}_{j,1990} = \alpha_j + \beta * [S^{CN}_{j,2005} - S^{CN}_{j,1990}] \qquad (1)$$

where *S* is the share of the economy's working population in industry *j*, and our interest lies in changes between 1990 and 2005 in these shares. Note that economy is divided into 64 sectors, with 32 within manufacturing. Our analysis is not structural in nature; rather, we examine the covariance between changes in the US and China and examine what they imply regarding different explanations for the trends in employment and other variables of interest. Equation (1) is the first model estimated in our empirical results, and slightly different versions are estimated throughout the results section, focusing on how the changing share of Chinese employment is correlated with trends in US trends in employment, profits, productivity, and wage inequality. Our empirical analysis also examines variation in the occupational mix across industries, to examine *which* types of workers have become more or less prevalent in the two countries. Consider the following identity:

$$S^{US}_{j,2005} = \sum_{k=1}^{k=14} \delta_k Occ_k$$

where we decompose the US economy in 2005 into its *j* industries and further examine their 14 principal occupation categories. Each occupation is assigned task content information and whether it can be regarded as "managerial" versus "production". As in Ebenstein et al. (2009) we consider the routine content of each occupation:

Each industry has a shifting composition of occupations in each sample, wherein we observe the task content of each occupation.

B. Empirical Results

In Table 3, we examine the correlation between changes in US and Chinese manufacturing employment. For both countries, we calculate each industries share of the labor force in each sample, with the shares summing to 1 across all industries. For both countries, we calculate the change in each industry's share of the economy. All regressions are weighted by the industry's share of US employment in 1990, prior to the large increase in US-China trade.

Column 1 indicates that a one percentage point increase in Chinese manufacturing employment between 1990 and 2005 is associated with a -0.341 percentage point decrease in American manufacturing employment, statistically significant at the 5% level. Columns 2 and 3 indicate that the employment changes were evenly spread over the time period, with correlated employment shifts between sectors occurring between 1990-2000 and 2000-2005 when these periods are examined separately. Interestingly, the most statistically significant result is found column 4, where we examine the trends from 1990-2009, where we are forced to use Chinese data for 2005 in lieu of employment data for 2009. The result indicates that a one percentage point increase in Chinese manufacturing employment between 1990 and 2009 is associated with a -0.365 percentage point decrease in American manufacturing employment, with the larger coefficient possibly explained by the Great Recession of 2008, in which US firms laid off many manufacturing employees.

Figure 2 provides visually persuasive evidence that US manufacturing industries which have declined in size between 1990 and 2005 have grown in China. As a proportion of the economy, nearly every industry in US manufacturing has declined between 0.5 to 1 percentage points, with the larger industries declining slightly more on average. Interestingly, the figure also indicates that while most Chinese manufacturing industries have grown from 1990-2005 in absolute terms as a share of the Chinese economy, some industries have declined, possibly due to technology or demand shocks. For example, workers in the paper and paper products industry have declined as a share of both US and Chinese employment, possibly due to the Internet and declining demand. While our analysis here relies on only a single explanatory variable, and other factors such as demand are ignored, we still find an R squared of .317 for 1990-2005, which suggests that a significant fraction of the variation in employment changes in the US can be explained simply by correlated changes in China.

We also examine further *which* jobs have been sent overseas by breaking down each industry into its component occupations. Based on Autor et al. 2003, we were able to measure the routineness of the tasks involved in a given occupation for all manufacturing workers. Figure 3 indicates that occupations which involved more routine tasks decreased in number in the US between 1990 and 2005, routine jobs increased in number and as a share of Chinese manufacturing employment. We disaggregate US manufacturing workers into 278 occupations and Chinese workers into 46 categories. The scatter plot and linear trend indicates that the relationship between an occupations routine-ness and its change in size between 1990 and 2005 is highly significant in both countries. For the US and China, the linear fit indicates that a 1 unit increase in the routine index is associated with a -.176 percentage point decline in US employment and a .331 percentage point increase in China, with both estimates statistically significant at the 5% level. This is evidence that (a) as predicted, routine jobs are sent to China and (b) technical change may be overstated as an explanation of declining US employment in routine occupations in manufacturing. While it may be true that these tasks would have been replaced by technology even without China's availability as production source, the table is evidence that many of these jobs are stil probably being performed by people rather than machines.

As an alternative strategy, we consider how the mix of managers to production workers has changed in each country. Based on Dorn (2009), we classify workers as either managers or engaged in production using their occupation and a consistent scheme for the US and China, shown in Apendix Table 2. Figure 4 indicates that the ratio of production workers to managers in the US has decreased from a ratio of 4:1 in 1990 to about 3:1 in 2005. In contrast, the ratio of production workers to managers in China has *increased* from a ratio of 8:1 in 1990 to almost 12:1 in 2005. Furthermore, we find that these changes were correlated across industries, with the US industries experiencing the largest increase in the manager-worker ratio having the large decline in China. This result is presented in Table 4: a 1 unit increase in the manager-worker ratio in the US is associated with a 1.58 unit decrease in China, significant at the 5% level. Since technical change may differentially affect occupations, we also add task content controls, where we control for average task content for workers in the industry in the US in 1990. Our estimate is very similar (1.55) and remains statistically significant. The results suggest that managers in China are being displaced by managers in the US, while production workers in the US are being displaced by Chinese production workers.

As a result of the strong evidence supporting a claim of American jobs being sent overseas, we considered how this might manifest itself in US productivity data. As suggested by Houseman (2007), problems with both BLS methodology and data quality[5] make it difficult to distinguish cheaper input substitution from real productivity gains. One concern is also a "batting

[5] Houseman discusses several products where it is particularly difficult for the BLS to hedonically adjust for quality, such as for computers or electronics, where quality is changing rapidly.

average effect", where the US shipping lower value added tasks overseas leaves US manufacturing firms with a higher average productivity level.

Table 5 estimates the link between increasing US labor productivity, declining unit labor costs, and the change in Chinese manufacturing employment. Labor productivity is defined as the average change over time in the relationship between the output of an industry and the labor hours expended on that output, while the unit cost of labor is defined as average industry change in the cost of a unit of labor. The base year is 2002 (=100).

