The Contribution of Offshoring to the Convexification of the U.S. Wage Distribution

Sarah Kroeger*

January 18, 2013

Abstract

Hourly wage data from 1990 to 2011 show a narrowing gap between the median wage and the 10th percentile wage, but an increasing gap between the median and 90th percentile wages. In this paper, I investigate the impact of offshoring on the employment and wage distributions to determine whether it has contributed to this convexification. I use a task-based framework of the labor market with three inputs and model what happens when the world price for the middle task input declines. The model predicts both a decline in domestic employment and a reduction in the wage paid to workers in this task, resulting in a rise in upper tail unemployment. However, I demonstrate that observed wages within an industry can rise due to selection. I construct a proxy measure of offshoring for both service and material inputs, and use industry level production and trade data from the US Census Bureau's Census of Manufactures, and individual level wage data from the US Census and the American Community Survey to test the implications of the model. Offshoring has the anticipated effects on employment and convexification. I find a negative effect of offshoring on employment and a positive effect of offshoring on upper tail wage inequality. Moreover, current levels of industry offshoring are significantly correlated with an industry's lagged occupational composition. In particular, both forms of offshoring decrease with the share of manual occupations and service offshoring increases with the share of routine occupations.

The most recent version of this paper is available at http://people.bu.edu/skroeger/research.htm.
Contact: skroeger@bu.edu

Keywords: inequality, offshoring, skill premium.

JEL classification: J23, J24, J31, F16, F23.

*Department of Economics, Boston University. I thank Daniele Paserman, Claudia Olivetti, Kevin Lang and Stefania Garetto for their invaluable advice and support. I am extremely grateful for helpful comments from Michael Manove, Randy Ellis, Cem Tintin, Tskin Julian Chan, Laura Salisbury, and Paolo Naticchioni. Additionally, I thank David Autor for guidance on harmonization of industry data, and use of the O*NET dataset. I thank the participants of the Boston University Empirical Micro lunch, the BU Micro Dissertation Workshop, the 2012 SciencePo Workshop on Inequality and Globalization for their comments and feedback. All errors are my own.

1 Introduction

Although overall wage inequality has been increasing in the U.S. since the 1970s, starting in the mid-1980s, lower-tail inequality stopped growing and declined slightly while upper-tail inequality increased at an accelerating pace. I use the term convexification to describe the accelerating wage growth for high earning workers, and the stagnation and relative decline of the middle class. During this same period, the employment shares of highly paid professionals and low paid service workers rose while the employment shares of mid-level manufacturing workers and office workers fell.[1] These employment and wage changes suggest a decrease in the relative demand for middle skilled labor.

At the same time, improvements in communication and transportation technology contributed to offshoring in both manufacturing and service. The ability to hire cheap foreign workers should decrease the relative demand for the domestic workers of similar abilities. Recent work by Goos and Manning (2007) [12], and Autor and Dorn (2012) [4], offers a "routinization hypothesis:" mid-level jobs are highly routine, and therefore have the highest degree of substitutability with foreign labor. While some circumstantial evidence links routine tasks to wage convexification, the wage inequality literature lacks a direct empirical analysis of the impact of offshoring on relative wages. Moreover, the existing research focuses on manufacturing even though the majority of jobs in the American economy are comprised of services.

In this paper I measure the extent to which offshoring by U.S. industries has increased the wage gap between the median wage and the 90th percentile wage but narrowed the gap between the 10th percentile and the median, thereby contributing to the observed convexification. First, I present a simple task-based model of labor supply and wages to illustrate the predicted effects of offshoring on upper and lower tail wage inequality. I represent offshoring by a drop in the global price for routine task inputs, and show how this differs from a skill-biased technological change. Secondly, I construct a measure of offshoring for both material and service inputs, and apply this measure to 128 industries in both the manufacturing and service sectors for the years 1990, 2000, and 2011. This approach for offshoring

[1] Autor and Acemoglu (2011).

measurement was initially introduced by Feenstra and Hanson [10] for material offshoring, and to my knowledge only Amiti and Wei [2] have employed this measure for service offshoring. Rather than focusing solely on either the manufacturing or service sector in isolation, I include the full economy to provide a comprehensive view of the impact of offshoring. The analysis also covers a relatively long time frame, using wage and industry data that span a 21 year period. Thirdly, I employ a fixed effects regression model to estimate the effect of offshoring on wages and employment and test the implications of the model. I estimate separately the effects on the lower half of the wage distribution (the 50/10 spread) from the effects on the upper half of the distribution (the 90/50 spread).

