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ABSTRACT

Previous studies typically find small or insignificant effects of globalization on US workers. We argue that much of the impact on wages has been missed because globalization has led workers to move from higher paid manufacturing jobs to lower paid service jobs. To show this, we link industry-level data on trade and offshoring with individual-level worker data from the Current Population Surveys. Previous research focused on industry-level exposure to globalization, which we show has no significant impact on worker wages. Our new measure of occupational exposure to globalization shows significant effects of globalization on wages. Offshoring to low wage countries is associated with wage declines for US workers, and the workers most affected are those performing routine tasks. Import competition is associated with wage declines, while exports are associated with wage increases. We present evidence that globalization has led to the reallocation of workers away from higher wage manufacturing jobs into other sectors and other occupations. We estimate that occupation switching due to trade led to real wage losses of 12 to 17 percent.

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I. Introduction

Between 1983 and 2002, the United States economy experienced a boom in offshoring and a doubling of imports of manufactured goods from low-income countries. Over this same period, roughly 6 million jobs were lost in manufacturing and income inequality soared. These parallel developments led some critics of globalization to conclude that "good" manufacturing jobs had been shipped overseas, putting downward pressure on wages of middle-class American workers. Yet the degree to which changes in the US labor market are related to growth in international trade and offshoring is still the subject of heated debate.

The standard approach to identifying effects of import competition on wages is to use variation in the prices (or quantities) of imported goods across different manufacturing industries and examine their impact within manufacturing. For example, Feenstra and Hanson (1999) use a two-step procedure, first identifying the impact of outsourcing and high technology investments on productivity and prices and then tracing through the impact of induced productivity and price changes on relative wages among production and non-production workers within manufacturing. Using data for the US manufacturing sector between 1979 and 1990, they find that the real wages of production workers were likely unaffected by offshoring activities. Bernard, Jensen, and Schott (2006), in the first paper to distinguish between imports from high-income versus low-income countries, find that only low-income imports negatively affected firm exit, survival, and employment growth within the manufacturing sector. But what if globalization affects the US labor market by pushing workers out of manufacturing?

A key limitation of the previous literature is that it typically focuses on changes within manufacturing. In this paper, we focus on potential wage impacts *across* occupations, both within manufacturing and in the rest of the economy. We create a new measure of "occupational exposure” to international trade or offshoring activities.[1] Our key insight is that much of the impact of globalization on wages has operated by shifting workers out of higher paid manufacturing into lower paid service jobs. Using the panel aspect of the CPS, we show that wages fall both when workers remain within the same occupation but shift from manufacturing to services, as well as when workers switch occupations. This effect cannot be identified by focusing on differential exposure to imports or offshoring for a worker who remains in the same occupation within the manufacturing sector.

To do the analysis, we construct a merged dataset using industry-level data on trade and offshoring and individual-level worker data from the Current Population Surveys. We first show that an analysis restricted to individuals who remain within manufacturing yields no significant impact of exposure to trade or offshoring on worker wages. However, with our new measure of occupational exposure to globalization, we show that using this measure results in significant effects of globalization on wages.

Offshoring to low wage countries is associated with wage declines for US workers, and the workers most affected are those performing routine tasks. These results are consistent with recent empirical work demonstrating the importance of occupational tenure and downplaying the importance of tenure within a particular industry for a worker’s wages (Kambourov and Manovskii 2009a and 2009b).[2]

We also explore how the impact of globalization on wage outcomes has changed over time. A number of scholars have suggested that wage pressure from developing countries is

[1] We are greatly indebted to Gordon Hanson for suggesting this idea.
[2] Kambourov and Manovskii (2009a) find that “returns to occupational tenure are substantial.” They also indicate that “when occupational experience is taken into account, tenure with an industry or employer has relatively little importance in accounting for the wage one receives. This finding is consistent with human capital being occupation specific.” Their results imply that switching occupations will have a much greater impact on worker wages than switching industries.

likely to have increased during the 1990s. Feenstra (2008) singles out expanded competition from China as having exerted pressure on US wages, and he is not alone in this view (see also Freeman (1995) and Krugman (2008)). Empirical evidence for this conjecture is limited, however.[3] We find that while the impact of trade and offshoring on US wages through the mid-1990s was small in magnitude and insignificant, the effects became much larger in the second half of the 1990s. By the end of our sample period in 2002, we find significant and economically important effects of globalization on wages using our occupational exposure measure. Based on our study, it is likely that the impact of globalization on US wages in the post-2002 period is even larger as import competition has continued to grow and more firms now offshore manufacturing activities.[4]

Our results indicate that a ten percent increase in occupational exposure to import competition is associated with a 3 to 4.4 percent decline in real wages for workers who perform routine tasks.[5] We also find substantial wage effects of offshoring to low wage countries: a ten percentage point increase in occupation-specific exposure to overseas employment in low wage countries is associated with a 0.7 percent decline in real wages for workers performing routine tasks for our entire sample, and a 2.0 percent decline for 1997-2002. For routine occupations with significant export activity, wages are positively linked to export growth. For these workers, a ten percentage point increase in export share at the occupation level is associated with a 6.7

[3] One important exception is Autor, Dorn, and Hanson (2012), who exploit differences in US regional exposure to import competition from China to show significant effects on employment, unemployment and wages during the 1990 through 2007 period.

[4] Since the CPS changed its occupational coding scheme in 2003, analysis beyond 2002 is not attempted in this paper. Analysis by the authors of Bureau of Economic Analysis data indicates that offshoring to low wage countries has increased markedly since 2002, with employment in low income countries (e.g. China) exceeding that of high wage countries.

[5] This finding is consistent with recent work highlighting the differential impact of offshoring by worker skill type. Hummels, Jøgensen, Munch and Xiang (2011) use matched worker and firm data from Denmark and find that offshoring raises skilled worker wages but lowers unskilled worker wages, while exporting raises the wages of all types of workers.

percentage point increase in wages over the sample period. For the end of the period (1997-2002), every percentage point increase in export shares for routine workers is associated with a percentage point increase in wages.

We also find that globalization has put downward pressure on worker wages through a shift of workers out of trade-vulnerable occupations. First, we find that domestic employment has declined in industries with expansion in low income country employment, consistent with evidence that multinational firms have shifted production overseas.[6] Then, using a subset of the CPS data where we are able to match the same worker over time, we estimate a first stage equation with the exposure of an occupation to trade as an instrument for whether or not a worker switched occupations. In the second stage, we find that occupation switching due to trade led to real wage losses of 12 to 17 percentage points between 1984 and 2002.[7]

The associated distributional implications are potentially important, given the historically large wage premia paid to manufacturing (relative to service) workers in the United States (see Figure 1 for a graphical exposition) and significant empirical evidence that industries compensate workers differently.[8] It is also worth noting that our results are unlikely to be explained by the fact that weaker workers are more likely to switch occupations (Trefler and Lui (2011)). When we control for unobserved differences in worker quality among those who switch

[6] Our results corroborate results on employment declines within manufacturing by Harrison and McMillan (2011) who use firm-level data on multinational manufacturing firms, but stand in contrast to Desai, Foley, and Hines (2009). Desai, Foley, and Hines do not distinguish between high wage and low wage affiliate employment and find that offshoring is unambiguously positive for US employment.

[7] Other scholarship has documented the cost of trade-induced shifts in employment. Menezes-Filho and Muendler (2011) use a Brazilian trade reform to document significant short run costs to workers and sticky intersectoral labor reallocation. Artuc, Chaudhuri and McLaren (2010) develop a theoretical model which shows that adjustment costs for workers are likely to be significant and can explain why there is likely to be sluggish reallocation and short-term negative wage effects on workers under trade liberalization. Cosar (2011) also explores sluggish labor market adjustments by developing a two-sector small open economy overlapping generations model which is calibrated to Brazilian data. The paper finds that human capital is a much bigger barrier to labor mobility than search frictions.

[8] See for example Katz and Summers (1989) and Krueger and Summers (1988).

occupations, we continue to find suggestive results that the wage declines associated with globalization are due to workers switching occupations.

An important issue for our study (and other papers in this literature) is that we are unable to fully separate the impact of trade and offshoring from other changes in the labor market. Two primary identification challenges exist. First, it may be that trade and offshoring are the *result* of changes in the domestic labor market. If firms move operations offshore in response to changes in the domestic labor market (e.g. unions), this reverse causality would invalidate the causal interpretation of our results. Second, technological change may be correlated with trade in a manner preventing causal interpretation of our coefficient estimates. If workers face competitive pressure from low-wage workers in foreign countries *and* automation, it will be difficult to separately identify the impact of either.

We address these concerns in several ways. First, by combining industry level trade or offshoring data with individual level information on wages and worker characteristics, we hope to side-step the issue of reverse causality since it is difficult for one worker to affect aggregate trade outcomes. Second, we pay considerable attention to capturing technological change across industries that could influence both worker wages and globalization outcomes. We include annual measures of total factor productivity, capital accumulation, the price of investment goods by industry and computer use rates by industry and occupation, which represent our best attempt to account for technical change that could potentially affect workers directly. Third, we explore the robustness of our results to instrumental variable estimation where we exploit factors that should affect the tradability of certain goods, or the desirability of certain offshore locations.[9]

[9] Due to space constraints, our instrumental variable results are made available in online appendices. In a recent paper, Jensen and Kletzer (2005) attempt to measure the tradability of service sector goods using an approach which considers the spatial concentration of service industries and occupations. They posit that more spatially-concentrated industries or occupations are more tradable, and find evidence consistent with this hypothesis in US data. We chose

The paper is organized as follows. Section II describes our data, documents broad trends in trade, offshoring, wages and employment, and presents the empirical specification. Section III presents our main empirical findings regarding the impact of globalization on domestic wages at the occupation versus the industry level. Section IV presents evidence showing that the mechanism is due to workers moving out of higher paid manufacturing into lower paid service jobs, and Section V concludes.

II. Data Description, Empirical Strategy, and Trends

A. Data Description

Our sample of US workers is taken from the Current Population Survey Merged Outgoing Rotation Groups for 1983-2002, which provides data for over 3.4 million workers who are assigned a consistent classification for their industry and occupation during the period.[10] Offshore activity in each industry is measured by the total employment of foreign affiliates among multinational US firms, separated into high and low-income affiliate locations, as collected by the Bureau of Economic Analysis (BEA).[11] Our data on import penetration and export shares are taken from Bernard at al. (2006), which we recalculated and updated through 2002. Since relative price series for imports and exports are incomplete, we substitute for prices by using the share of exports in production and import penetration at the four-digit SIC 1987

not to pursue this strategy, as geographical concentration may reflect other factors, such as state-specific regulations that lead to clustering of certain industries or occupations.

[10] We would like to express our gratitude to David Autor for providing us with concordances that provided a consistent coding scheme of industries and occupations for the period. The CPS occupation and industry codes were reclassified in 2003 to correspond to the North American Industrial Classification System, which made it difficult to compare data before and after the change. We begin with 1984 because occupation codes for the 1979 through 1981 period are not consistent with the classification for later years and we use lags in our empirical specification which leads us to drop 1983.

[11] The BEA sample of multi-national firms accounted for 80 percent of total output in manufacturing in 1980, suggesting that the coverage is fairly extensive. However, using these data we are unable to distinguish between imports from affiliates (arms-length trade between firms) and imports from non-affiliates.

level.[12] We control for productivity changes that could also affect labor demand as well as wages using the NBER's calculations of total factor productivity provided by Wayne Gray. This data source also provides us with measures of the prices of investment goods, capital to labor ratios, and the real price of shipments by industry and year.[13] These are included in our main specifications to control for technological change that could also affect wage rates. Lastly, we match our worker data with information on computer use rates by industry and occupation from CPS computer supplements conducted during our sample period (1984, 1989, 1993, 1997, 2000). Using the available surveys, we interpolate and extrapolate computer use rates for the entire window.[14] Summary statistics for the individual worker sample matched to our offshoring, trade, technology, and price data are available in Table A1.

We use Autor et al.'s (2003) distinction between routine and non-routine tasks to allow us to separately identify the impact of different measures of globalization across different types of workers. To the extent that routine tasks are more easily offshored or replaced with imports, we would expect globalization to have a larger impact on workers performing these types of tasks. While Autor et al. (2003) use routine-ness to designate which jobs can be easily performed by computers, we would argue that routine jobs are also more readily codified, communicated, and consequently transferred overseas. Examples of these jobs include attaching hands to faces of watches, sewing fasteners and decorative trimming to articles, and services tasks that we think of as offshorable, such as answering telephones.

[12] Results using prices instead of quantities are available in the online appendix. The results are qualitatively similar to our main results using quantities.
[13] These data were aggregated from the 4-digit to 3-digit SIC level using the employment distribution in 1979. The 3-digit SIC level was converted to our industry classification scheme using a concordance provided by David Autor that was a census-based scheme that consistently defined industries for our sample period. A similar method was used to match CPS workers to the trade data.
[14] These data were also provided by David Autor and are used in Autor et al. (1998). Autor et al. (2003) describe routine jobs as "tasks that can be expressed using procedural or 'rules-based' logic, that is, codified in a fully specified sequence of logical programming commands ("If-Then-Do" statements) that designate unambiguously what actions the machine will perform and in what sequence at each contingency to achieve the desired result."

Following Autor et al. (2003), we aggregate five different measures of the routine-ness of tasks into a single index for each occupation *k*. Two indicators, Routine Manual and Routine Cognitive, measure the routine-ness of tasks by occupation in each of these dimensions. These range from 1 for tasks that are not routine to 10 for tasks that are fully routine. The three other measures are: (1) Direction, Control, and Planning of Activities (DCP) which measures non-routine cognitive tasks (2) Eye, Foot, and Hand coordination (EFH) activities which require non-routine manual task completion and (3) The Math indicator which measures the quantitative or analytical reasoning skills required. 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.[15] The last three terms DCP, EFH and Math 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. Empirical Strategy

Our empirical strategy is to regress log wages of worker *i* in industry *j* in period *t* (W_{ijt}) on lagged measures of exposure to offshoring and international trade ($G_{ijt\text{-}1}$) using annual data from 1983 to 2002, first at the industry level and subsequently at the occupation level, which we define below.

[15] 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. More details on this classification scheme are available in the online appendix.