Column one indicates that a one percentage point increase in Chinese manufacturing employment between 1990 and 2005 is associated with a .60 percent increase in US productivity, relative to the base year of 2002. While the coefficient is large in size, the results are not statistically significant. We decided to add task content controls in column two. After adding task controls, the coefficient remains similar in magnitude, and remains statistically significant at the 5% level. The R squared rises from .39 to .59 for labor productivity by adding the task content controls, suggesting that both the task content in 1990 and the industry's growth in China were highly predictive of which industries would experience productivity gains. In column 3, we examine the relationship between Chinese employment growth and changes in the the unit cost of labor. We find that a 1 percentage point increase in Chinese employment is associated with a 1.23 percent decrease in the unit costs of labor, significant at the 5% level. Adding task controls in column 4 increases the magnitude of the coefficient slightly (1.29) and increases the precision of the estimate, which is statistically significant at the 1% level. The R squared on unit labor costs increases to .61 indicating that changes in US labor costs across 29 manufacturing industries can be explained reasonably well with only 4 repressors: Chinese employment, and our 3 task content controls. Our results indicate that Chinese labor has saved firms labor costs, either through the ability to shift operations overseas or increased leverage in wage bargaining, and that the shifts in employment may be in part responsible for rapid productivity gains in manufacturing.

Figure 5 provides visually persuasive evidence that the increases in foreign employment are linked to the gains in US labor productivity. Panel A shows the trends in US labor productivity from 1950 to 2010. As shown in Panel A, between 1950 and 1990 the US manufacturing industry the average annual productivity gain was 1.31 percentage points. Between 1990 and 2010, productivity increased by a staggering 5.30 percentage points annually. Interestingly, as shown in Panel B, the trend-break in labor productivity growth coincides with offshoring by US firms. Using BLS data on domestic US manufacturing employment and COMPUSTAT data on international employment, we observe a large wedge emerge between the two series, between 1990 and 2010, after closely tracking each other from 1980-1990. While computers and other automation techniques became available during the window, the striking shift in productivity suggests that the change is at least in part induced by trade. One possibility is that US labor productivity gains in manufacturing are due to a “batting average effect”; since more labor-intensive tasks are performed more cheaply overseas, the remaining workers in the US are on average more productive. A second possibility is that less efficient firms were forced to exit the market in the wake of trade (Melitz 2003), and a third possibility is that increased competition forced firms to adopt more efficient technologies. These hypotheses are left for future work and require detailed firm-level data for both countries.

In Table 6, we examine whether firms have increased profits during this period, in order to assess whether firms have been able to capture any of the gains from declining labor costs or passed all the gains to consumers. We examine corporate profit growth in our sample from 1990-

2005, 1990-2000, and 200-2005. Only the result for 1990-2005 is statistically significant, and indicates that a 1 percentage point increase in Chinese employment is associated with a .94 log change in corporate profits. These results are relatively weak, either because rising overall profits were uncorrelated with Chinese employment changes, or measurement error in net income and slippage in creating a concordance from the NAICS-based profit data and Chinese census data.

In Table 7, we examine how wage inequality with manufacturing has been affected by rising Chinese employment. As shown in column one, a one percentage point increase in Chinese manufacturing employment between 1990 and 2005 is associated with a 0.0997 percentage point increase in the log (90th/10th) ratio, and is significant at the 1% level. In column 2, we introduce rich demographic controls such as years of education, age, the female share of the workforce, and the minority share of the workforce. The results are similar to column 1 (.0998). In columns 3 through 6, we present results for other measures of inequality such as the ($75^{th}/25^{th}$) ratio and ($60^{th}/40^{th}$) ratio. The results suggest that all measures of inequality have increased as a result of the changes in Chinese employment, with the largest impact found for workers in the middle of the income distribution ($60^{th}/40^{th}$ percentiles). We present a visual analogue to these regressions in Figure 7, where we plot the log change in the $75^{th}/25^{th}$ ratio against changes in Chinese employment, weighted by each industry's share of US employment in 1990. The figure reflects large increases in inequality in industries with the largest employment increase in China. This may be due to offshoring of "middle skill" production jobs, with the remaining US workers concentrated in high-paying managerial positions and low-paying clerical positions.

VI. Conclusion

This paper has examined the recent trends in manufacturing of declining employment and rising productivity and found that trade with China may have played a more critical role than often recognized. While many scholars have focused on technology for explaining declining US employment in well-paying manufacturing jobs, we have documented large correlated increases in Chinese employment. In fact, we see that *routine* jobs have expanded in China, which are precisely the tasks that are generally thought to now be performed by machines. While it is difficult to prove that in a counterfactual world, the US firms would not have otherwise replaced American workers with machines, our evidence is difficult to reconcile with a purely technological explanation for declining US employment. The striking correspondence between the two countries, and the timing of US employment declines and Chinese expansion, are much more likely to be driven by trade and offshoring than coincident technical change.

We then present evidence that these employment shifts may be responsible for the trend-break in US productivity growth in the early 1990s. The case that offshoring and productivity gains in manufacturing are related is further supported by evidence that Chinese employment growth is correlated with US productivity growth across industries. The consequences of these shifts have been hugely important for American firms and workers. We find rising corporate profits but increasing wage inequality in the most affected industries. This suggests that the major beneficiary of globalization has been American firms, with the welfare impact on workers being far less clear. Shifting employment to industries with higher wage inequality, and rising inequality within manufacturing, suggests that trade may have played a critical role in the recent increase in US wage inequality. Also, insofar as the distribution of corporate ownership is more skewed than the wage distribution, it may be that the recent increase in US wealth inequality can also be partly attributed to trade, which provided firms leverage over workers in wage bargaining due to their ability to relocate plans to China.

While our analysis is insufficient to perform a full welfare analysis of US-China trade, and we have not examined the benefits to Chinese workers in higher wages or American consumers due to cheaper product prices, our results suggest that there have been both winners and losers from bilateral trade between the countries. Free trade has brought many gains and may still be good policy, but it may be sensible for future free trade agreements to provide mechanisms for redistribution between the winners and losers, in light of the potential negative welfare consequences for lower skilled US workers.

References

Antras, Pol, Luis Garicano, and Esteban Rossi-Hansberg. 2006. "*Offshoring in a Knowledge Economy*," *Quarterly Journal of Economics* 121(1): 31-77.

Autor, David, Frank Levy, Richard Murane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118(4): 1279-1334.

Autor, David, Lawrence Katz, and Melissa Kearney. 2008. "Trends in U.S Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*, 90(2): 300-323.

Autor, David, David Dorn, and Gordon Hanson. 2011 "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." Mimeo.

Davis, Steven J., John C. Haltiwanger and Scott Schuh. 1996. *Job Creation and Destruction.* Cambridge, MA: MIT Press.

Dinardo, John, Nicole Fortin and Thomas Lemieux. 1995. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." NBER Working Papers 5093.