The results of the empirical analysis show that offshoring has a positive effect on wages throughout the wage distribution. The magnitude of this impact is greatest at the top of the distribution; hence there is a statistically significant positive impact of offshoring on upper tail wage inequality. An increase in service offshoring of one standard deviation explains about 6% of the observed increase in the upper tail wage spread, and one standard deviation increase in material offshoring can explain nearly 13% of the observed change. Controlling for industry productivity does not alter the estimated effect of offshoring on wage levels and spreads. It is plausible that selection in layoffs is driving this effect: if industries are offshoring jobs previously done by workers from the bottom half of the wage distribution, the measured wages in those industries will be higher than they were prior to the introduction of offshoring. I apply a bounding exercise to provide an upper bound estimate of the effects of selection on wages, and show that all of the wage effects could be due to selection. Finally, in order to investigate the impact of routinization, I control for the task composition of each industry. The estimated offshoring effect does change when lagged industry occupational shares are included in the regression. This suggests that the current industry-specific patterns of offshoring are influenced by the past occupational distributions. The analysis on occupational composition shows that the lagged task content of each industry is a statistically significant predictor of both material and service offshoring. In particular, the share of routine occupations has a positive causal effect on service offshoring. However, this same measure has a significantly negative causal effect on material offshoring. These results offer empirical support for the routinization hypothesis when it is applied to service offshoring, but not with respect to material offshoring.

In Section 2 I provide an overview of U.S. wage convexification, and highlight how my paper contributes to the literature. Section 3 describes offshoring and discusses the associated measurement challenges. Section 4 explains the theoretical model that serves as a framework for the empirical analysis. Section 5 discusses the empirical methodology. Section 6 examines the results in the context of three mechanisms that potentially connect offshoring with the wage distribution, and section 7 concludes.

2 Wage Convexification Overview

In addition to the increase in overall wage inequality, the change in relative wages has not been homogenous over the entirety of the distribution. This heterogeneity is especially pronounced with regards to the last two decades. Figure 1 displays the evolution over time of three points in the male wage distribution: the 10th percentile, 50th percentile, and 90th percentile. We can see that the gap between low-skilled workers (represented by the 10th percentile position) and median wage earners increased from the mid 1970s until the mid-1980s, but for later periods this 50/10 gap is either constant or decreasing. In contrast, the gap between the 90th percentile wage earner and the median wage earner continued to increase throughout the entire time span of the graph. In particular, the 90/50 gap shows a large expansion from the late 1990s to 2010, indicating a sharp rise in the high-skill premium. The same data for female wages (Figure 2) shows a wage distribution that is slightly less polarized, but still reflects a greater spread increase in upper half of the distribution than the lower half.

What is driving this wage convexification? In very broad terms, the research on wage inequality points to changes in institutional factors, and skill biased technical change (SBTC). Institutional factors such as unionization and declining real minimum wage are credited in driving lower tail inequality (see Lee (1999) [14], Card and Dinardo (2002), Lemieux (2006)[15]). However, by 1990, the real minimum wage had fallen sufficiently that minimum wage laws were no longer binding above the 10th percentile wage level.[2] A growing body of work in the early 2000s focused on SBTC as the source of upper tail inequality (including Katz and Autor (1999)

But, increasing returns to education is only part of the story of the upper tail wage spread, since residual (within group) inequality tracks a similar pattern to the divergence we see in Figure 1(see Card and Dinardo (2002) [8], Bogliacino (2008 wp)). Autor, Levy and Murnane (2003) [7] and Autor and Acemoglu (2011) point out that the canonical model used in the SBTC thesis is insufficient for explaining the type of convexification observed in the U.S. distribution. The key shortcoming in the canonical SBTC model is that it does not distinguish between skills (college versus high school education) and tasks (occupational characteristics that are not perfectly mapped to educational background).

As an alternative framework, Autor et al. (2011, 2012) lay out the "routinization" hypothesis as follows: workers in the middle of the wage distribution are primarily in occupations with a high level of routine tasks (for example: record keeping, routine customer service jobs, repetitive assembly, or sorting goods in a warehouse). These occupations are characterized by the fact that they can be fully described in a computer algorithm or in a list of instructions to a foreign worker. As a result, they are highly prone to substitution by technology or offshore labor.[3] Along a similar vein, Autor Katz and Kearney (2006, 2008) [5] propose a model of computerization to explain the divergence in lower tail and upper tail inequality: computerization complements complex cognitive tasks, replaces routine tasks, and has little impact on nonroutine manual tasks.