We use lagged measures of exposure to offshoring and trade for two reasons. First, since offshoring requires time to implement, and wage adjustment is not instantaneous, it is unlikely that the causal effect of offshoring on wages will play out within a single calendar year. Second, within a given year, offshoring, trade exposure, and wages are likely to be affected by simultaneous shocks. We use four measures of exposure to offshoring and international trade: offshoring to low-income affiliate locations, offshoring to high-income affiliate locations, export shares, and import penetration. Offshoring is measured as the log of employment in sector j by US multinationals in low and high-income countries.

There are three additional challenges to identifying the causal effect of globalization on wages. First, the industries that are most likely to globalize may also be those with lower wages or greater volatility. We address this concern by including industry fixed effects (I_j) in our specification. Second, globalization and wages may be jointly affected by common time-varying shocks, such as the business cycle and exchange rate fluctuations. We control for these by including time fixed effects (d_t). Third, we control for time-varying shocks at the industry level that could be confounded with changes in globalization by adding a number of additional controls. TFP_{jt-1} captures changes in productivity by industry and year that could affect demand for labor.[16] We also control for productivity changes including two (arguably) exogenous measures, the price of investment goods and computer use rates. The price of investment goods $PINV_{jt-1}$ captures in part the role of falling computer prices and the potential impact of labor-saving technology on labor market outcomes. We also control for industry factor intensity (lagged capital to labor ratio $KLRATIO_{jt-1}$) and computer use rates by industry and year ($COMP_{jt}$) to account for contemporaneous changes in an industry's wage rate based on the ability to

[16] Since total factor productivity is a function of wages, we estimate our equations with and without total factor productivity. The results are similar with and without controlling for TFP.

substitute for labor with computers.[17] Finally, we control for individual characteristics of the labor force by including age, sex, race, experience, education, and location (Z_{ijt}). The estimating equation at the industry level (for manufacturing only) is given by:

$$(1a) W_{ijt} = \beta_0 Z_{ijt} + \beta_1 G_{jt-1} + \beta_2 TFP_{jt-1} + \beta_3 PINV_{jt-1} + \beta_4 KLRATIO_{jt-1} + \beta_5 COMP_{jt} + \beta_6 d_t + \beta_7 I_j + \varepsilon_{ijt}.$$

To examine the relationship between wages and globalization at the occupation level, we retain the same setup as in (1a) but expand the sample to include workers outside of manufacturing. We also modify the *G* vector to create a measure of occupational exposure to offshoring or trade. Each variable in the *G* vector was created from a merged dataset of BEA offshore employment data, trade data, and CPS monthly outgoing rotation group individual-level data, by industry and year. We calculate for each occupation its exposure to trade using as weights the distribution of workers employed in this occupation *across* industries in 1983. For each occupation *k* and industry *j*, we have: $\alpha_{kj83} = \frac{L_{kj83}}{L_{k83}}$ where L_{kj83} is the total number of workers in occupation *k* and industry *j* in 1983, and L_{k83} is the total number of workers across all industries in occupation *k*. We then calculate occupation-specific import penetration in year *t* for occupation *k* as:

$$\sum_{j=1}^{J} \alpha_{kj83} IMP_{jt},$$

where IMP_{jt} is the measure of import penetration for goods in industry *j* in year *t*. We continue to control for technological changes by industry, and set these technological changes equal to unity for workers outside of manufacturing.[18]

[17] Our results are similar if we control for computer use rates in the previous year.
[18] An alternative approach would be to create occupation-specific measures of each of our control variables. In the online appendix, we estimate models with occupational-specific measures of TFP, the price of investment goods,

This leads to a specification of the form:

$$(1b) W_{ijkt} = \beta_0 Z_{ijkt} + \beta_1 G_{kt-1} +$$
$$\beta_2 TFP_{jt-1} + \beta_3 PINV_{jt-1} + \beta_4 KLRATIO_{jt-1} + \beta_5 COMP_{kt} + \beta_6 d_t + \beta_7 I_j + \beta_8 Occupation_k + \varepsilon_{ijkt}$$

where *k* indexes the worker's occupation, and workers within the same *k* occupation may be in different *j* industries.[19] Our *G* vector is now an occupation-specific measure for each worker, and we have added occupation fixed effects to absorb variation specific to time invariant features of occupations. Note that we also control for variation in computer use rates by occupation and year, which is meant to account for wage changes driven by the ability of some occupations to benefit from computer technology (Autor et al. 1998). We will estimate this specification for routine and non-routine workers separately. [20]

C. Trends in Offshoring, Trade, Employment, and Wages

In this section we outline broad trends in the data for employment, wages, and the relationship between wages and measures of globalization. In Figure 1, we compare the trends in employment and wages in the manufacturing sector alongside the same trends in the service sector between 1979 and 2002. We present these trends separately for workers performing routine and non-routine tasks. Total manufacturing employment (using the CPS employment numbers) fell from 22 to 17 million from 1979 to 2002, with rapid declines at the beginning of the early 1980s and in the late 1990s. Within manufacturing, the labor force has become increasingly high-skilled with a large decline of roughly 6 million in the number of workers in

and the capital to labor ratio. The results are qualitatively similar to the results presented in the main text. These are presented in Table A9.

[19] For workers outside of manufacturing, the control variables for TFP, PIINV, and REALSHIP are not available and are therefore assumed constant in our main specifications.

[20] One important implicit assumption in our approach is that barriers to changing occupations are similar across routine and non-routine occupations. Kambourov and Manovskii (2008) show this to be the case. They also decompose occupation switching across routine and non-routine occupations and show that between 1968 and 1997 workers were not able to escape routine occupations by switching into non-routine ones.

routine occupations, and a modest increase of roughly 1 million in the number of workers performing non-routine occupations.

In contrast, demand for both types of workers continued to grow in the service sector, and many of the displaced routine manufacturing workers may have found employment in the service sector. These trends have important implications for the US wage distribution. As shown in the bottom of Figure 1, where we report the real hourly wage among CPS workers, manufacturing workers enjoyed a large wage premium during the entire period among both routine and non-routine workers. Insofar as manufacturing provided an opportunity to earn high relative wages – even for low-skill workers – the fall in manufacturing employment might also have played a role in increasing US income inequality during the period.[21]

The three panels displaying wage trends exhibit significant differences during the sample period. Real wages grew in the 1980s, fell or stagnated in the 1990s, and then begin increasing around 1995-1996. Over the entire period, the gap between manufacturing and service wages narrowed, particularly from the mid-1990s onwards. These different trends are one factor which leads us to break our samples into different time periods. We turn now to an examination of how offshoring and trade may be related to these employment and wage trends within manufacturing and in the overall economy.

As shown in Figure 2, foreign affiliate employment in low-income countries by US based multinationals nearly doubled over the entire sample period, while affiliate employment in high-

[21] See Autor et al. (2008) for a review of these trends. It is worth noting that while the trends in Figure 1 are informative, they do not control for other factors that affect income, such as sex, age, and experience. We redid the trends in wages by educational attainment using wage residuals. These wage residuals were computed using Lemieux's (2006) approach for each educational category separately. We also added industry dummies to control for inter-industry wage differentials. The wage residuals show similar trends, with falling wage premia for less educated workers and rising wage premia for more educated workers. Similar results are observed for wage premia when workers are stratified by routine-ness of occupation. Results are available from the authors upon request.

income countries remained roughly constant. The increase in developing country activity has been accompanied by a reduction in the US workforce for these parents from almost 12 million workers in 1982 to 7 million workers in 2002.

In Figure 3, we report changes in the distribution of occupation wage residuals across the 476 occupations in the CPS. Each point in the figure represents the occupation-specific wage premium in 1983 and 2002. The wage premium was calculated by taking the residual in a regression of real log wages on education category dummies, experience category dummies, an interaction of education and experience, controls for sex, race, year and state.[22] These premia were then collapsed into one term for each occupation and year. In order to compare the occupational wage residual changes by their potential exposure to offshoring, we stratify occupations by whether they are above the median occupation in terms of routine task content. As shown in Figure 3, over the sample period routine occupations were more likely to experience declines in wage premiums, possibly because these tasks can be performed overseas at lower cost. Of 240 routine occupations, 187 experienced wage premium declines and only 53 had increases in their wage premium. In contrast, among 236 non-routine occupations, 134 experienced increases and only 102 experienced declines.

Before estimating equations (1A) and (1B), in Table 1 we provide a descriptive regression that is consistent with the results presented in Figure 3. In particular, Table 1 shows that an industry's share of routine jobs in 1983 is a good indicator of subsequent offshoring to low-income locations and increasing import penetration. The dependent variables are the log difference between 1983 and 2002 in employment offshored to low-income countries (in columns (1) and (2)) or high-income countries (in columns (3) and (4)) and the change in import

[22] All data sets and STATA code are available online at the author's website and at Dataverse.

penetration (in columns (5) and (6)). As shown in column (1), an industry's share of routine jobs in 1983 is a significant predictor of the subsequent increase in employment offshored to low-income countries, explaining roughly 7 percent of the variation across industries as a single regressor. We estimate that industries with 1 percentage point more routine jobs in 1983 experienced a 5.1 percent increase in offshore employment to low-income countries by 2002, and this result is statistically significant at the 5 percent level. However, in column (3) there is no significant relationship with offshoring to high-income countries. The significant relationship between an industry's share of routine jobs in 1983 and subsequent offshoring to low-income countries, which stands in contrast to high income country offshoring, is one reason to maintain the distinction between offshoring to high and low income countries in the subsequent analysis.

Column (5) shows that the industry share of routine jobs in 1983 is also a significant predictor of future increases in import penetration. We find a 1.2 percentage point increase in our import penetration measure among industries with 1 percentage point more routine jobs, suggesting that industries with more routine jobs have also faced greater import competition. In columns (2), (4), and (6), we include a range of additional predictors, and continue to find similar effects for the industry share of routine jobs. Our control variables, which include industry averages of the price of investment goods, total factor productivity, capital to labor ratios, and computer use rates, do not qualitatively affect the results.

In the remainder of the paper, we continue to make a distinction between high and low-income offshore locations, and to differentiate workers by the routine content of their jobs. The patterns in the figures and Table 1 indicate rising trade and offshoring to low-income countries in industries with workers whose jobs are characterized by a high routine content.

III. Offshoring, Trade, and the Impact on Domestic Workers

A. Wage Impacts of Offshoring and Trade at the Industry versus Occupation Level

In Table 2, we present our main results showing how the impact of offshoring and trade differ when using industry versus occupation measures of exposure. In the first four columns, we present our estimates for equation (1a) which defines exposure to trade or offshoring at the industry level. In the last four columns, we redo the analysis using our occupation exposure measure, as outlined in equation (1b). Note that the standard errors are clustered by industry and five year period in columns (1) through (4) and by occupation and five year period in the last four columns. Industry regressions include industry fixed effects and occupation regressions include occupation as well as industry fixed effects.

Columns (1) through (4) of Table 2 identify the impact on wages of workers in industries which were more exposed to international trade or offshoring during the 1984 through 2002 period.[23] In these four columns, only workers within the manufacturing sector are included in the estimation. The results suggest a very limited role for offshoring or trade in explaining log wages. There is no statistically significant relationship between low-income-affiliate employment, lagged export share, or lagged import penetration and industry-level wages; indeed, the point estimates are close to zero. There is a positive and statistically significant relationship between high-income-affiliate employment and domestic wages, although the magnitude is not large: the point estimate suggests that a one percent increase in affiliate employment in high income countries is associated with a 0.01 percent increase in wages, and this is found even for workers in the most routine occupations. In these first four columns, which rely on differences in

[23] Note that we exclude 1983 for consistency with our occupation results, which can only be estimated from 1984-2002, since occupation was only coded consistently from 1983 and on, and we are using lagged measures of our independent variables.

exposure to trade or offshoring across industries, the evidence suggests that trade has no substantial negative effect on worker wages for either routine or non-routine workers.

In columns (5) through (8) of Table 2, we present results from specification (1b) where we measure exposure to trade or offshoring at the occupation level. The effects of both offshoring and trade are larger in sign and generally significant at the five percent level. In the first row of column (5), the coefficient on low-income affiliate employment suggests that a ten percent increase in employment offshored within an occupation is associated with a 0.4 percent wage reduction for U.S. workers. For workers in the most routine occupations, we find that a ten percent increase in low-income affiliate employment abroad is associated with a 0.7 percent decline in domestic wages, whereas workers in less routine occupations were largely unaffected by offshoring. Although the magnitude of the effect is small, the results are consistent with an interpretation that workers in low-income locations perform the same tasks that low-skilled workers perform in the US and are therefore substitutes for workers in the US.

We also find a positive effect of lagged high-income affiliate employment on wages. Workers in high-income locations appear to perform tasks that are complementary to workers in the US and so expansion of employment in high-income countries can benefit domestic workers. These results are robust to a range of specification choices, including whether we use prices of imported and exported goods instead of quantities, and our chosen set of control variables, such as controlling for the real price of shipments by sector to account for variation in product demand.[24] The results are qualitatively similar to the results presented here, and are available in the online appendix.

[24] The results indicate that workers with price decreases in their product market have suffered the largest wage declines, with this pattern most pronounced in routine occupations. Similar to our core results, however, this effect is only observed using occupational exposure measures of import price changes. Special thanks to Lawrence Edwards for generous use of his price series data on imports. Other specifications we have tested include removing measures

Our results indicate that a ten percent increase in occupational exposure to import competition is associated with nearly a 3 percent decline in real wages for workers who perform routine tasks. While some occupations have experienced no increase in import competition (such as teachers), import competition in other occupations (such as shoe manufacturing) has increased by as much as 40 percentage points.[25] For occupations with significant export activity, wages are positively linked to export growth. For these workers, a ten percentage point increase in export share at the occupation level is associated with a 6.6 percentage point increase in wages over the sample period.

Krugman (2008) and Feenstra (2008) both hypothesize that the effects of international trade and offshoring may have increased recently relative to earlier decades. In Table 3, we split the sample into earlier and later time periods. In particular, we allow the impact of globalization to vary between 1984 and 1991, and 1992 through 2002 when our sample ends. We also explore whether the impact of globalization varied by gender, union status, education, and age.

The results in Table 3 suggest that there is no significant association between log wages and employment in offshore locations in the early years of our sample (1984-1991, 1984-1996). However, in the later periods (1992-2002, 1997-2002) worker wages are negatively and significantly associated with increased offshore employment in low-income affiliate locations. In the years 1997-2002, the coefficient estimates in the fourth row of Table 3 indicate that a 10 percent increase in low-income affiliate employment is associated with a one percent decrease in domestic wages. These negative coefficients contrast with the positive coefficients on high-

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of TFP and controlling for price changes in the service sector using a CPI/PPI index, both of which provide results similar to those presented in Table 2. Likewise, the results including the real price of shipments are similar to the results in Table 2.