Dorn, David. 2009. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." See his appendix table 2. Available for download at http://www1.unisg.ch/www/edis.nsf/SysLkpByIdentifier/3613/$FILE/dis3613.pdf

Ebenstein, Avraham, Ann Harrison, Margaret McMillan, Shannon Phillips. 2009. "Estimating the Impact of Trade and Offshoring Using the Current Population Surveys. NBER Working Paper 15107

Ebenstein, Avraham. 2011. "Winners and Losers of Multinational Firm Entry into Developing Countries: Evidence from the Special Economic Zones of the People's Republic of China." ADB Economic Working Paper Series No. 276.

Edwards, Lawrence and Robert Lawrence. "Trade and Jobs: Exploring the Public's Concerns."

Firpo, Sergio, Nicole Fortin, and Thomas Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure." IZA Discussion Paper No. 5542.

Grossman, Gene M. and Esteban Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, 98(5): 1978-1997.

Helpman, Elhanan, Marc Melitz, and Stephen Yeaple. 2004. "Export Versus FDI with Heterogeneous Firms," *American Economic Review*, 94(2):300-316.

Houseman, Susan. 2007. "Outsourcing, Offshoring, and Productivity Measurement in United States Manufacturing." *International Labour Review*, Vol. 146 (1-2), 61-80.

Lawrence, Edwards and Lawrence, Robert: Exploring the Public's Concerns.

Lee, David. 1999. "Wage Inequality in the United States During the 1980s: Rising Dispersion or Falling Minimum Wage?" *Quarterly Journal of Economics*, 114(3), 977-1023.

Melitz, Marc. 2003. "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71: 1696-1725.

Spence, Michael and Sandile Hlatshwayo. 2011. "The Evolving Structure of the American Economy and the Employment Challenge." Council on Foreign Relations Working Paper.

Data Appendix:

A. Integrated Public Use Microdata Series (IPUMS)

We use the 5% sample for 1990 and 2000 and the 1% American Community Survey (ACS) sample for 2005 and 2009. All of the above samples are weighted samples. Our sample includes data on industry, occupation, employment status, wages, years of education, and demographic characteristics such as age, sex and race. In order to create a consistent industry scheme with China, industries are converted to 64 consistent categories (Appendix Table 1). In addition, occupations are converted to 14 categories, based on Dorn (2009). The calculated nominal wage is converted to a real wage using the Consumer Price Index for 2005.

Sources:
Dorn, David. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." See his appendix table 2. Available for download at
http://www1.unisg.ch/www/edis.nsf/SysLkpByIdentifier/3613/$FILE/dis3613.pdf

Our source for the CPI is the Bureau of Labor Statistics and is available for download at ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt

B. US Bureau of Labor Statistics

Our data on labor productivity comes from the US Bureau of Labor Statistics, and is available for the years 1950-2010. Industry labor productivity measures have been developed for all manufacturing and retail trade industries as well as selected mining, transportation, communications and services industries. The labor productivity indexes show changes over time in the relationship between the output of an industry and the labor hours expended on that output. These data are available in both NAICS and SIC format. In addition, the BLS is the source of our annual manufacturing employment data for the years 1980-2010.

C. Compustat North America Firms Database

Our data on American firms' profits is based on the most comprehensive available data and is based on Standard & Poor's Compustat database of U.S. and Canadian fundamental and market data. S&P collects public data on the activities of U.S. and Canadian publically-traded companies based on Security and Exchange Commission (SEC) filings and annual and quarterly reports to shareholders, among other sources. We use the data collected on manufacturing corporations. We also create a concordance between these data and our 64 industry categories (Appendix Table 1). Using these data we generate a sum total of manufacturing profits for each year from 1982 to 2010. In addition, we generate a sum total of manufacturing employees, which includes all domestic and foreign employees of North American Firms for the years 1980-2010.

D. US Census Bureau

Our data on prices of imports and exports are recorded by the U.S. Census Bureau using the Harmonized System (HS). The data was made available in six-digit North American Industry Classification System (NAICS) by Schott (2008)

Source: Schott, Peter. "The Relative Sophistication of Chinese Exports." The data is available for download at http://faculty.som.yale.edu/peterschott/sub_international.htm

E. US Bureau of Economic Analysis

Our data on offshoring is based on the most comprehensive available data and is based on firm-level surveys on US direct investment abroad, collected each year by the Bureau of Economic Analysis (BEA) of the US Department of Commerce. The BEA collects confidential data on the activities of US-based multinationals. Multinationals are defined a parent company, the US entity that made at least one direct investment in a foreign affiliate, defined as a foreign business enterprise. We use the data collected on majority-owned, non-bank foreign affiliates and non-bank US parents for the years from 1982 to 2002. The foreign affiliate survey forms that US multinationals are required to complete on an annual basis include detailed information on the number of employees hired abroad. In previous work we have cross-checked these data with national survey data from other countries and found the employment numbers to be remarkably similar. Using these data, we construct a panel of number of employees hired abroad by country by year.

F. China Census Data

We use the 1% sample for the 1990 Census, 0.1% sample for 2000, and the 20% sample of the 2005 1% Population Sample Survey (sometimes referred as mini-census). Our samples include data on industry and occupation affiliation, while our 2005 sample includes additional data such as employment status, wages, years of education, and demographic characteristics such as age, sex and ethnicity. In order to create a consistent industry scheme across samples, we aggregate several industries and occupations. We create a consistent 2-digit industry code across samples based on Chinese industrial classification codes (GB4754-84, GB/T4754-1994 and GB4754/T-2002) and a consistent 2-digit occupation code across samples based on Chinese occupation codes (GB6565-86, GB/T 6565-1999). We also use income information in 2005 data to calculate wage and wage inequality for 2005.

G. China Urban Household Survey

We use China's Urban Household Survey to calculate wage and wage inequality for 1990 and 2000. Since the Urban Household Survey covers only urban areas, we also restrict our 2005 mini-census sample to urban areas to make our wage data comparable across years. Wages for each year are adjusted by CPI reported in China's statistic yearbook using 2005 as the base year.

H. China Manufacturing Census

We calculate firm productivity in the manufacturing sector from 1998 to 2007 using China's annual survey for manufacturing enterprises. Each year of this survey covers more than 150 thousand manufacturing firms.

I. Concordances

We present a mapping between the US and Chinese census data coding scheme for industries (Appendix Table 1) and occupations (Appendix Table 2) that is consistent across samples.