[25] See the online appendix for further information on import exposure by occupation.

income affiliate employment. For 1997 through 2002, a 10 percent increase in high-income affiliate employment is associated with nearly a 1 percent increase in domestic wages.

Table 3 also reports the coefficient on lagged imports and exports, measured at the occupation level. The point estimates for occupation-specific import penetration are statistically significant across all time periods, with the coefficients ranging from -0.21 to -0.32. These coefficients indicate that a ten percentage point increase in import penetration is associated with a wage decline in the exposed occupation of 2 to 3 percent. The coefficients become larger and more negative in magnitude in the later time periods. The evidence also points to a positive and significant association between export share and domestic wages, but the point estimates are positive and significant for export share only in the later part of the sample period.

In Table 3, we also explore heterogeneity in our results across different demographic groups. Anecdotes in the popular press and elsewhere suggest that women, union workers, less educated workers and older workers may have been disproportionately affected by international competition. If we restrict the sample to either women or union workers, there is no evidence that their wages were more negatively affected than the rest of the sample. In fact, the wages of unionized workers appear to have been relatively unaffected by either export activity or import competition. However, the wages of workers without higher education and older workers do appear to have been disproportionately affected by offshoring activities, as the point estimates are larger for these groups of workers. The estimates in Table 3 indicate that all of the negative and significant effects of offshore employment and import penetration were concentrated on workers with a high school education or less.

Since the results point to much stronger effects of offshore activities on domestic wages in the later part of the sample period, we reproduce Table 2 for the 1997 through 2002 period in

Table 4. The results confirm that, for the last five years of our sample, offshoring and international trade exerted much larger effects on occupation-specific wages than the earlier years. The results also confirm that over the most recent sample period, industry-level wage effects are negligible. In columns (1) through (4), all but two of the point estimates are statistically insignificant and the magnitudes are close to zero, indicating offshoring or trade does not significantly affect industry-level wage premia.

Columns (5) through (8) suggest that occupation-specific changes in offshoring and trade are associated with significant wage effects, particularly for workers in the most routine occupations. For these workers, a ten percent increase in offshoring to low-income countries is associated with a 2 percent decrease in wages. In contrast, , a ten percentage point increase in offshoring to high-income countries associated with a 1.7 percent increase in wages for routine workers. One explanation is that workers in high-income locations perform tasks that are complementary to routine workers in the US. A one percent increase in export shares is associated with a one percent increase in wages while a one percent increase in import penetration is associated with a -0.44 percent decline in wages. The effects of trade are generally small in magnitude and insignificant for individuals who work in the occupations with the least routine content.

While we control for a number of observables, there are other shocks which might be difficult to control for and could affect workers in routine occupations. To verify that our results are not driven by secular trends in which wage changes, globalization, and technological change are all moving together over time, we present a falsification exercise in Table 5. In particular, we regress current period wage changes for 1984 through 1989 on future globalization shocks for 2002. Our future globalization shocks are the logs of low and high income affiliate employment in 2002, as well as export shares and import penetration in 2002. If the analysis is driven by spurious trends, then the coefficient on 2002 measures of globalization should be significant in explaining wages for the 1984 through 1989 period. Table 5 shows that 2002 measures of globalization do not significantly affect wages in the earlier period. In contrast, 2002 measures of globalization do significantly affect wages in 1997 through 2002. For example, our offshoring measure to low income countries is significantly negatively correlated with wage changes among workers during this later period. This is additional evidence that our results are not being driven simply by a spurious correlation between offshoring and domestic wage changes.[26]

IV. Mechanisms: Globalization and the Reallocation of Labor

In this section, we identify mechanisms for the differences between industry-level and occupation-level exposure to offshoring and trade. Our evidence and previous research suggests that switching occupations, but not sectors within manufacturing, significantly affects worker wages. In this section, we directly link changes in occupations for the same individual with changes in globalization and explore the impact on wages. We begin by examining the wage consequences of switching industries, sectors, and occupations using a panel of CPS workers who are followed for more than one period.

To explore the impact of switching sectors or occupations, we construct a sample of manufacturing workers observed in CPS samples in consecutive years between 1983 and 2002. We regress the change in log wages between period *t* and *t*+1 for a given worker on an indicator

[26] It is worth discussing alternative possibilities that could undermine our interpretations of our findings. For example, it may be that even if the US had engaged in autarky in this later period, domestic workers would have been replaced by machines, thereby implicating offshoring when the workers' decline was inevitable. This possibility naturally cannot be evaluated in our data. Also, if our technology control variables are measured with error, it may be that the wage declines we observe are a byproduct of the substitutability between these workers and capital. However, we would argue that the strong correlation between the timing of increased offshore employment and declining domestic wages seems unlikely to be fully explained by stories of this nature.

for switching industries, sectors, or occupations. We also include a rich set of controls for the worker's age, sex, education, race, union status in the first period, and industry in the first period. If occupational exposure to globalization puts downward pressure on wages by inducing workers to exit high wage jobs in manufacturing, then we would expect the data to show this. In particular, we would expect wages of manufacturing workers who retain their jobs to be relatively unaffected by globalization, whereas those who shift sectors or occupations are more negatively affected. In Table 6, we examine the impact on a worker's wages of shifting across manufacturing sectors, leaving manufacturing, and leaving an occupation within manufacturing.

The first panel (Panel A) of Table 6 examines the impact on wages for workers who switch industries but remain within manufacturing during both periods. Consistent with the results in Tables 2 through 5, we see that switching sectors (from textiles to steel, for example) but remaining in the same occupation within manufacturing is not associated with significant wage changes. For all types of occupations, including the most routine occupations, switching industries has no significant impact on worker wages. In Panel B of Table 6, we examine how wages of an individual are affected when that worker leaves manufacturing. On average, a worker who leaves the manufacturing sector experiences a real wage decline of three percentage points from one period to the next. In Panel B of Table 6, the wage decline for workers who leave manufacturing is highest in routine occupations, at almost 4 percentage points. The documented wage decline for an individual worker in the CPS who leaves manufacturing is consistent with Figure 1 showing a wage premium for workers in manufacturing. However, unlike Figure 1, the regression results in Table 6 control for a wide range of individual worker characteristics.

The last panel of Table 6 shows the highest real wage declines for workers who leave manufacturing *and* switch occupations. On average, workers who leave manufacturing and switch occupations experienced a real wage decline 6 percentage points, with a range of 4.2 to 10.6 percent. To summarize, Table 6 shows that (1) remaining in the same occupation but switching industries within manufacturing does not significantly affect a worker's wages (2) leaving manufacturing but remaining within the same occupation has a negative impact on an individual's real wage and (3) leaving manufacturing is particularly costly for workers who also switch occupations.

The evidence presented in Table 6 is consistent with the results presented earlier in the paper but does not establish a direct link with trade or offshoring. In the remainder of this section, we explore direct linkages between switching sectors or occupations and our different globalization measures. We begin by decomposing the results in the last four columns of Table 2 into manufacturing only and services only. Those results are reported in online Appendix Table A7. The impact of offshoring and trade is significant using the occupational exposure measure for both manufacturing (only) and services (only). What is particularly noteworthy is that the coefficients are the most negative for the last four columns, which measure the impact of occupational exposure to globalization on workers in the services sector. Paul Krugman has argued that globalization could not possibly affect wage outcomes in the United States because manufacturing is too small relative to the other sectors of the economy, so the "tail can't wag the dog". However, our results suggest that, in fact, the significant exposure at the occupational level to trade or offshoring does affect services sector wages. This is likely to operate both through the falling wages of workers who have moved from manufacturing to services (as documented in Figure 1 and Table 6) as well as by putting downward pressure on the wages of workers in services as labor supply in services shifts out to absorb workers formerly in manufacturing.

The next question we explore is whether globalization per se has been systematically associated with switching occupations. Using our matched sample of CPS ORG workers who are observed in consecutive years, we compare the wage difference in period *t* and *t*+1 for workers who switch occupations versus those who do not. In Panel A, we examine workers who switch across 3-digit occupational categories. The difference between this sample and the sample in Table 6 is that now we look at occupation switching for all workers, not just workers who switched occupations and left manufacturing.

In column 1, we examine the wage impact of all occupation switched and find that the impact is negligible; an occupation change is associated with 0.54 percent increase in wages. One possible explanation for this result is that some switches are upwards (as measured by average occupational wages), and others are downward, leaving a mixed result for all switches. This hypothesis is put forward in Trefler and Liu (2011), who find evidence that switches of both types are common in response to trade.

In order to examine the impact of trade-induced occupational switching on wage outcomes, we consider a system of equations for estimation. In our first stage, we examine the impact of occupational exposure on the probability of switching occupations between periods. We create a dichotomous measure for our instrument. All workers who are employed in occupations above the median level of offshore exposure from low income countries are considered “tradable”. The results, presented in column 2, indicate that a being in a tradable occupation is associated with a 9.4 percentage point increase in the probability of switching occupations between periods. In our second stage, we examine the relationship between switching occupations and wage declines, when this switch is induced by trade. We find that trade-induced occupation switches are associated with a 12.1 percent decline in wages between periods. This result is consistent with our earlier results highlighting negative consequences of globalization on wages of workers who perform tasks that can be performed in low income countries. In Panel B, we perform a similar analysis but use a broader classification of occupation. If a more narrow definition of occupation implies that a worker is more likely to be performing a similar task, these switches will presumably have less important wage consequences. Consistent with this hypothesis, the results in Panel 2 indicate that trade is less likely to induce a switch to a new 2-digit occupation (6.9 percentage points) but upon switching, the negative wage consequences are even more severe: a trade-induced occupational switch across 2-digit categories is associated with a 17.2 percent decline in wages. These results suggest that switching occupations is very costly to workers, and provides support for our main results suggesting that occupational exposure to competition from trade or offshoring has more significant consequences than industry exposure.

One possibility is that workers who switch occupations in a "downward" manner are less productive in unobserved dimensions of worker quality. Weaker workers may sort into less demanding occupations, and this may not be captured by the human capital measures available in the CPS (e.g. education). While we are unable to observe variation in the quality of workers on unobserved dimensions, we attempt to address this possibility by adding an additional control to the wage equation, which is the difference between the inter-occupation wage differential for all workers in a sector, and the inter-occupation wage differential for workers who leave that sector in the following period. If workers who remain and those who leave a sector are similar, then this difference should be close to zero and adding it as an additional control should have no impact on our estimate. The negative impact of switching occupations on wages is unaffected by the inclusion of the inter-occupation wage differential term (see also Trefler and Liu (2011) for an application to services). Our results are suggestive that in manufacturing, worker heterogeneity does not explain the significant decline in wages of workers who leave their occupation due to trade or offshoring pressures.

Our results are consistent with work by Kambourov and Manovskii (2008, 2009a, 2009b) who find large wage declines among workers who switch occupations; this evidence suggests an important role for occupation-specific human capital in a worker's wage profile. Kambourov and Manovskii (2008, 2009a, 2009b) also argue that occupation-switching may be an important cause of the increase in US wage inequality, as younger workers are missing out on the benefits to occupational tenure enjoyed by workers in previous decades. Insofar as this is partly driven by competition from overseas, this highlights another mechanism by which offshoring may be responsible for declining US wages and increasing wage inequality.

V. Conclusion

This paper examines the impact of trade and offshoring—two important aspects to globalization—on the wages of US workers. Using CPS data merged with exports, imports, and BEA data on offshoring, we make three main contributions. First, we draw a distinction between the impact of globalization on industrial wage differentials and on occupation wage differentials. To do this, we create a new measure of *occupational exposure* to globalization. Globalization has had small or insignificant effects on industry wage differentials but significant effects on occupation wage differentials. These results are consistent with recent empirical work demonstrating the importance of occupational tenure and downplaying the importance of tenure within a particular industry in determining a worker's wage.

Second, we extend previous analyses which focused exclusively on manufacturing sector workers to explore the impact of trade and offshoring on all workers. Our results show that restricting the analysis to within manufacturing has led researchers to mistakenly conclude that trade or offshoring has insignificant effects on wages. This is partly because much of the impact of trade or offshoring on worker wages operates by moving workers from higher paid manufacturing jobs to lower wage jobs elsewhere.

Third, we use a two stage approach following the same worker over time to document the mechanisms through which globalization affects wages. Globalization puts downward pressure on US worker wages by (1) moving workers from the manufacturing sector into services, which affects the wages of both the workers who came from manufacturing and those already in services and by (2) inducing workers to change occupations. Using a CPS panel of workers and the exposure of an occupation to trade as an instrument for whether or not a worker switched occupations, we find that occupation switching due to trade led to real wage losses of 12 to 17 percentage points between 1983 and 2002. The results are robust to the inclusion of a term from Trefler and Lui (2011) which captures the possibility that the least able workers are most likely to switch into lower paying occupations.

Our results provide new evidence that the negative consequences of trade on workers are mediated through a reallocation of labor across sectors and into different occupations. While older models of trade posited that workers could move in a costless manner to new jobs in the face of pressure from foreign labor, we identify large and significant wage declines among workers who leave manufacturing, and the wage decline is particularly pronounced for those who switch occupations. These results are consistent with new trade models which introduce frictions into the labor reallocation process, such as Cosar (2011) and Artuc, Chaudhuri, and McLaren (2010). Our evidence is consistent with greater frictions in moving across occupations rather than across industries.

We also explored how the impact of globalization on wages has changed over time. Our different measures of globalization have no significant impact on wages during the first half of our sample. While our sample extends from 1984 to 2002, both offshoring and trade exert significant effects on wages only in the second half of this period. The effects of these globalization measures are confined to individuals who work in "routine" occupations, indicating that much of the brunt of globalization is born by individuals who perform tasks which are easily copied by workers elsewhere.

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Table 1: OLS Estimates of Change in Offshoring and Import Penetration Given Industry Skill Composition in 1983

	Dependent Variable: Log Difference in Employment Offshored (1983-2002)				Dependent Variable: Import Penetration Difference (1983-2002)	
	Low Income Countries		High Income Countries			
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Share of Routine Jobs in 1983	5.132**	5.501**	-0.980	-0.053	1.217***	1.237***
	(2.40)	(2.59)	(2.03)	(2.26)	(0.34)	(0.33)
Difference in log of price of investment between 1983 and 2002		-0.262		0.234		-0.079
		(0.45)		(0.40)		(0.06)
Difference in total factor productivity level between 1983 and 2002		0.084		-0.056		0.0242**
		(0.07)		(0.06)		(0.01)
Difference in capital to labor ratio between 1983 and 2002		-0.230		-1.218		-0.249
		(1.21)		(1.06)		(0.16)
Difference in computer use rates between 1983 and 2002		0.441		-0.391		0.028
		(0.68)		(0.59)		(0.09)
Number of observations	66	59	66	59	66	61
R-squared	0.07	0.12	0.00	0.07	0.17	0.35

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

Source : Affiliate (or offshore) employment data are taken from the Bureau of Economic Analysis annual survey of US firms with multinational affiliates for 1983-2002. Low income countries are defined according to the World Bank income categories. Employment data are taken from all workers in the Current Population Surveys Merged Outgoing Rotation Groups for the same period. Import penetration and export share are taken from Bernard, Jensen, and Schott (2006). Investment good prices, total factor productivity measures, and the capital to labor ratio by industry and year are taken from the NBER productivity database. Computer use rates are taken from October CPS supplements during the sample period. Details for each of the data sources are available in the data appendix.

Note: Robust standard errors are reported in parentheses below the coefficient estimates.

Table 2: OLS Estimates of Wage Determinants using Occupational versus Industry Exposure to Offshoring and Trade, 1984-2002

Dependent Variable: Log Wage

	Offshoring and Trade Measured by Industry-Specific Exposure, Manufacturing Only				Offshoring and Trade Measured by Occupation-Specific Exposure, All Sectors			
Variable	All Occupations	Most Routine	Intermediate Routine	Least Routine	All Occupations	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	0.001	0.002	0.000	0.002	-0.0401**	-0.0702***	0.018	0.072
	(0.002)	(0.002)	(0.003)	(0.003)	(0.016)	(0.016)	(0.029)	(0.056)
Lagged log of high income affiliate employment	0.0143***	0.00793*	0.011	0.0239***	0.0339**	0.0508***	-0.003	-0.045
	(0.005)	(0.005)	(0.007)	(0.008)	(0.015)	(0.014)	(0.026)	(0.048)
Lagged export share	0.022	-0.021	0.002	0.047	0.255**	0.667***	0.232	-0.815*
	(0.043)	(0.058)	(0.048)	(0.045)	(0.121)	(0.157)	(0.184)	(0.420)
Lagged import penetration	0.077	0.090	0.042	-0.050	-0.290***	-0.296***	-0.761	1.083
	(0.050)	(0.061)	(0.057)	(0.074)	(0.091)	(0.099)	(0.466)	(0.750)
Number of observations	551,528	316,048	150,319	85,161	3,068,095	1,109,835	1,156,208	802,052
R-squared	0.46	0.39	0.41	0.38	0.50	0.42	0.54	0.40

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

Source : See Table 1.

Note : Robust standard errors are reported in parentheses below the coefficient estimates. The workers are taken from CPS samples from 1984-2002, with their lagged values of the independent variables taken from 1983-2001. The standard errors are clustered by industry and 5 year period in columns (1-4), and by occupation and 5 year period in columns (5-8). The classification of occupations into routine categories is determined by the proportion of tasks which are routine in each occupation, with low being occupations with more than 2/3rd, intermediate being between 1/3rd and 2/3rd, and high being occupations with less than 1/3rd of tasks designated routine. We also control for the lagged log price of investment, lagged total factor productivity, and lagged capital to labor ratio among manufacturing workers. Among non-manufacturing workers, these controls are set equal to unity. Wage specifications control for a worker's gender, age, race, experience, whether in a union, and include industry, year, education and state fixed effects. The occupation-specific exposure regressions also include 2-digit occupation fixed effects. Controls for computer use rates are imputed by the worker's industry (columns 1-4) and by occupation (columns 5-8).

Table 3: OLS Estimates of Wage Determinants using Occupational Exposure to Offshoring and Trade Among Subsamples of CPS workers, 1984-2002

Dependent Variable: Log Wage

Specification	Lagged Log of Low Income Affiliate Emp	Lagged Log of High Income Affiliate Emp	Lagged Export Share	Lagged Import Penetration	Obser-vations	R-Squared
1984-1991	0.003	-0.005	0.06	-0.215***	1,390,331	0.52
	(0.012)	(0.01)	(0.109)	(0.067)		
1992-2002	-0.0558***	0.0449***	0.490***	-0.321***	1,677,763	0.49
	(0.013)	(0.011)	(0.081)	(0.062)		
1984-1996	-0.015	0.0102	0.181**	-0.261***	2,181,111	0.51
	(0.009)	(0.008)	(0.076)	(0.057)		
1997-2002	-0.107***	0.0946***	0.478***	-0.306***	886,983	0.48
	(0.026)	(0.024)	(0.118)	(0.093)		
Female	-0.0477***	0.0434***	0.376***	-0.178***	1,491,461	0.49
	(0.013)	(0.012)	(0.093)	(0.038)		
Union	0.004	-0.011	-0.104	-0.075	549,055	0.37
	(0.01)	(0.009)	(0.077)	(0.073)		
High School or Less	-0.0407***	0.0319***	0.227***	-0.209***	1,475,119	0.44
	(0.009)	(0.008)	(0.081)	(0.049)		
College or More	-0.0250**	0.0228**	0.12	-0.116	1,592,975	0.44
	(0.011)	(0.01)	(0.073)	(0.111)		
Over 40	-0.0560***	0.0482***	0.11	-0.202***	1,262,929	0.48
	(0.01)	(0.009)	(0.071)	(0.053)		
Over 50	-0.0552***	0.0487***	0.11	-0.287***	550,041	0.48
	(0.013)	(0.012)	(0.088)	(0.064)		

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

Source : See Table 1.

Note : Each row represents a separate regression. The independent variables are listed in the column headings, and the subsample of interest is listed in the row heading. Robust standard errors are clustered by occupation and 5 year period, and are reported in parentheses below the coefficient estimates. Wage specifications control for a worker's gender, age, race, experience, whether in a union, imputed computer use rate by occupation and include year, education, state, industry, and two-digit occupation fixed effects.

Table 4: OLS Estimates of Wage Determinants using Occupational versus Industry Exposure to Offshoring and Trade, 1997-2002

Dependent Variable: Log Wage

	Offshoring and Trade Measured by Industry-Specific Exposure, Manufacturing Only				Offshoring and Trade Measured by Occupation-Specific Exposure, All Sectors			
Variable	All Occupations	Most Routine	Intermediate Routine	Least Routine	All Occupations	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	-0.009	-0.005	-0.0221***	0.002	-0.107***	-0.198***	0.147***	0.330*
	(0.006)	(0.008)	(0.008)	(0.013)	(0.040)	(0.038)	(0.050)	(0.165)
Lagged log of high income affiliate employment	-0.002	-0.014	0.004	0.016	0.0947**	0.169***	-0.140***	-0.299**
	(0.009)	(0.010)	(0.013)	(0.022)	(0.037)	(0.035)	(0.042)	(0.143)
Lagged export share	-0.021	-0.111	0.039	0.049	0.478***	0.999***	0.292	-0.808
	(0.072)	(0.078)	(0.092)	(0.075)	(0.178)	(0.240)	(0.271)	(0.948)
Lagged import penetration	0.119	0.196**	-0.067	-0.094	-0.306**	-0.437***	-0.035	1.668
	(0.073)	(0.094)	(0.150)	(0.176)	(0.146)	(0.160)	(0.587)	(1.419)
Number of observations	132,104	71,985	36,982	23,137	886,984	291,894	337,057	258,033
R-squared	0.44	0.35	0.40	0.34	0.48	0.39	0.51	0.37

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

Source : See Table 1.

Note : Robust standard errors are reported in parentheses below the coefficient estimates. The workers are taken from CPS samples from 1997-2002, with their lagged values of the independent variables taken from 1996-2001. The standard errors are clustered by industry and 5 year period in columns (1-4), and by occupation and 5 year period in columns (5-8). The classification of occupations into routine categories is determined by the proportion of tasks which are routine in each occupation, with low being occupations with more than 2/3rd, intermediate being between 1/3rd and 2/3rd, and high being occupations with less than 1/3rd of tasks designated routine. We also control for the lagged log price of investment, lagged total factor productivity, and lagged capital to labor ratio among manufacturing workers. Among non-manufacturing workers, these controls are set equal to unity. Wage specifications control for a worker's gender, age, race, experience, whether in a union, and include industry, year, education and state fixed effects. The occupation-specific exposure regressions also include 2-digit occupation fixed effects. Controls for computer use rates are imputed by the worker's industry (columns 1-4) and by occupation (columns 5-8).

Table 5: Falsification Exercise using Exposure to Offshoring and Trade in 2002 and Wage Impact by Period

Dependent Variable: Log Wage

Variable	Offshoring and Trade Measured by Occupation-Specific Exposure in 2002	
	1984-1989	1997-2002
Log of low income affiliate employment in 2002	0.015	-0.0862**
	(0.055)	(0.042)
Log of high income affiliate employment in 2002	-0.014	0.0769**
	(0.050)	(0.038)
Export share in 2002	-0.079	0.445***
	(0.248)	(0.157)
Import penetration in 2002	-0.118	-0.358***
	(0.150)	(0.124)
Number of observations	1,036,302	886,958
R-squared	0.53	0.48

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

Source : See Table 1.

Note : Robust standard errors are clustered at the occupation level and reported in parentheses below the coefficient estimates. The independent variables reported for the globalization exposure are taken from the worker's occupational exposure in 2002. The sample in each column includes workers in all sectors for the listed period. The regressions include the same controls that are included in the regressions using occupational exposure in Table 2.

Table 6: Wage Changes Among Manufacturing Workers Observed 2 Periods Who Switch Industry, 1983-2002

Dependent Variable: Log Wage Change Between Periods

	All Occupations	Most Routine	Intermediate Routine	Least Routine
Panel A: Sample of Workers who Stay in Manufacturing both Periods				
Switched Industry Classification (1=yes)	-0.003 (0.003)	0.000 (0.003)	-0.002 (0.005)	-0.0154* (0.008)
Observations	147,865	83,026	41,827	23,012
Panel B: Sample of Workers who Switch Industry Classification between Periods				
Left Manufacturing (1=yes)	-0.0314*** (0.004)	-0.0364*** (0.006)	-0.0253*** (0.006)	-0.0276*** (0.010)
Observations	170,545	93,689	49,015	27,841
Panel C: Sample of Workers who Leave Manufacturing between Periods				
Switched Occupation (1=yes)	-0.0590*** (0.010)	-0.0441*** (0.011)	-0.0420*** (0.013)	-0.106*** (0.021)
Observations	22,680	10,663	7,188	4,829

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

Source : Sample is composed of CPS MORG workers observed in two consecutive samples and employed in manufacturing in the first period.

Note : Robust standard errors reported in parentheses below coefficient estimates. Standard errors are clustered by occupation. All models include year, state and education level fixed effects. Other demographic controls are age, sex, non-white, and union status in the first period. Industries and occupations are defined by 3-digit census classifications. Classification of routine is based on first period occupation. The classification of occupations into routine categories is determined by the proportion of tasks which are routine in each occupation, with low being occupations with more than 2/3rd, intermediate being between 1/3rd and 2/3rd, and high being occupations with less than 1/3rd of tasks designated routine.

Table 7: Wage Impact of Switching Occupations using CPS Workers in Repeated Samples, 1984-2002

	OLS	First-Stage	Two-stage Least Squares
	Log Wage Difference	Switched Occupation	Log Wage Difference
	(1)	(2)	(3)
Panel A: Defining an Occupation Switch by Switching 3-digit Occupation			
Switched Occupations Between T and T+1	0.0054		-0.121**
	(0.005)		(0.051)
Inter-Occupation Wage Differential Gap Term[1]	0.281		0.190
	(0.223)		(0.252)
Tradable Occupation (1=yes)		0.0942***	
		(0.022)	
Number of Observations	851,467	851,467	851,467
F Test of Instrument		18.91	
Panel B: Defining an Occupation Switch by Switching 1-digit Occupation			
Switched Occupations Between T and T+1	-0.00153		-0.172***
	(0.001)		(0.059)
Inter-Occupation Wage Differential Gap Term	-0.0506		-0.0594
	(0.076)		(0.131)
Tradable Occupation (1=yes)		0.0693***	
		(0.020)	
Number of Observations	851,467	851,467	851,467
F Test of Instrument		11.66	

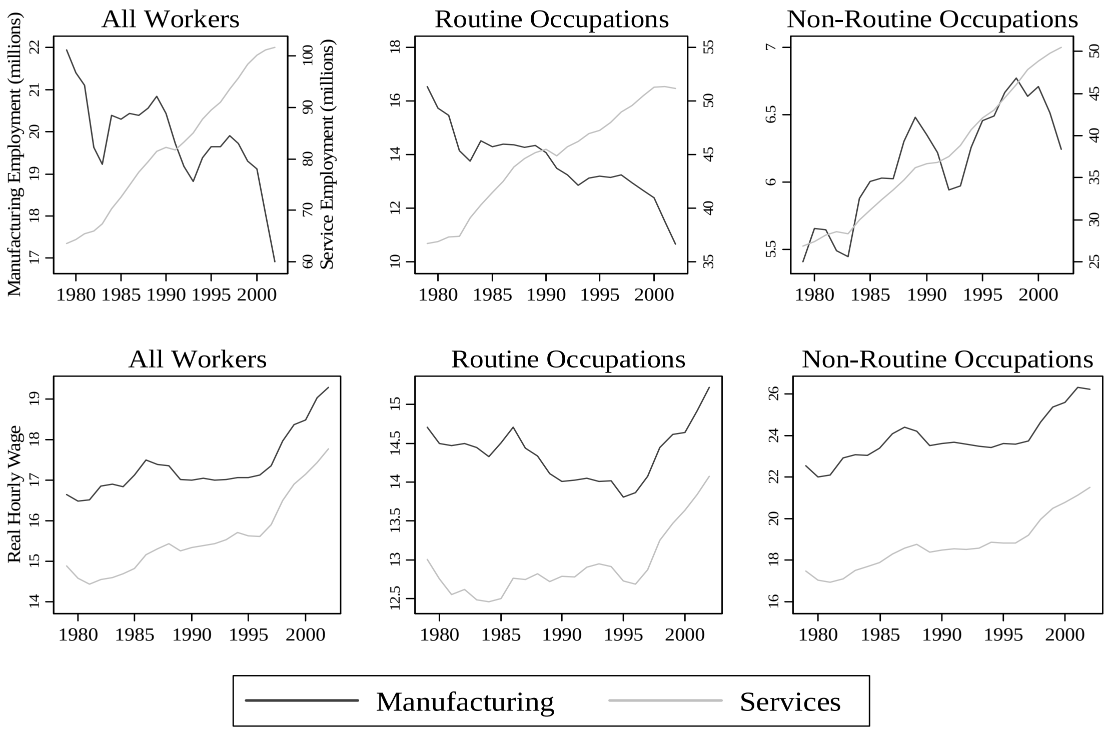
* significant at 10% ** significant at 5%. *** significant at 1%.