Table 1

Employment Structure of the United States and China Economies, 1990-2009

	USA				China		
	1990	2000	2005	2009	1990	2000	2005
Total Labor Force (000's)	123,753	137,743	145,872	155,845	636,941	642,977	671,956
Agriculture (000's)	2,374	2,026	1,994	2,117	455,305	407,116	373,157
	1.92%	*1.47%*	*1.37%*	*1.36%*	*71.20%*	*63.32%*	*55.49%*
Manufacturing (000's)	22,132	20,672	18,550	17,061	85,350	90,193	108,050
	17.88%	*15.01%*	*12.72%*	*10.95%*	*13.35%*	*14.03%*	*16.14%*
Construction (000's)	7,201	8,805	10,551	9,495	12,964	18,206	24,264
	5.82%	*6.39%*	*7.23%*	*6.09%*	*2.03%*	*2.83%*	*3.61%*
Services (000's)	84,280	98,278	104,646	111,695	83,322	127,462	166,485
	68.10%	*71.35%*	*71.74%*	*71.67%*	*13.03%*	*19.82%*	*24.76%*
Unemployed (000's)	7,766	7,962	10,131	15,476	-	-	-
	6.28%	*5.78%*	*6.95%*	*9.93%*	-	-	-

Source: United States Public Use Microsample (1990 5% sample, 2000 5% sample, 2005 ACS 1% sample, 2009 ACS 1% sample), China National Bureau of Statistics (1990 1% sample, 2000 0.1% sample, 2005 0.2% sample).

Note : Sample excludes individuals out of the labor force. The US and Chinese data are placed on a uniform industrial classification system that is comrpised of 64 consistent employment categories, shown in Appendix Table 1. Each sector's share of the workforce is listed in italics. Unemployment data are unavailable for China.

Table 2

Wage Levels and Wage Inequality in the United States and China, 1990-2009

	USA				China		
	1990	2000	2005	2009	1990	2000	2005
Total Economy							
Monthly Income (mean)	$2,743	$3,026	$3,093	$3,053	$117	$258	$277
Monthly Income (median)	$2,184	$2,268	$2,333	$2,276	$112	$209	$200
Mean to Median Ratio	1.26	1.33	1.33	1.34	1.04	1.24	1.38
Agriculture							
Monthly Income (mean)	$2,366	$2,623	$2,596	$2,685	-	-	$98
Monthly Income (median)	$1,751	$1,989	$1,972	$2,010	-	-	$75
Mean to Median Ratio	1.35	1.32	1.32	1.34	-	-	1.31
Manufacturing							
Monthly Income (mean)	$3,430	$3,822	$3,903	$4,039	$112	$227	$274
Monthly Income (median)	$3,012	$3,197	$3,237	$3,294	$107	$182	$215
Mean to Median Ratio	1.14	1.20	1.21	1.23	1.05	1.25	1.27
Services							
Monthly Income (mean)	$2,941	$3,352	$3,446	$3,486	$120	$277	$324
Monthly Income (median)	$2,416	$2,639	$2,747	$2,755	$116	$224	$250
Mean to Median Ratio	1.22	1.27	1.25	1.27	1.03	1.24	1.30

Source: See Table 1. Data on wages for 1990 and 2000 are taken from the China Urban Household Survey.

Note : Income data are unavailable for the Chinese agricultural sector for 1990 and 2000 since the Urban Household Survey is our data source for these years. We restict our sample to the urban surveyed area when calculating the income distribution for 2005 in order to compare the data to 1990 and 2000. Sample excludes individuals out of the labor force. Income calculations exclude those who report working and no income. Monthly income in the UHS data is cacluated by dividing annual income by 12. Unemployed persons are included in the first panel, even if they report no income. The coefficient of variation is the ratio of the standard deviation of income in the sample to the mean. Exchange rates during the period between China and the US indicate 1 ¥=$0.125. We employ a PPP index where ¥1=$0.25 for this table. Income has been adjusted by CPI for both US and China using 2005 as the base year.

Table 3

Manufacturing Employment Changes in the US and China

	LHS: Change in Industry's Share of US Employment			
	1990-2005	1990-2000	2000-2005	1990-2009[1]
	(1)	(2)	(3)	(4)
Change in Industry's Share of Chinese Employment	-0.341**	-0.269**	-0.239**	-0.365**
	(0.142)	(0.112)	(0.109)	(0.178)
Observations	32	32	32	32
R^2	0.317	0.252	0.323	0.211

* significant at 10% ** significant at 5%. *** significant at 1%.

Source: See Table 1.

Notes: Standard errors are robust. The sample is composed of 32 industries within manufacturing. The measure of an industry's employment is its share of total employment in the respective country and year, with all industries summing to 1. Change in employment is the percentage point increase or decrease in the industry's share of total employment. The regression is weighted by the industry's share of US employment in 1990.

[1]Chinese data is not available beyond 2005, and so 2005 values are used in combination with US data for 2009.

Table 4

Manufacturing Manager to Production Worker Ratios, China and US 1990-2005

	LHS: Change in US Manager-Worker Ratio	
	(1)	(2)
Change in Chinese Manager-Worker Ratio	-1.582** (0.652)	-1.555*** (0.526)
Task Content Controls	No	Yes
Observations	32	32
R^2	0.331	0.353

* significant at 10% ** significant at 5%. *** significant at 1%.

Source: See Table 1.

Notes: Standard errors are robust. Sample is restricted to manufacturing industries. The definitions of manager and production worker are based on Dorn (2009) (See appendix table 2). The independent variable is the change in the Chinese manger to production worker ratio between 1990 and 2005. The dependent variable is the change in the US manger to production worker ratio between 1990 and 2005. The task content controls are averages in task content for workers in the industry in the US in 1990, and are taken from Department of Transporation codes for required manual, routine, and abstract skills to perform a given occupation.

Table 5

US Labor Productivity and Unit Labor Costs (1990-2005)

	LHS: Industry Change in Labor Productivity (Output per US Worker)		LHS: Industry Change in Unit Cost of Labor (per US Worker)	
	(1)	(2)	(3)	(4)
Change in Industry's Share of Chinese Employment	60.17 (37.62)	59.62** (28.60)	-123.4* (68.39)	-123.9** (53.82)
Task Content Controls	No	Yes	No	Yes
Observations	29	29	29	29
R^2	0.39	0.59	0.44	0.61

* significant at 10% ** significant at 5%. *** significant at 1%.

Source: United States Public Use Microsample (1990 5% sample), China National Bureau of Statistics (1990 1% sample, 2005 0.2% sample), United States Bureau of Labor Statistics (1990, 2005)

Notes: Standard errors are robust. Sample is restricted to manufacturing industries. Data on productivity are taken from the Bureau of Labor Statistics series on productivity and unit labor costs, transfered to a coding scheme consistent with US and China census classifications. BLS series data are equal to 100 in 2002. The independent variable in all regressions is the industry's change in share of the Chinese employment between 1990 and 2005. The dependent variable is the log change in productivity (first two columns) or unit labor costs (second two columns) between 1990 and 2005. The task content controls are averages in task content for workers in the industry in the US in 1990, and are taken from Department of Transporation codes for required manual, routine, and abstract skills to perform a given occupation.