Source : Sample is composed of CPS MORG workers observed in two consecutive samples.

Note : Robust standard errors reported in parentheses below coefficient estimates. Standard errors are clustered by 3-digit occupation. All models include year, state and education level fixed effects. Other demographic controls are age, sex, non-white, and union status in the first period. An occupation is defined as tradable if the occupational exposure from low-income countries (as described in Table 2) is above the median level among manufacturing workers in the sample. This is used to generate a binary variable for all workers in the sample, and is the instrument for occupational switches. In Panel A, we define an occupation switch by the worker reporting a different 3-digit occupation. In Panel B, an occupation switch is defined by a worker reporting a different 1-digit occupation. [1]The Inter-Occupation Wage Differential Gap term is calculated by regressing the workers' log wage on observable characteristics and a set of occupation dummies among all workers, and among workers who switch occupations between periods. The difference in means of these terms is included in our regressions to control for potential selection on unobservables of those who switch occupations.

Figure 1

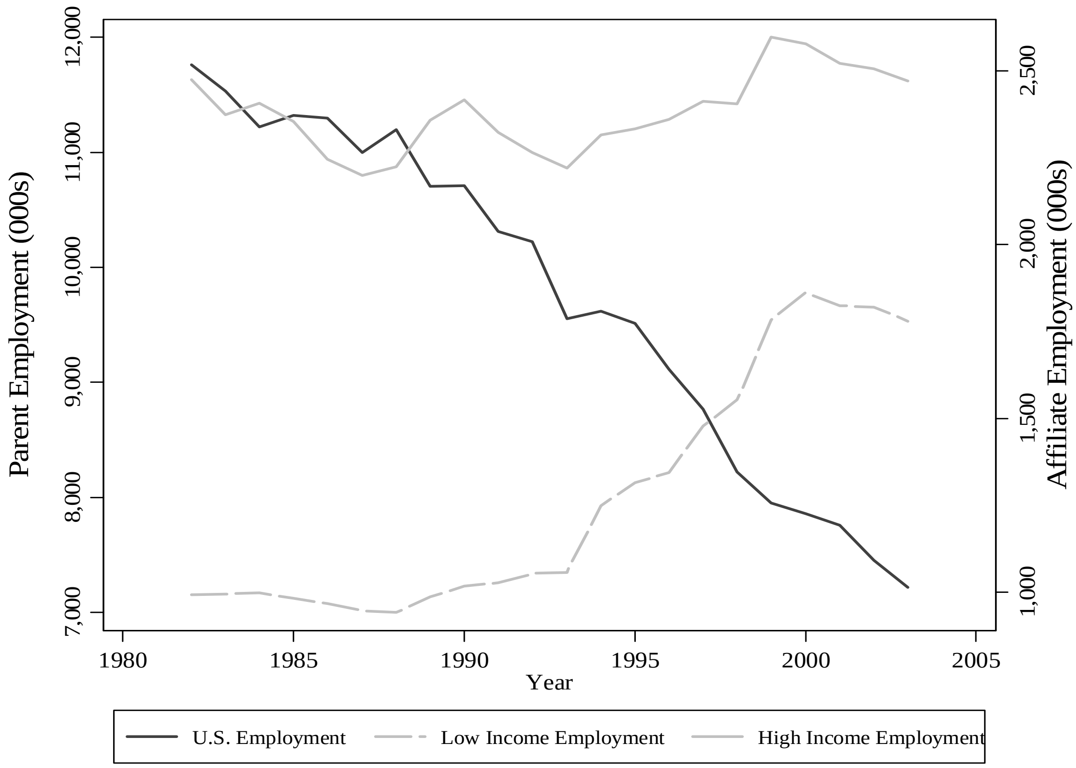
Trends in Employment and Wages in the Manufacturing and Service Sectors



Notes : Employment and wage calculations are based on the Current Population Survey Merged Outgoing Rotation Groups (MORG). Sample includes all part-time and full-time workers. Wages are in 2005 dollars. Definition of routine workers is based on occupational task content. Details are available in the data appendix.

Figure 2

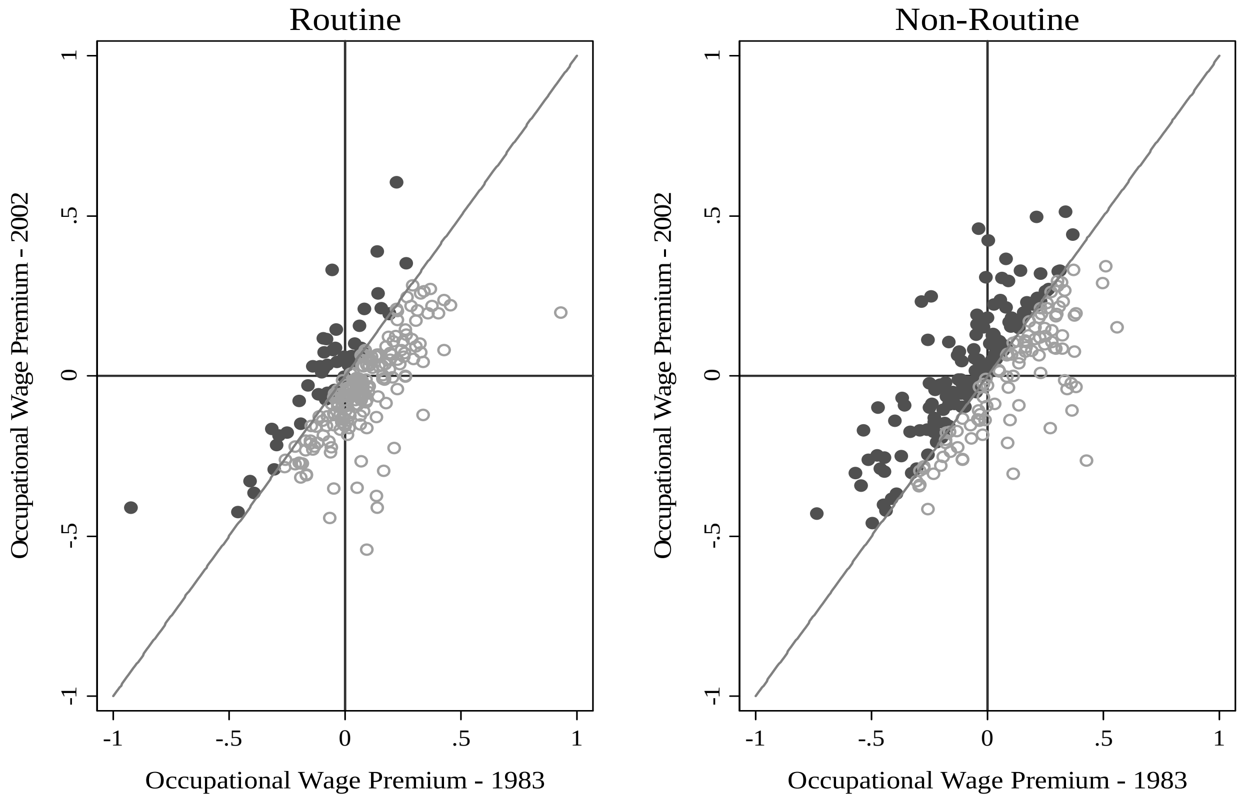
Trends in Domestic and Affiliate Employment among Multinational Firms



Notes : Author's calculations 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. Using these data, we compute number of employees hired abroad by country and year, and then aggregate employment by Low (High) Income country according to World Bank income classifications.

Figure 3

Occupational Wage Premiums in 1983 and 2002 among Routine and Non-Routine Occupations



Notes : Wage premium are calculated by a standard Mincerian regression of the log wage on education, experience, age, sex, race, year fixed efffects and state fixed effects among all workers in the CPS MORG between in 1983 and 2002. Each point in the plot is a separate occupation identified in the CPS (N=464). The occupations are considered routine if the share of tasks that is routine is greater than the median occupation. Occupations with higher wage premiums in 2002 than in 1983 are shaded in.

Online Appendix Materials for "Why are American Workers getting Poorer? Estimating the Impact of Trade and Offshoring on American Workers Using the CPS"

In this appendix, we present materials that supplement our results in the main text, but were not included due to space considerations. In Section I of this appendix, we describe our data sets and present summary statistics for the sample of CPS workers. In Section II, we present a set of calculations that are related to our analysis. We first examine the impact of globalization on manufacturing employment, and the robustness of these results. We then present a thorough breakdown of imports by occupation. This is followed by a set of alternative specifications and robustness checks of our main results presented in Table 2. We conclude with analysis on our matched sample of CPS workers to further explore mechanisms underlying the results in Table 2.

I. Data Appendix:

A. Current Population Survey

We use the CPS Merged Outgoing Rotation Groups for the years 1979 to 2002. Note that our analysis relies on the MORG copy prepared by the Center for Policy and Economic Research (CEPR). The CEPR MORG files are created from the National Bureau of Economic Research version of these data, and we rely on the processing performed by CEPR to produce consistent variables for wages, education, and other demographic characteristics of the MORG sample. Our sample includes wage/salary for workers ages 16 to 64 in current employment. Earnings weights, equal to the product of CPS sampling weights and hours worked in the prior week, are used in all calculations. Hourly wages are the logarithm of reported hourly earnings for those paid by the hour, and the logarithm of usual weekly earnings divided by usual weekly hours among salaried workers. Overtime, tips, and commissions are included in wages, and top-coded wages are computed by assuming a log-normal distribution for weekly earnings as described by Schmitt (2003). The calculated nominal hourly wage is converted to a real wage using the Consumer Price Index for 2006, and then trimmed to values between $1 and $100 per hour.

Source: Schmitt, John. 2003. "Creating a consistent hourly wage series from the Current Population Survey's Outgoing Rotation Group, 1979-2002." Available for download at http://www.ceprdata.org/cps/cps_documentation.php.

B. 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.

C. Trade Data

Our data on import penetration were made available at the 4-digit ISIC level by Bernard et al. (2006). We also include a measure of the share of import penetration from low-wage countries, also computed by these authors. These data were aggregated from the 4-digit to 3-digit SIC level using the employment distribution in 1979. The 3-digit SIC level was converted to our industry classification scheme using a concordance provided by David Autor that was a census-based scheme that consistently defined industries for our sample period.

D. Data on Occupational Characteristics (United States Department of Labor, supplied by David Autor)

Definitions of the Nature of Tasks, taken from Autor et al. (2003)

Task Name	Task Description
DCP: Direction, Control, and Planning of Activities	Measures nonroutine cognitive tasks, intended to capture interactive, communication, and managerial skills. This variable captures the extent to which the occupation involves direction, control, and planning of activities. It takes on high values for occupations requiring interpersonal and managerial tasks.
GED-MATH	Measures quantitative or analytical reasoning skills.
STS: Set limits, Tolerances or Standards	Measures routine cognitive tasks. Measures adaptability to work requiring the setting of limits, tolerances or standards.
FINGDEX: Finger Dexterity	Measures routine manual activity. FINGDEX is an abbreviation for finger dexterity.
EYEHAND	Measures non-routine manual task requirements. EYEHAND is an abbreviation for eye, hand, foot coordination.
Notes: Our measure of routine-ness is defined as the sum of the cognitive and manual routine measures divided by all the measures. Routine = (sts + fingdex)/(sts + fingdex + math + dcp + eyehand)	

E. Price of Investment, Total Factor Productivity, and the Real Price of Shipments

The price of investment, which varies by industry and year, is taken from the NBER's productivity database. Total factor productivity is computed by the NBER for all years through 1996, and was updated through 2002 using data provided to the authors by Wayne Gray. The real price of shipments is taken from this database as well. These data were aggregated from the 4-digit to 3-digit SIC level using the employment distribution in 1979. The 3-digit SIC level was converted to our industry classification scheme using a concordance provided by David Autor that was a census-based scheme that consistently defined industries for our sample period.

F. Bureau of Labor Statistics Imports and Export Prices

Our data on prices of imports and exports are recorded by the Bureau of Labor Statistics using the Standard Industrial Trade Classification scheme and are weighted by purchases of goods within each industry. These are converted to the 3-digit SIC coding scheme, and then made compatible with the CPS industrial codes using code provided by David Autor. These concordances between SIC coding and CPS coding are available in the online appendix to Autor et al. (1998).

G. Panel Data Set of Current Population Survey Workers

We construct a panel data set from the CPS Merged Outgoing Rotation Groups by matching individuals surveyed in two consecutive years between 1983 and 2002. Each month, one quarter of survey respondents are asked questions about their job including wage, occupation and industry. One year later, half of these individuals are again asked these same job-related questions. We use Madrian and Lefgren's (2000) matching algorithm to first match an individual based on their household identifier, household number and individual line number. Based on this naive match criteria, a high non-matching rate results, as survey respondents who move out of a housing unit are replaced in the sample by those who move in and given the same unique identifiers, as well as non-response, mortality and migration. A naive match is then dropped if it does not match on sex, race or age criterion. Based on these criteria, the match rate is 50%, with 871,917 individuals matched, or 1,743,834 observations out of a possible 3,481,692 observations.

H. Imputing Computer Use Rates to CPS Workers

We calculate average industry and occupation computer use rates from the October 1984, 1989, 1993, 1997, and August 2000 CPS Internet and Computer Use Supplement files. The use rate within an industry or occupation is the fraction of respondents who report using a computer or the internet at work. We impute computer use rates for the remaining years by linearizing the percent change within an occupation or industry between available years. We use the linear trend from 1984-1989 to impute computer use rates for 1982-1983, setting a lower bound of 0%. We use the linear trend from 1997-2000 to impute computer use rates for 2001-2002, setting an upper bound of 100%.