Table 6

Corporate Profits in the US and Chinese Employment Changes

	LHS: % Change in Corporate Profits		
	1990-2005	1990-2000	2000-2005
	(1)	(2)	(3)
% Change in Chinese Employment	38.72 (45.73)	94.07** (43.01)	55.42 (41.89)
Observations	27	26	26
R^2	0.028	0.166	0.068

* significant at 10% ** significant at 5%. *** significant at 1%.

Source: Compustat North American Firms Database (1990-2010) China National Bureau of Statistics (1990 1% sample, 2005 0.2% sample)

Notes: Data on profits are taken from the COMPUSTAT records of net income from annual income statements for publicly-traded firms.

Table 7

Changes in Chinese Employment and US Wage Inequality, 1990-2005

	Change in Log Ratio of (90/10)		Change in Log Ratio of (75/25)		Change in Log Ratio of (60/40)	
	(1)	(2)	(3)	(4)	(5)	(6)
% Change in Chinese Employment	0.0997*** (0.0350)	0.0918*** (0.0222)	0.112** (0.0515)	0.0830** (0.0380)	0.299*** (0.0870)	0.218** (0.0877)
Years of Education	No	Yes	No	Yes	No	Yes
Age	No	Yes	No	Yes	No	Yes
Share Female	No	Yes	No	Yes	No	Yes
Share Minority	No	Yes	No	Yes	No	Yes
Observations	32	32	32	32	32	32
R^2	0.213	0.809	0.136	0.716	0.282	0.560

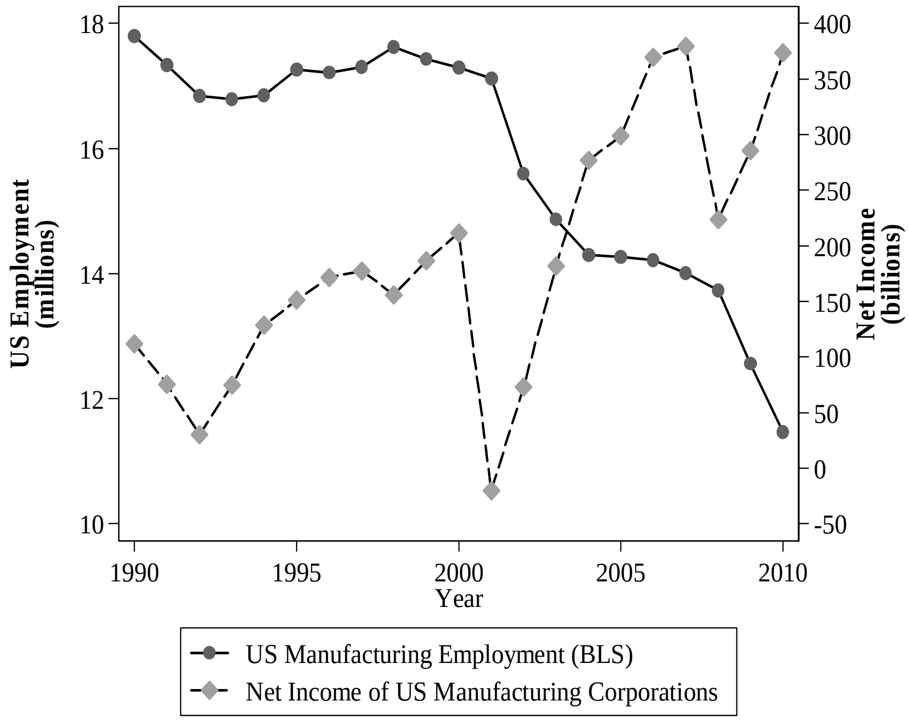
* significant at 10% ** significant at 5%. *** significant at 1%.

Source: See Table 1.

Notes: The sample is composed of 32 industries within manufacturing. The measure of an industry's employment is its share of total employment in the respective country and year, with all industries summing to 1. Change in employment is the percentage point increase or decrease in the industry's share of total employment. The regression is weighted by the industry's share of US employment in 1990.

Figure 1

US Manufacturing Corporate Profits and Employment Trends, 1990-2010

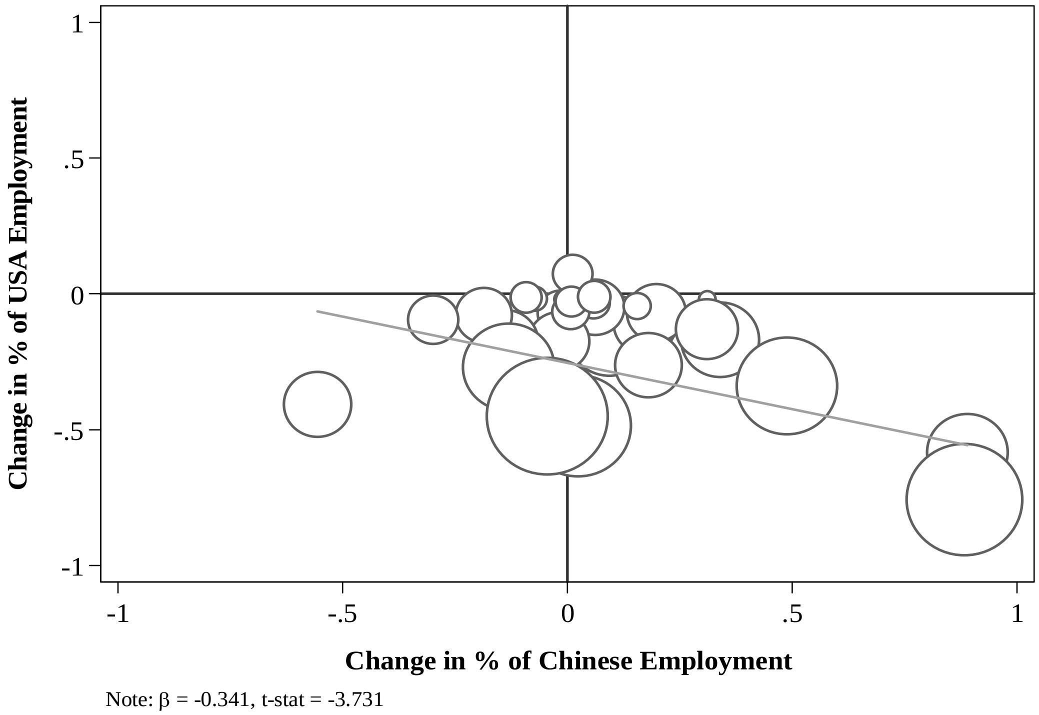


Source: Compustat North American Firms Database (1990-2010). United States Bureau of Labor Statistics (1990-2010)

Notes: Corporate profits (net income) are available for all publicly-traded firms.