I. Creating Price Indices by Industry

We create a set of price indices at the industry level using data from the Bureau of Labor Statistics (BLS) and the US Department of Agriculture (USDA). For most industries, a match is made to the industry-specific BLS Producer Price Index (PPI) data. For the four agricultural industries, we use an industry-specific Producer Price Index from the USDA. For 46 industries, a consistent PPI is not available across time; we instead use a product-specific Consumer Price Index from the BLS. For an additional 46 industries (mainly in the service sector), no consistent PPI or CPI is available for our entire time period; we instead use the economy-wide PPI from the

BLS. For eleven of the industries, coverage begins in 1985; we freeze prior years to the 1985 level. The series are simple averages across monthly values, and are not seasonally adjusted. We also create a series of import and export prices from BLS data. These data are downloaded at the 1, 2, and 3-digit SITC level. We then use the concordance between SITC and SIC codes received from Robert Feenstra and used in Feenstra et al. (2002) to create price series data at the SIC level. These data are then matched to our CPS industry coding scheme using a concordance created by the authors mapping each 3-digit SIC code into a corresponding CPS industry code. We then construct export and import price indices at the 1, 2 and 3-digit CPS industry codes.

A supplemental import price data series was also provided at the NAICS level generously by Robert Lawrence. We use a concordance between NAICS and SIC codes to create a series of import prices at the SIC level, which are then mapped to our CPS industry classification scheme. For many-to-one matches between the SIC code and CPS industry codes, we use the SIC code with non-missing import prices.

These data are used in our supplementary online materials and summary statistics for these variables are available upon request.

J. Summary Statistics

In Table A1, we present summary statistics for our sample of individual CPS workers, and their assigned values for offshoring, trade, and technology measures. We present summary statistics for the entire sample (1983-2002), the 1983 sample, and the 2002 sample of workers. In Panel A, we report over 3.4 million workers in the data, with a noticeable decline in the fraction of workers who are employed in the manufacturing sector during the sample period. The workforce has become better educated, a slightly higher fraction of females, and real wages have risen. Hourly wages are higher in manufacturing than services, but this difference declined from \$2.49 in 1983 to \$1.78 in 2002. In Panel B, we report our offshoring and trade measures, which reflect a marked increase in all offshoring and activity between 1983 and 2002. Though all measures of offshoring and trade increased during the period, offshoring to low income countries and import penetration nearly doubled. Offshoring to high-income countries and exports increased more modestly, which may be due to the increased access during the period to markets in low income countries such as China and India. In Panel C, we report these offshoring and trade measures but we use our occupational- exposure measures instead, which capture the essential intuition behind our empirical results in Tables 2-4: that offshoring and trade may have affected workers not in the “tradable” manufacturing sector, but rather may have importantly affected workers in services as well. In Panel D, we report the summary statistics for our technology variables. These variables are meant to account for differential technical change across industries that may have affected relative demand for labor. For example, we report large increases in computer use rates, which may have also affected the wages earned by workers depending on their ability to benefit from the technology (Autor et al. 1998).

II. Additional Empirical Results

A. Employment Determinants in Manufacturing

In Table A2, we present summary statistics for the analysis underlying Table A3, where we investigate the relationship between offshoring, trade, and employment in manufacturing. The data are organized by education X year X industry cells and our outcome is the log of total manufacturing employment, as measured by the sum of the sample weights of the CPS workers in the cell. In each cell, we also record affiliate employment to low income countries, affiliate employment to high income countries, and import and export penetration. We also report the summary statistics for measured total factor productivity, the price of investment, and the real value of shipments in each cell.

In Table A3, we present an analysis of employment trends in manufacturing in response to offshoring. Our unit of analysis is each education × industry × year cell. There are five education categories for workers, 67 manufacturing industries, and 19 years of data (1984-2002). In column (1), we present pooled results for all industries, and in the remaining columns we split industries by the fraction of an industry's workforce performing routine tasks. Pooling across all task types, the results in column (1) indicate that the impact of offshoring depends on whether affiliate employment is located in high or low-income countries. A one percent increase in employment in low-income countries reduces domestic employment by 0.02 percent while a one percent increase in employment in high-income countries increases domestic employment by 0.07 percent. Breaking the results down according to how routine the workforce is, we see that the negative effects of offshoring to low-income countries are largest for workers in the most routine industries. The point estimate in column (2), at -0.041, suggests that a one percent increase in affiliate employment in low-income locations is associated with a 0.041 percent reduction in employment of workers in the most routine occupations.

In contrast, greater offshoring to high wage countries is associated with a significant increase in employment in the U.S. Across all workers, the evidence suggests that a one percent increase in affiliate employment in high-income locations is associated with a .074 percent increase in employment at home. For routine workers, the impact is more positive, with a one percentage point increase in offshore employment in high income countries associated with a .15 to .19 percent increase in U.S. employment. This evidence suggests that offshore employment in high-income locations is complementary with employment at home. The evidence presented in Table A3 is consistent with Harrison and McMillan (2011), who use firm-level Bureau of Economic Analysis data to show that domestic employment of US multinationals is complementary with their employment in high income locations but that increasing employment of US firms in low income locations substitutes for employment in the US.[1]

The coefficients on offshoring in Table A3 are significant but small in magnitude, and suggest both substitution (in low-income countries) and complementarity (in high-income locations). In contrast, the coefficients are large and negative but imprecisely estimated for both import penetration and export activity. For the pooled sample, a one percentage point increase in import penetration reduces US manufacturing employment by 0.61 percent. While it is not surprising that the coefficient on import competition is negative, the negative coefficient on sectoral export shares is less intuitive and deserves explanation. The negative coefficients may indicate that export growth was labor-saving for workers with less than a college degree, which is sensible if a significant degree of offshoring takes place through exports for further processing. Likewise, the negative and significant coefficient on total factor productivity suggests that

[1] Our online appendix includes a rich set of robustness checks for these results. Among these are a set of results based on instrumental variables estimation where we instrument for trade and offshoring using the variables that capture changes over time in the cost of trade and offshoring. The instruments are: Internet access, telephone connections including cell phone usage, and the industry share of routine jobs. The results confirm the negative relationship between offshoring to low-income countries, import penetration and manufacturing employment.

productivity growth has been labor saving for most educational categories.[2] Productivity growth in manufacturing has been achieved in conjunction with falling employment.

The results in Table A3 suggest that productivity growth, export growth, and import competition have been associated with (sometimes significant) declines in domestic manufacturing employment and that the effects of offshoring have been smaller in magnitude and mixed in sign. These results are important insofar as they suggest a fluid labor market where changes in other factor prices and global competition lead to employment reallocation. Furthermore, these results provide an explanation for our finding in Table 2 that the within-industry wage effects of trade and offshoring are smaller than the within-occupation effects. If trade and offshoring lead some workers to shift sectors (in particular, to exit high wage jobs in manufacturing), then it is possible that the wages of those who retain their jobs or find new jobs in the same industry are not significantly affected by offshoring, whereas those who shift sectors or occupations are more negatively affected.[3]

In Table A4, we demonstrate that the results presented in Table A3 are robust to a range of alternative specifications. Columns (2) and (3) report the results of the first specification when only imports or exports are controlled for. In column (3), the negative association between export orientation and employment becomes statistically significant, which could be indicative of collinearity between export and import shares. The point estimate , at -0.57, suggests that a 1 percentage point increase in export shares is associated with nearly a .6 percentage point decline in employment, suggesting that export growth is labor-saving. The results are even stronger in column (4), where we eliminate the control for total factor productivity—which is likely to be associated with changes in trade orientation. Similarly, the negative association between import shares and employment become significant and negative in column (6) when we omit the control for export shares, consistent with possibility collinearity between exports and imports at the industry level. The results in columns (3), (4), (6) and (7) suggest a strong and significant negative association between trade shares and employment if either export shares or import penetration are included independently. In columns (8) through (11) we remove trade shares to ensure that the relationship between offshoring and employment is robust to these alternative specifications. We also explore the robustness of the results to using import and export prices as measures of trade in goods instead of trade shares. Finally, in the last two columns we explore the robustness of the results to the inclusion of lags of the dependent variable.

In Table A5, we account for the fact that trade and offshoring are simultaneously determined with employment. Note that this is not as much of a concern with our wage regressions since wages are at the individual level. To take into account the possibility that simultaneity bias may be driving the results in Table 5, we instrument for trade and offshoring using the variables suggested by Grossman and Rossi-Hansberg that capture changes over time in the cost of offshoring. These variables include: internet access, telephone (including cell phones) access and education. In addition, we use the industry share of routine jobs.

The results in the first row of Table A4 confirm the results already presented in Table A3: both offshoring and trade are increasing in the share of routine jobs by industry. The effects are statistically significant at the 1 percent level and quantitatively large. Internet access is positively

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[2] The results in Table A3 are robust to excluding total factor productivity as a control variable.

[3] In results available in the online appendix, we directly assess the wage consequences among those who switch industries within manufacturing. We find that (1) switching within manufacturing has mild wage consequences (2) but leaving manufacturing has a more negative impact and (3) leaving manufacturing is particularly costly for workers who switch occupation. These were not included in the main text due to space considerations.

associated with offshoring to both high and low wage countries and appears to have little effect on trade. Education levels in low wage countries is a significant predictor of offshoring to both high and low wage countries and is also positively associated with import penetration indicating that import penetration is driven by countries with relatively higher degrees of educational attainment. Education in low wage countries is negatively correlated with export share, a possible indication that U.S. based multinationals prefer to send exports for further processing to lower wage countries where workers are less educated. Finally, education in high wages countries is negatively associated with offshoring to low wage countries and positively correlated with import penetration. In each case, the F-statistic exceeds 10 indicating that the instruments are indeed strong predictors of our trade and offshoring variables.

Second stage results are reported in column (5). The sign on offshoring to low wage countries remains negative and statistically significant, which is consistent with the results in Table A3. However, the magnitude of the coefficient increases significantly. The coefficient on offshoring to high wage countries retains its sign but is no longer significant. As in Table A3, the signs on total factor productivity and important penetration are negative and significant at the 1 percent level.

Consequently, we also report both IV and GMM results, using both lags of right-hand side variables as instruments and a number of appropriate excluded instruments for the endogenous regressors. If we allow for separate effects of foreign capital, employment, and trade flows from low and high income destinations, we have already six endogenous variables (in addition to import penetration at the sector level) that we need to instrument. For capital abroad, we use the following instruments: capital controls, distance, a dummy for the use of a common language, C02 emissions in metric tons per capita, the percentage of child labor, fixed line and mobile phone subscribers per 1000 people, internet users per 1000 people, and number of telephone main lines per 1000 people. The last three measures capture the ease with which parents are able to communicate with their affiliates and should be positively correlated with investment abroad. Emissions and child labor are also likely to adversely affect foreign investment, as firms now care increasingly about corporate responsibility. A dirty environment is increasingly regarded as a potential liability, in addition to the problems incurred in trying to manufacture high quality goods in a dirty environment.

For intra-firm trade, as instruments we use air transport (in million tons per kilometer), aircraft departures, and trade agreements. These all are correlated with bilateral trade but should be excluded from the estimating equation. Finally, candidate instruments for employment in high and low income locations include the total labor force in each affiliate location, the percentage of the labor force engaged in manufacturing, the percentage of national income spent on education, the local unemployment rate, and the number of PCs per 1000 people. The measures we use determine both the supply of labor available as well as the quality of that labor, yet should only affect U.S. labor market outcomes through their impact on the choice of employment in affiliate locations.

B. Imports and Trends in Wage Premiums by Occupation

In Table A6, we present a breakdown of occupations and their trends in globalization exposure and wage premia. The most affected workers were shoe machine operators, for whom occupation-specific import penetration increased from 37.2 percent in 1983 to 77.4 percent in 2002. Since this represents a routine occupation, for these workers, the coefficient on import penetration in column (5) of Table 2, which is -.296, implies that their real wages fell by nearly

12 percent as a result of competition from trade. The contrasting experiences of workers in textiles and apparel related sectors compared to many service sector employees such as teachers helps to explain why some parts of the U.S. economy have been deeply affected by globalization while others have not. On average, occupation-specific import and export shares only increased from an average of 2 to 4 percent during the 1983 through 2002 period, in large part because of the importance of services and the lack of global competition in service occupations. Consequently, the average effect of an increase from .02 to .04 for occupation-specific import competition is quite small. However, what Table A6 makes clear is that some groups of occupations experienced significant wage declines as a consequence of rising (occupation-specific) import competition. Since occupation-specific import penetration is correlated with offshore employment in low wage countries, this provides insight into the occupations most affected by offshoring as well.

C. Imports and Exports using Prices instead of Quantities

In Table 2 in the paper, we examine the impact of import penetration and the quantity of exports on worker's wages. It is worth examining the impact of prices of imported or exported goods on workers wages, since most traditional models of trade presume that changing relative prices are the catalyst for wage effects. In Table A7, we replace our quantity measures for imports and exports with price series data for each. Our data on the prices of imports were generously provided by Robert Lawrence, which catalogue prices within manufacturing by 4-digit NAICS industry codes. We used a concordance to translate this into prices for each CPS industry. Our data on export prices are taken from the Bureau of Labor Statistics export price series data. The results are qualitatively similar to the results in the paper: while we see little or no wage effects within manufacturing, occupational exposure to import price declines has affected workers across sectors. In particular, we find that a 1 unit increase in the price index for imports raises a worker's real wage by .031 percent. We find no significant effect of our export price series on wages. For the wage impact of offshoring, our results are similar in sign and magnitude to those presented in the paper. This suggests that our core results are robust to our use of quantities for imports and exports. Since our data on quantity of imports and exports is more comprehensive than the price data we have for this period, we proceed in our other results with our quantity measures.

D. Focusing on Manufacturing and Occupational Wage Exposure

In Table A8, we examine how our results on occupational wage exposure change when we restrict the sample to manufacturing or service sector workers. While our results in Table 2 highlight the differences between industry- and occupation-exposure to offshoring the results, they combine the impact of changing our key independent variable as well as the impact of changing our sample from manufacturing-only to the entire economy. As shown in Table A8, the analysis using occupational exposure restricted to manufacturing, or restricted to service workers - both show stronger and more significant results than the traditional cross-industry analysis. As reported in Table 2, combining the new approach of using occupational exposure and adding all workers leads to even stronger results.

E. Controlling for the Real Price of Shipments

In Table A9, we examine how sensitive our results are to controlling for the total demand by industry. Since the demand for a particular good may affect a worker's wages, it may be important to control for shifts in demand. However, since the total output of an industry may be endogenous to the quantity of production shifted to lower-cost locations overseas, controlling for total output may be problematic. In light of these tradeoffs, we have included a specification without controlling for the real price of shipments and reproduce our main results here with the added control. The results are similar to those presented in Table 2.

F. Occupational Exposure Versions of the Technology Controls

In Table A10, we examine how sensitive our results are to using occupation offshore exposure measures for all the control variables. In the main text, we control for technological change among manufacturing workers with data taken from the NBER productivity database and set it equal to unity for workers in the service sector. A reasonable alternative would be to calculate occupation-specific offshore measures for all the control variables, and include them for all workers. This is presented in Table A10, and the results are largely consistent with the results presented in Table 2, with routine workers being the most responsive to trade and offshoring.

G. Using the CPS matched sample of workers

In Table A11 we examine how (a) switching industries within manufacturing, (b) leaving manufacturing, or (c) leaving manufacturing and switching occupations entirely affects a worker's wages. Our sample is composed of manufacturing workers observed in CPS samples in consecutive years between 1983 and 2002. We regress the change in log wages between period t and t+1 for a given worker on an indicator for switching industry or occupation, including a rich set of controls for the worker's age, sex, education, race, union status in the first period, and industry in the first period.

In Panel A, we examine how switching industries within manufacturing affects wages relative to staying in the same industry. The table reflects almost no wage consequence of switching industries, provided the worker stays within manufacturing. In Panel B, we restrict the sample to workers who switched sectors, and examine whether leaving manufacturing has larger wage consequences than switching industries but staying in manufacturing. We estimate that wages decline by 3.1 percent when leaving manufacturing, with slightly larger wage losses for workers in occupations with the most routine content (3.6 percent) than for workers occupations with the least routine content (2.8 percent). This suggests the shedding of manufacturing jobs due to offshoring may negatively affect domestic workers, especially those performing occupations with a high degree of routine content. In Panel C, we restrict the sample to workers who exited manufacturing and examine whether switching occupations induced a greater wage decline than switching sectors; we find that switching occupations costs the worker an additional 5.9 percent of wages. Since our results in Tables 2 to 4 are within-occupation, they do not capture the wage consequences of trade-induced occupation switching (although this is a relatively small proportion of workers: 22,680 workers switch occupations compared to over 170,000 workers who switch industries). Nonetheless, insofar as switching occupations is costly to workers, it highlights an inelasticity to occupational choice that could leave workers vulnerable to shifting demand for labor due to offshoring and import penetration.

Table A1: Summary Statistics of Current Population Survey Merged Outgoing Rotation Group Workers, Means and (Standard Deviations), 1983-2002

	Overall Sample				1983				2002			
	All	Manufact-uring	Services	Agriculture	All	Manufact-uring	Services	Agriculture	All	Manufact-uring	Services	Agriculture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel 1: Demographic and Wage Information												
Number of Observations	3,481,692	647,105	2,770,662	63,925	176,454	38,071	134,239	4,144	185,798	26,229	156,319	3,250
Age	37.3	38.8	37.0	34.2	36.2	38.1	35.8	32.4	39.2	41.2	38.9	36.0
	(12.1)	(11.4)	(12.2)	(12.8)	(12.6)	(12.2)	(12.6)	(13.1)	(12.1)	(11.0)	(12.3)	(12.9)
Female	0.48	0.32	0.52	0.27	0.46	0.32	0.50	0.27	0.49	0.30	0.52	0.27
	(0.50)	(0.47)	(0.50)	(0.44)	(0.50)	(0.47)	(0.50)	(0.45)	(0.50)	(0.46)	(0.50)	(0.45)
Years of Education	13.2	12.7	13.3	12.0	12.9	12.4	13.0	11.8	13.4	13.0	13.5	12.3
	(2.3)	(2.1)	(2.3)	(2.2)	(2.3)	(2.1)	(2.3)	(2.2)	(2.3)	(2.1)	(2.3)	(2.1)
Real Hourly Wage ($2006)	16.28	17.86	16.02	10.34	15.00	17.04	14.55	9.52	18.44	20.06	18.28	12.20
	(10.83)	(10.68)	(10.87)	(6.98)	(9.47)	(9.62)	(9.38)	(6.34)	(12.70)	(12.20)	(12.81)	(7.87)
Panel 2: Offshoring and Trade Data												
Low Income Affiliate	44,984	44,984	.	.	35,054	35,054	.	.	68,868	68,868	.	.
Employment	(65,409)	(65,409)	.	.	(44,962)	(44,962)	.	.	(94,642)	(94,642)	.	.
High Income Affiliate	90,939	90,939	.	.	85,826	85,826	.	.	101,637	101,637	.	.
Employment	(103,309)	(103,309)	.	.	(99,695)	(99,695)	.	.	(114,111)	(114,111)	.	.
Import Penetration	0.13	0.13	.	.	0.09	0.09	.	.	0.16	0.16	.	.
	(0.10)	(0.10)	.	.	(0.07)	(0.07)	.	.	(0.12)	(0.12)	.	.
Export Share	0.11	0.11	.	.	0.08	0.08	.	.	0.14	0.14	.	.
	(0.09)	(0.09)	.	.	(0.07)	(0.07)	.	.	(0.11)	(0.11)	.	.
Panel 3: Offshoring and Trade Data, Occupational Exposure Measure												
Low Income Affiliate	7,269	21,168	4,150	1,786	5,301	14,532	2,813	1,073	9,668	32,440	5,986	2,969
Employment	(14,166)	(24,569)	(7,429)	(4,522)	(9,335)	(14,932)	(4,490)	(2,882)	(17,559)	(31,679)	-9781.4	-6550.5
High Income Affiliate	13,268	38,507	7,609	3,082	13,097	35,600	7,046	2,386	12,669	42,105	7,909	4,064
Employment	(22,270)	(35,341)	(12,122)	(7,686)	(21,828)	(33,269)	(11,274)	(6,986)	(21,675)	(37,442)	(12,324)	(9,008)
Import Penetration	0.025	0.072	0.014	0.006	0.017	0.047	0.008	0.004	0.028	0.091	0.018	0.009
	(0.039)	(0.059)	(0.021)	(0.014)	(0.028)	(0.042)	(0.013)	(0.008)	(0.044)	(0.068)	(0.027)	(0.018)
Export Share	0.022	0.061	0.013	0.006	0.016	0.041	0.009	0.004	0.025	0.078	0.017	0.008
	(0.033)	(0.047)	(0.021)	(0.015)	(0.023)	(0.031)	(0.014)	(0.010)	(0.038)	(0.056)	(0.025)	(0.015)
Panel 4: Technology Measures and Price Indices												
Real Price of Investment	1.05	1.04	.	.	0.94	0.94	.	.	1.00	1.00	.	.
	(0.03)	(0.05)	.	.	(0.02)	(0.03)	.	.	(0.06)	(0.03)	.	.
Total Factor Productivity	1.07	1.07	.	.	0.95	0.95	.	.	1.40	1.41	.	.
	(0.66)	(0.30)	.	.	(0.08)	(0.08)	.	.	(1.89)	(1.89)	.	.
Capital to Labor Ratio	95.68	95.71	.	.	77.68	77.70	.	.	142.85	142.90	.	.
(000s per worker)	(109.01)	(109.04)	.	.	(84.21)	(84.23)	.	.	(159.90)	(159.95)	.	.
Real Price of Shipments	24,334	.	.	.	13,704	.	.	.	38,841	.	.	.
	(44,437)	.	.	.	(16,427)	.	.	.	(77,503)	.	.	.
Computer Use Rate	0.42	0.37	0.44	0.16	0.23	0.22	0.24	0.07	0.60	0.55	0.62	0.26
	(0.31)	(0.30)	(0.31)	(0.24)	(0.22)	(0.23)	(0.22)	(0.14)	(0.35)	(0.33)	(0.35)	(0.32)
Prices from PPI/CPI	142.8	128.9	146.7	113.2	101.5	103.5	101.1	98.8	191.4	159.4	198.1	129.1
	(57.1)	(40.0)	(60.1)	(35.4)	(6.5)	(9.5)	(5.3)	(2.8)	(95.5)	(67.0)	(98.5)	(61.7)

Source : Sample consists of Current Population Surveys Merged Outgoing Rotation Group Workers for 1983-2002. Affiliate (or offshore) employment data are taken from the Bureau of Economic Analysis annual survey of US firms with multinational affiliates for the same period. Low income countries are defined according to the World Bank income categories. Import penetration and export share are taken from Bernard, Jensen, and Schott (2006). Computer use rates are taken from October CPS supplements during the sample period. Investment good prices, total factor productivity measures, capital to labor ratios, and the real price of shipments are taken from the NBER productivity database. The producer and consumer price index data are taken from the Bureau of Labor Statistics.

Table A2: Summary Statistics on Industry-Year Cells

Variables	Number of Observations	Mean	Std. Dev.	Min	Max
Log U.S. manufacturing sector employment	6,675	10.09	1.48	4.63	13.34
Log of low income affiliate employment	6,615	9.52	1.39	4.97	12.80
Log of high income affiliate employment	6,635	10.47	1.06	6.07	13.14
Log of price of investment	6,437	4.68	0.13	3.60	4.86
Total factor productivity level	6,583	1.01	0.32	0	5.31
Export share	6,583	0.11	0.09	0	0.58
Import penetration	6,583	0.13	0.13	0	0.83
Log of real price of shipments	6,437	8.94	1.13	5.70	13.14
Education level	6,675	2.97	1.40	1	5

Source : Employment data taken from Current Population Surveys Merged Outgoing Rotation Groups for the years 1982 and 2002. Affiliate (or offshore) employment data is taken from the Bureau of Economic Analysis annual survey of US firms with multinational affiliates. The price of investment, which varies by industry and year, is taken from the NBER's productivity database. Total factor productivity is computed by the NBER for all years through 1996, and was updated through 2002 using data provided to the authors by Wayne Gray. Import penetration trends by source are taken from Bernard et al. (2006), and are calculated as a share of the total product market. Export share measures are taken from Bernard, Schott, and Jensen (2006) and are measured between zero and one.

Table A3 OLS Estimates of Employment Determinants in Manufacturing, 1984-2002

Dependent Variable: Log U.S. Manufacturing Sector Employment

Variable	All	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	-0.0202*	-0.0413**	0.007	-0.046
	(0.011)	(0.02)	(0.021)	(0.044)
Lagged log of high income affiliate employment	0.0736**	0.148**	0.192***	0.013
	(0.031)	(0.064)	(0.05)	(0.132)
Lagged log of price of investment	0.124	0.489***	0.197	-0.094
	(0.093)	(0.16)	(0.209)	(0.52)
Lagged total factor productivity level	0.000	0.0680**	-0.0612***	0.602
	(0.017)	(0.033)	(0.023)	(0.632)
Lagged export share	-0.393	-0.555	0.112	-0.216
	(0.258)	(0.666)	(0.321)	(1.326)
Lagged import penetration	-0.614*	-0.313	-0.084	0.133
	(0.356)	(0.682)	(0.338)	(1.547)
Lagged capital to labor ratio	-0.867**	-0.983	-1.108**	-0.338
	(0.373)	(1.043)	(0.436)	(1.504)
Lagged computer use rates by industry	-0.036	0.049	-0.122	-0.700
	(0.147)	(0.269)	(0.207)	(0.482)
Number of observations	6,399	1,662	4,248	489
R-squared	0.86	0.78	0.55	0.65

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

Source : See Table 1.

Note : Robust standard errors are reported in parentheses below the coefficient estimates, and are clustered by industry. All models include year and industry fixed effects. Low-income affiliate employment is defined according to the World Bank income categories. The sample size corresponds to 5 education groupings X 19 years X 67 industries, less missing values. The results shown in columns 2-4 are (2) industry and year combinations where more than 2/3 of the tasks are routine, (3) cells where between 1/3 and 2/3 of tasks are routine, and (4) cells with than a 1/3 of the tasks are routine.

Table A4: Robustness Checks of Estimates of Employment Determinants, 1984-2002

Dependent Variable: Log U.S. Manufacturing Sector Employment

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Lagged log U.S. manufacturing sector												0.35***	0.35***
employment												(0.07)	(0.07)
Lagged log of low income affiliate	-0.02**	-0.02**	-0.03**	-0.03**	-0.02**	-0.02**	-0.03**	-0.03**	-0.03**	-0.03**	-0.02***	-0.03*	-0.03*
employment[1]	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Lagged log of high income affiliate	0.08**	0.08***	0.09***	0.10***	0.08***	0.07**	0.09***	0.09***	0.09***	0.09**	0.02	0.10***	0.10***
employment[1]	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.09)	(0.03)	(0.03)
Lagged log of price of investment	-0.07	0.06	-0.04	0.10	0.11	-0.07	-0.04	-0.02	-0.01	-0.06	-0.01	0.37*	0.37*
	(0.17)	(0.16)	(0.19)	(0.18)	(0.1)	(0.17)	(0.19)	(0.21)	(0.21)	(0.19)	(0.22)	(0.22)	(0.22)
Lagged total factor productivity level	-0.16**		-0.17**		-0.01	-0.17**	-0.17**	-0.20**	-0.19**	-0.14*	0.01	0.05	0.05
	(0.07)		(0.07)		(0.03)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.07)	(0.07)
Lagged export share	-0.28	-0.34	-0.57**	-0.65**	-0.37		-0.57**						
	(0.27)	(0.27)	(0.25)	(0.25)	(0.27)		(0.25)						
Lagged import penetration	-0.60*	-0.64*			-0.59	-0.75***							
	(0.32)	(0.35)			(0.36)	(0.28)							
Lagged log of real price of shipments	0.15**	0.05	0.15**	0.04		0.16**	0.15**	0.16**	0.16**	0.13*	0.03	-0.06	-0.06
	(0.06)	(0.04)	(0.07)	(0.05)		(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.09)	(0.07)	(0.07)
Log price of exports									-0.017	0.148	-0.168		
									(0.16)	(0.14)	(0.29)		
Log price of imports									-0.04	-0.001	0.55**		
									(0.13)	(0.15)	(0.25)		
Prices at 1-digit level									Y	N	N		
Prices at 2-digit level									N	Y	N		
Prices at 3-digit level									N	N	Y		
Industry-Specific Time Trend													-0.01***
													(0.003)
Number of observations	6,427	6,427	6,427	6,427	6,427	6,427	6,427	6,427	6,382	5,284	1,596	1,173	1,173
R-squared	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.87	.	.

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

Source : See Table 1.

Note : Robust standard errors reported in parentheses below coefficient estimates. All employment specifications include industry and year fixed effects; 'All Education' regression also includes education fixed effects. Low-income affiliate employment is defined according to the World Bank income categories. Regressions in columns 11 and and 12 are Arellano-Bond dynamic panel data regressions include current rather than lagged offshoring to low and high income countries.