Figure 2

Manufacturing Employment Changes by Industry, China and US 1990-2005



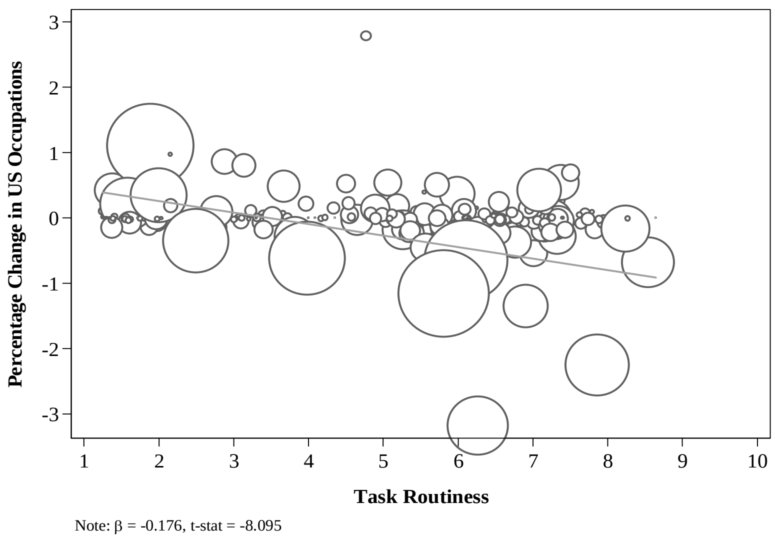
Source: See Table 1.

Notes: Each circle's size is in proportion to the industry's share of the US economy in 1990. Each industry is measured as a proportion of the economy in the country and year for 1990 and 2005.

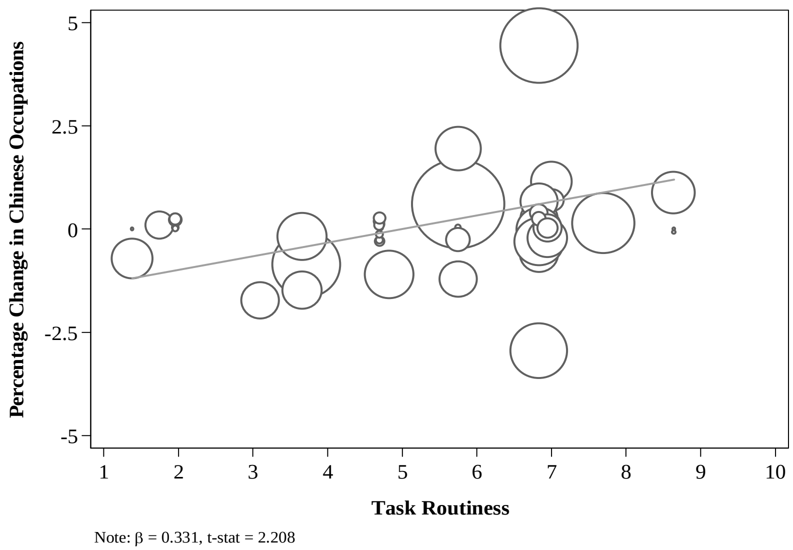
Figure 3

Occupational Task Content and Changes in Employment, 1990-2005

A. United States



B. China

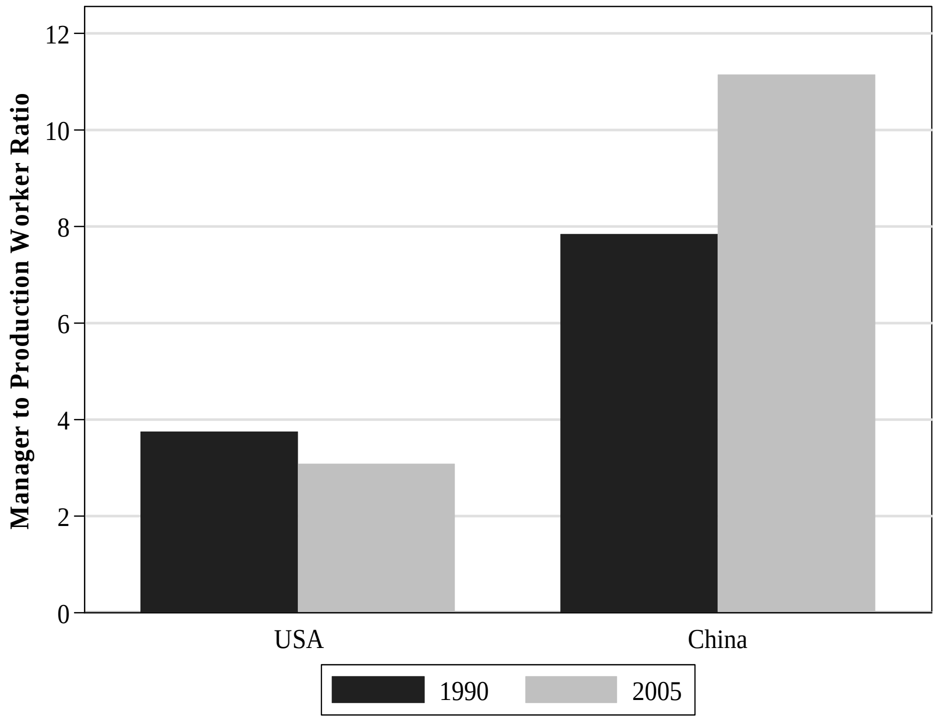


Source: See Table 1.

Notes: Each observation is an occupation. The US workers are placed into one of 278 categories, and the Chinese workers are placed into one of 46 categories. Sample is restricted to manufacturing workers. Observations are weighted by the occupation's share of employment in 1990 for US and China respectively.