Table A5: Instrumental Variable Estimates of Employment Determinants Overall, 1984-2002

	First Stage				Second Stage
Variable	Lagged log of low income affiliate employment	Lagged log of high income affiliate employment	Import Share Using 1979 Weights	Export Share Using 1979 Weights	Log U.S. Manufacturing Sector Employment
Industry share of routine jobs	0.68***	1.31***	0.23***	0.37***	
	(0.27)	(0.21)	(0.040	(0.04)	
Internet access	0.003***	0.001***	0.00	.0.00007***	
	(0.00010)	(0.00009)	(0.00002)	(0.00002)	
Fixed line and mobile phone subscribers (per 1,000 people)	0.0003***	-0.0003***	0.00009***	0.00	
	(0.00010)	(0.00010)	(0.00001)	(0.00002)	
Lower education	0.03***	0.009***	0.003***	-0.002***	
	(0.010)	(0.003)	(0.001)	(0.001)	
Higher education	-0.02***	-0.02	.0.002***	0.00	
	(0.005)	(0.004)	(0.001)	(0.001)	
Lagged log of low income affiliate employment					-0.57**
					(0.26)
Lagged log of high income affiliate employment					0.02
					(0.71)
Lagged log of price of investment	-0.53***	-0.15***	0.31***	0.08***	0.96
	(0.090)	(0.070)	.(0.01)	(0.010)	(0.920)
Lagged total factor productivity level	0.296***	0.03	0.19***	0.06***	-0.89***
	(0.050)	(0.040)	(0.008)	(0.004)	(0.380)
Lagged export share					-0.82
					(2.86)
Lagged import penetration					-0.92***
					(0.25)
Lagged log of real price of shipments	-0.23***	-0.06***	-0.18***	0.08***	0.84***
	(0.030)	(0.020)	(0.004)	(0.010)	(0.420)
F statistic	18.96	17.31	12.09	19.20	
Sargan Chi-sq (1) P-Value					0.22
Number of observations	1,756	1,756	1,756	1,756	1,756

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

Source : Affiliate (or offshore) employment data is taken from the Bureau of Economic Analysis annual survey of US firms with multinational affiliates.

Note : Robust standard errors reported in parentheses below coefficient estimates. All specifications include year, education, industry and location fixed effects.

Table A6 **Import Penetration in 1983 and 2002, for 40 Occupations with Highest Import Penetration in 2002**

	Import Penetration		Log Wage Difference
Occupation	**1983**	**2002**	**1983-2002**
Industrial engineers	0.070	0.157	0.098
Miscellaneous machine operators	0.078	0.157	0.085
Agricultural engineers	0.093	0.160	0.108
Adjusters and calibrators	0.081	0.160	0.584
Metal plating machine operators	0.074	0.164	0.041
Grinding, abrading, buffing, and polishing machine operators	0.090	0.164	0.032
Shaping and joining machine operators	0.091	0.164	0.159
Precision grinders, filers, and tool sharpeners	0.096	0.167	0.101
Wood lathe, routing, and planing machine operators	0.086	0.167	0.077
Miscellaneous metal, plastic, stone, and glass working machine operators	0.096	0.168	0.119
Nailing and tacking machine operators	0.062	0.169	0.456
Production samplers and weighers	0.067	0.172	0.065
Production inspectors, checkers, and examiners	0.080	0.174	0.102
Cabinet makers and bench carpenters	0.074	0.177	0.078
Patternmakers and model makers, wood	0.095	0.177	-0.401
Miscellaneous woodworking machine operators	0.082	0.177	0.313
Lathe and turning machine operators	0.097	0.180	0.115
Mechanical engineering technicians	0.085	0.183	0.162
Drilling and boring machine operators	0.094	0.183	-0.039
Milling and planing machine operators	0.092	0.184	0.002
Tool and die makers	0.096	0.188	0.067
Patternmakers, lay-out workers, and cutters	0.091	0.188	-0.256
Folding machine operators	0.068	0.188	-0.016
Lathe and turning machine set-up operators	0.105	0.188	0.073
Hand molding, casting, and forming occupations	0.103	0.188	0.404
Cementing and gluing machine operators	0.089	0.194	0.274
Miscellaneous precision woodworkers	0.061	0.195	-1.426
Precision assemblers, metal	0.084	0.201	0.087
Tool and die maker apprentices	0.102	0.203	0.072
Assemblers	0.099	0.204	0.084
Numerical control machine operators	0.107	0.204	0.154
Production testers	0.072	0.205	0.089
Knitting, looping, taping, and weaving machine operators	0.046	0.207	0.201
Miscellaneous textile machine operators	0.077	0.209	0.116
Solderers and brazers	0.095	0.217	0.061
Electrical and electronic equipment assemblers	0.090	0.219	0.172
Textile cutting machine operators	0.092	0.245	0.183
Textile sewing machine operators	0.135	0.304	0.146
Shoe repairers	0.182	0.379	0.184
Shoe machine operators	0.372	0.774	0.108

Source : Worker data taken from Current Population Surveys Merged Outgoing Rotation Groups for the years 1983 and 2002. Import penetration measures are taken from Bernard, Schott, and Jensen (2006) and are measured between zero and one.

Table A7: Robustness of OLS Estimates of Wage Determinants to using Import Prices instead of Quantities, using Occupational versus Industry Exposure to Offshoring and Trade, 1984-2002

Dependent Variable: Log Wage

	Offshoring and Trade Measured by Industry-Specific Exposure, Manufacturing Only				Offshoring and Trade Measured by Occupation-Specific Exposure, All Sectors			
Variable	All Occupations	Most Routine	Intermediate Routine	Least Routine	All Occupations	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	-0.0106*	-0.0156***	-0.004	0.007	-0.0728***	-0.0910***	-0.002	0.0768*
	(0.006)	(0.006)	(0.007)	(0.011)	(0.021)	(0.019)	(0.051)	(0.040)
Lagged log of high income affiliate employment	0.014	0.013	0.012	0.006	0.0561***	0.0662***	0.002	-0.048
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.05)	(0.04)
Lagged export share using 1979 weights	0.09	0.05	0.05	0.101*	0.20	0.476***	0.280**	-0.02
	(0.06)	(0.09)	(0.06)	(0.05)	(0.13)	(0.17)	(0.14)	(0.36)
Lagged import prices	0.01	0.001	-0.005	0.0384*	0.01	0.0305***	0.01	0.0246*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Lagged computer use rate	-0.04	0.01	-0.04	-0.07	0.262***	0.140***	0.283***	0.185***
	(0.04)	(0.05)	(0.04)	(0.08)	(0.02)	(0.02)	(0.04)	(0.04)
Number of observations	204,364	113,108	58,699	32,557	1,470,051	597,699	521,986	350,366
R-squared	0.44	0.34	0.38	0.35	0.50	0.40	0.54	0.41

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

Source : See Table 1.

Note : Robust standard errors reported in parentheses below coefficient estimates. The classification of occupations into routine categories is determined by the proportion of tasks which are routine in each occupation, with low being occupations with more than 2/3rd, intermediate being between 1/3rd and 2/3rd, and high being occupations with less than 1/3rd of tasks designated routine. Industry-specific regressions also control for lagged log price of investment, lagged total factor productivity, and lagged log real price of shipments. Wage specifications control for a worker's gender, age, race, experience, whether in a union, and include industry, year, education and state fixed effects. The occupation-specific exposure regressions also include 2-digit occupation fixed effects. Controls for computer use rates are imputed by the worker's industry (columns 1-4) and by occupation (columns 5-8).

Table A8: OLS Estimates of Wage Determinants using Occupational Exposure of Offshoring and Trade Among Manufacturing and Service Sector CPS Workers, 1984-2002

Dependent Variable: Log Wage

	Offshoring and Trade Measured by Occupation-Specific Exposure, Manufacturing Only				Offshoring and Trade Measured by Occupation-Specific Exposure, Services Only			
Variable	All Occupations	Most Routine	Intermediate Routine	Least Routine	All Occupations	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	0.004	-0.0235**	0.0489***	-0.121**	-0.0643**	-0.147***	-0.033	0.163**
	(0.011)	(0.011)	(0.017)	(0.049)	(0.030)	(0.040)	(0.050)	(0.064)
Lagged log of high income affiliate employment	-0.011	0.013	-0.0482***	0.0932**	0.0619**	0.109***	0.041	-0.113**
	(0.011)	(0.010)	(0.014)	(0.040)	(0.027)	(0.036)	(0.044)	(0.056)
Lagged export share	0.054	0.430***	-0.097	-1.181**	0.601***	2.166***	0.125	-0.453
	(0.123)	(0.115)	(0.140)	(0.458)	(0.179)	(0.388)	(0.268)	(0.498)
Lagged import penetration	-0.196**	-0.296***	0.197	2.234***	-0.336	-0.631**	-0.415	0.113
	(0.093)	(0.088)	(0.306)	(0.791)	(0.227)	(0.274)	(0.609)	(0.778)
Number of observations	576,189	328,254	157,318	90,617	2,491,905	781,581	998,889	711,435
R-squared	0.52	0.42	0.46	0.41	0.50	0.42	0.53	0.38

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

Source: See Table 1.

Note: Robust standard errors are clustered by occupation and are reported in parentheses below coefficient estimates. This table can be compared to columns (5) through (8) of Table 2 in the paper, but restricted to manufacturing workers or service workers.

Table A9: OLS Estimates of Wage Determinants using Occupational Exposure of Offshoring and Trade Including the Real Price of Shipments, 1984-2002

Dependent Variable: Log Wage

	Offshoring and Trade Measured by Occupation-Specific Exposure, All Sectors			
Variable	All Occupations	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	-0.0404*	-0.0706***	0.018	0.073
	(0.021)	(0.023)	(0.030)	(0.076)
Lagged log of high income affiliate employment	0.0341*	0.0511**	-0.002	-0.046
	(0.019)	(0.021)	(0.029)	(0.067)
Lagged export share	0.256	0.669***	0.235	-0.819
	(0.163)	(0.226)	(0.267)	(0.515)
Lagged import penetration	-0.289**	-0.296*	-0.767	1.085
	(0.138)	(0.157)	(0.669)	(1.041)
Number of observations	3,068,094	1,109,835	1,156,206	802,053
R-squared	0.50	0.42	0.54	0.40

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

Source : See Table 1.

Note : Robust standard errors are clustered by occupation and reported in parentheses below coefficient estimates. This table can be compared to columns (5) through (8) of Table 2 in the paper, but with the additional control for the real price of shipments.

Table A10: OLS Estimates of Wage Determinants using Occupational Exposure of Offshoring and Trade using Occupational Exposure Equivalents of All Controls, 1984-2002

Dependent Variable: Log Wage

	Offshoring and Trade Measured by Occupation-Specific Exposure, All Sectors			
Variable	All Occupations	Most Routine	Intermediate Routine	Least Routine
Lagged log of low income affiliate employment	-0.012	-0.0766***	0.020	0.222***
	(0.018)	(0.018)	(0.045)	(0.071)
Lagged log of high income affiliate employment	0.003	0.0571***	-0.012	-0.156**
	(0.016)	(0.015)	(0.040)	(0.062)
Lagged import penetration	-0.403***	-0.594***	-1.226	-1.012
	(0.101)	(0.128)	(0.793)	(1.382)
Lagged export share	0.451***	1.254***	0.207	-0.833
	(0.130)	(0.200)	(0.343)	(0.788)
Lagged log of price of investment by occupation	0.0288***	0.669***	0.235	-0.819
	(0.163)	(0.226)	(0.267)	(0.515)
Lagged capital to labor ratio by occupation	-0.289**	-0.296*	-0.767	1.085
	(0.138)	(0.157)	(0.669)	(1.041)
Lagged total factor productivity level by occupation	-0.041	-0.0416*	0.086	-0.203**
	(0.029)	(0.025)	(0.066)	(0.098)
Number of observations	3,076,973	1,113,788	1,158,314	804,871
R-squared	0.47	0.39	0.52	0.35

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

Source : See Table 1.

Note : Robust standard errors are clustered by occupation and reported in parentheses below coefficient estimates. This table can be compared to columns (5) through (8) of Table 2 in the paper, but with the controls measured at the occupational exposure level, and no industry fixed effects.

Table A11: Wage Changes Among CPS Workers Observed 2 Periods by Industry- and Occupation-Specific Exposure to Offshoring and Trade, 1984-2002

Dependent Variable: Log Wage Change Between Periods

	Offshoring and Trade Measured by Industry-Specific Exposure, Manufacturing Only			Offshoring and Trade Measured by Occupation-Specific Exposure, All Sectors		
Variable	All	Routine	Non-Routine	All	Routine	Non-Routine
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged log of low income affiliate employment	-0.002	-0.002	-0.002	-0.0154**	-0.0179**	0.020
	(0.002)	(0.002)	(0.004)	(0.007)	(0.008)	(0.022)
Lagged log of high income affiliate employment	0.005	0.00895*	-0.002	0.0134**	0.0163**	-0.014
	(0.004)	(0.005)	(0.008)	(0.007)	(0.007)	(0.019)
Lagged import penetration using 1979 weights	0.027	0.038	0.003	-0.033	-0.006	-0.660**
	(0.020)	(0.029)	(0.050)	(0.045)	(0.047)	(0.312)
Lagged export share using 1979 weights	-0.0512**	-0.0743**	0.000	0.091	0.049	0.415***
	(0.025)	(0.036)	(0.041)	(0.056)	(0.069)	(0.133)
Number of observations	162,285	110,281	52,004	797,124	447,299	349,825

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

Source : Sample is composed of CPS MORG workers observed in two consecutive samples.

Note : Robust standard errors are reported in parentheses below the coefficient estimates. The standard errors are clustered at the industry level in columns (1-4) and at the occupation level in columns (5-8). The classification of occupations into routine categories is determined by the proportion of tasks which are routine in each occupation, with routine being occupations with more than half. The regressions are run with the same controls as in Table 2. This includes controls for the worker's age, race, experience, union status, and sex. Fixed effects are included at the industry, year, and state levels in columns (1-3) and fixed effects for industry, occupation, year, and state in columns (4-6). Industry-specific regressions (columns 1-3) also control for lagged log price of investment, lagged total factor productivity, and lagged capital to labor ratio among manufacturing workers. Controls for computer use rates are imputed by the worker's industry (columns 1-4) and by occupation (columns 4-6).