Figure 4

Manager to Production Worker ratio, China and US 1990-2005



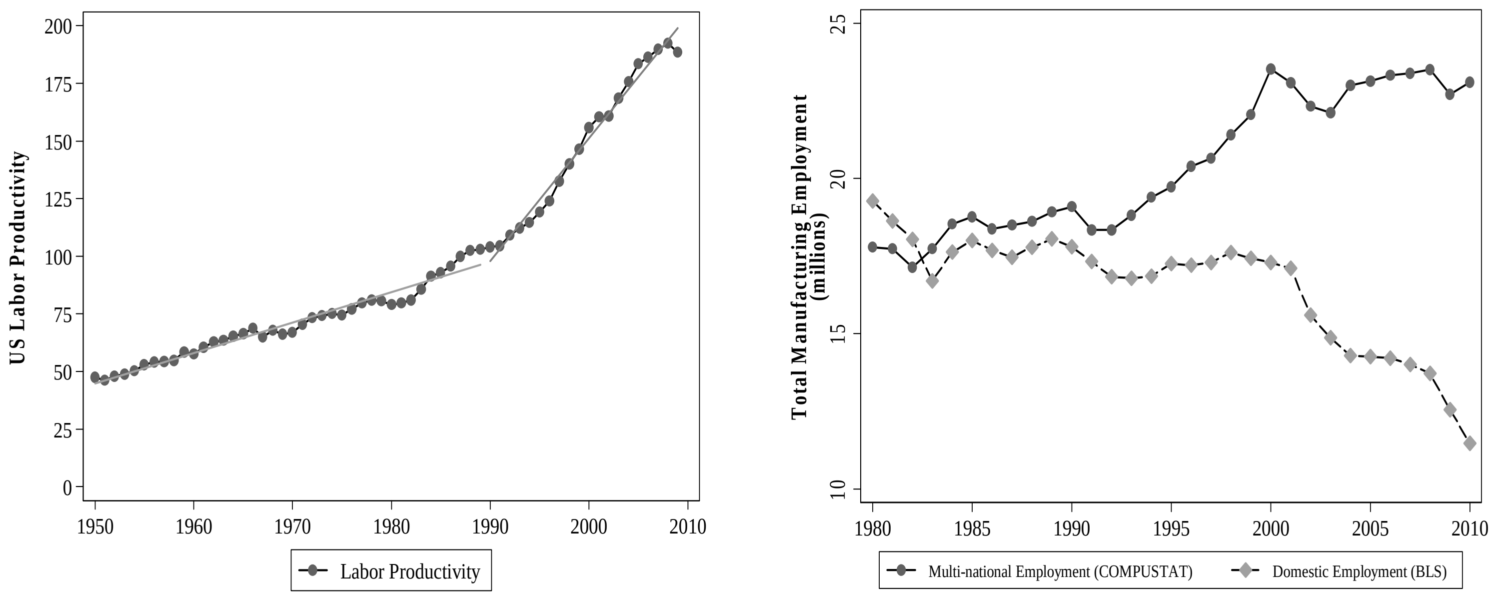
Source : See Table 1.

Notes: Managers include "Executive and Administrative" and "Management Related" and "Professional and Specialty". Production workers include "Mechanics and Repairers" , "Construction Trades", "Extractive", "Precision Production", "Machine Operators", and "Transportation and Material Moving". See appendix table 2 for a full listing of occupational coding schemes in the US and China.

Figure 5

US Manufacturing Labor Productivity and Employment, 1950-2010

A. Labor Productivity **B. Domestic and Total Employment**

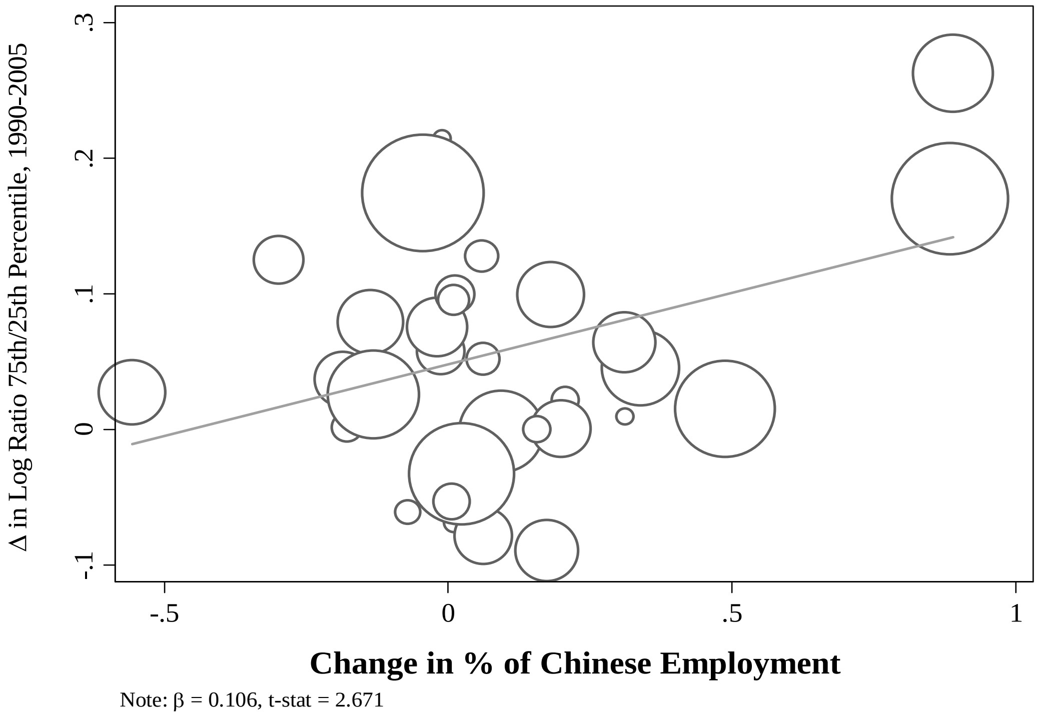


Source: Compustat North American Firms Database (1980-2010) United States Bureau of Labor Statistics (1950-2010)

Notes: In Panel A, each observation is the labor productivity reported by the BLS, with base year for technology set at 1987 (LP=100). The figure plots a linear trend between 1950 and 1990 (slope=1.31) and a linear trend between 1990 and 2010 (slope=5.30). In Panel B, we report total employment among manufacturing firms as measured by global employment among COMPUSTAT firms versus the BLS series of domestic US employment.

Figure 6

US Wage Inequality and Changes in Chinese Manufacturing Employment, 1990-2005



Source: See Table 1.

Notes: N=32. Each observation is an industry, where the size of the circle represents its share of the US labor force in 1990. The independent variable is the change in the percent of the Chinese labor force in the industry between 1990 and 2005, and the dependent variable is the change in the log ratio of the 75th/25th percentile of wages among American workers.

Appendix Table 1

Industrial Classification System of the United States and China Economies

	Concorded Industry Code	IPUMS Census Codes (IND1990)	Chinese Census Codes (IND)	SIC Code	NAICS Code
Coal mining	6	41	6	1220	2121
Oil and gas extraction	7	42	7	1381	211
Ferrous metal mining	8	40	8	1000	2122
Nonmetallic mineral mining	10	50	10	1400	2123
Food industries	14	100-102, 110-112, 121, 122	13, 14	2000	311
Beverage industries	15	120	15	2080	3121
Tobacco manufactures	16	130	16	2100	3122
Textile products	17	132, 140, 141, 142, 150	17	2200-2273, 2390	313-314
Textile clothing	18	151, 152, 221	18	2300-2340	315
Leather furs	19	220, 222	19	3100	316
Wood processing industry	20	230, 231, 232, 241	20	2400	321
Furniture	21	242	21	2510-2590	337
Paper and paper products	22	160, 161, 162	22	2600-2673	322
Printing	23	171, 172	23	2711-2780	323
Culture and education	24	390	24	7900	512, 515
Petroleum refining	25	200, 201	25	2911	324
Chemical materials	26	182, 190, 191, 192	26	2800-2810	3252
Pharmaceutical	27	181	27,28	2833-2835	3254, 3252
Rubber products	29	210, 211	29	2820	3262
Plastics products	30	180, 212	30	2821	3261
Nonmetal mineral products	31	250, 251, 252, 261, 262	31	3290	327
Ferrous metal forgings	32	270, 271, 272, 280	32, 33	3310-3312	332
Metal products	34	281, 282, 290, 291, 300	34	3390-3490	331
General purpose machinery	35	310, 320, 331	35	10-3541, 3560-35	333
Special purpose machinery	36	292, 311, 312, 332	36	3550-3559	3339
Transportation equipment	37	351, 352, 360-362, 370	37	3790	336
Electric equipment and machinery	39	340	39	3630	335
Computer Equipment	40	322, 341, 342, 350	40	3570-3577	3341
Instruments and meters	41	321, 371, 372, 380, 381	41, 42	78-3579, 3823-38	3345
Electricity, Production and Supply	44	450	44	4911	2211
Gas production and supply	45	451	45	4923	2212
Wate production and supply	46	470	46	4941	2213

Source: See Table 1.

Appendix Table 2

Occupational Classification System, United States and China

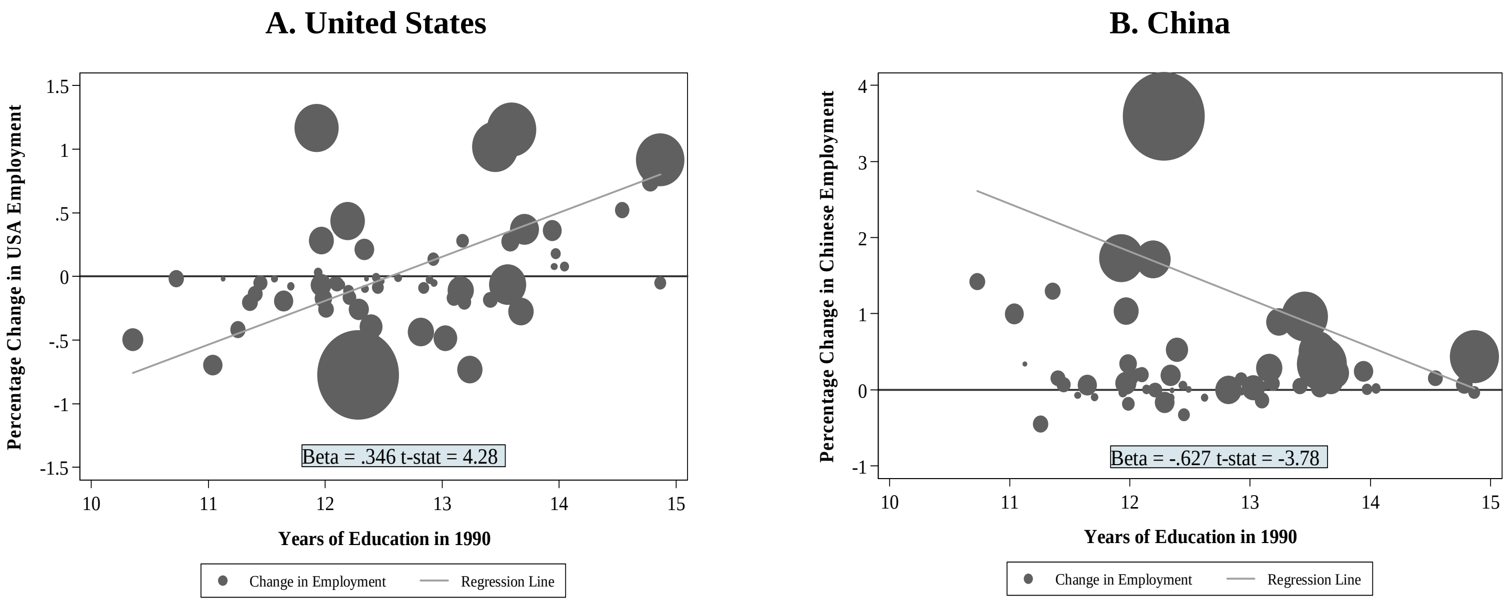
	Occupation Codes	IPUMS Census Codes (OCC1990[1])	Chinese Census Codes (OCC)
Panel A: Managerial Occupations			
Executive and Administratuve	1	4-22	1,2
Management Related	2	23-37	21
Professional Specialty	3	43-199	11, 12, 19, 23-28
Panel B: Technical, Sales, and Administrative Support Occupations			
Technicians and Related Support	4	203-235	13, 17, 18
Sales	5	243-283, 405-408, 433-472	41
Administrative Support	6	303-389	31, 33, 39
Panel C: Service Occupations			
Services	8	415-427	32
Panel D: Agricultural Occupations			
Farming	10	473-475, 479-498	51-55, 59
Panel E: Production Occupations			
Mechanics and Repairers	12	503-549	72
Construction Trades	13	558-599	82, 83, 88
Extractive	14	614-617	61
Precision Production	15	628-699	62, 64, 74-78, 81, 87
Machine Operators	16	703-799	66, 84-86, 93
Transportation and Material Moving	17	803-899	91, 99

Source: See Table 1.

Note : [1]The occupational coding scheme is based on codes from Dorn (2009), who generates a consistent coding scheme for occupations in US census data. We created a consistent scheme for Chinese census data that allows us to place workers in the census samples for both countries into one of 14 consistent categories.

Appendix Figure 1

Education Levels and % Point Changes in US Employment, 1990-2005



Source: See Table 1.

Notes: Industries are collapsed into 64 categories, based on the Chinses industry codes scheme. Observations are weighted by the American industry size in 1990. Education levels are US education levels in 1990.