The critical contribution of the task based framework is that it distinguishes between the demand for middle and low level tasks rather than lumping them together under the label of "low skilled labor". In contrast to the mid-level occupations, many low skill manual occupations are actually non-routine. That is, since the nature of such tasks demands human interaction these workers are not as easily replaced by computers or remote labor. These occupations are primarily of the low skilled service variety: for example, jobs in maintenance, janitorial work, sanitation , childcare, and hair and nail salons. On the other end of the complexity spectrum, highly analytic occupations require complicated decision

[2] Autor, Manning and Smith (2010).

[3] Blinder (2007) estimates that over 20 million domestic jobs are potentially offshorable due to their task characteristics

making beyond the scope of what can be contained in a computer algorithm. These jobs are concentrated at the top of the wage distribution. The task based model offers a plausible explanation for why workers near the median are in decline relative to both the top and the bottom earners.

Figure 3 depicts the 1990-2000 and 2000-2010 changes in employment share by occupational complexity.[4] The data shows a striking distinction between these two periods. During the 1990s, occupation employment share expansion was roughly monotonic in complexity. The least complex occupations declined while the most complex occupations gained employment share, and the relative employment in occupations near the middle of the ranking changed the least. However, in the latter period the occupations in the middle of the distribution actually lost employment shares, while both the least and most complex occupations increased their shares. Since the complexity rankings are highly correlated to wage rankings, similar patterns are observed when we use the occupation's mean 1990 wage percentile on the horizontal axis.

Figure 4 ranks occupations by their offshorability, and shows the relative change in employment by percentile. The offshorability measure follows the methodology used by Autor and Acemoglu [1] in the Handbook of Labor Economics (2011). It aggregates (normalized) O*NET measures regarding two task characteristics: each occupation's intensity of routine tasks, and the intensity of face to face interactions.[5] According to the routinization hypothesis, routine task intensity causes an occupation to be more easily offshored while the amount of face to face interactions limits offshorability. Consequently, the offshorability measure is defined as (routine intensity) + (-1)(face to face intensity) and normalized in the typical fashion. Unlike the convex effect of the complexity measure, the change in relative employment is strongly and monotonically negative in offshorability for both decades. Occupations that require face to face contact from workers appear to be protected from employment loss, whereas occupations that engage heavily in routine tasks are highly susceptible to declining employment.

[4]Occupation complexity measures the degree to which the occupation is classified as "Nonroutine Cognitive Analytic." The raw data is from the O*NET dataset, and the measure is constructed following Autor Katz and Kearney (2006).

[5]The measure for routine task intensity comes from the extent to which workers carry out physical assemply or equipment inspections, calibrations, and repairs based on established checklists or guidelines. "Face to face interaction" refers specifically to transactions that require physical proximity of the worker, for example: caring for patients in a hospital, or serving food to a restaurant patron.

In these figures we see that the data offer strong circumstantial evidence that the decline in mid-level employment and wages is linked to task characteristics. Whether an occupation is concentrated in routine or abstract tasks is clearly important in explaining changes in relative demand. However, the existing literature lacks direct empirical tests of this link, particularly with respect to offshoring (with the exception of a new working paper by Oldenski).[6] It is also important to point out that either type of middle task substitution, computerization or offshoring, is consistent with the routinization hypothesis.[7] Either mechanism, or a combination of the two, would result in a decrease in the relative demand for workers in the mid-level occupations, and produce a decline in the relative wage of median workers. Given this theoretical ambiguity, the relative importance of offshoring to expanding wage inequality is an empirical question that needs to be addressed.

The objective of this paper is to address this gap in the empirical literature. Specifically, this paper asks the following questions:

1. How much of the observed increase in upper tail inequality can be explained by offshoring?
2. Are these effects due to selection?
3. How well does the task based model apply to the contribution of offshoring: does offshoring act as a substitute for routine tasks, and/or does offshoring increase the relative returns to nonroutine cognitive tasks?

3 Offshoring

Public opinion polls[8] show that a majority of Americans believe that increased globalization, in the forms of immigration, trade, and offshoring, is harmful to the wages and employment prospects of native workers. Whereas in the past it was primarily manufacturing workers who held the view that

[6]Recent work by Oldenski (October 2012[17]) supports the claim that offshoring can be explained by routinization in the years 2002 to 2008.

[7]Feenstra and Hanson (1999) remains one of the primary studies that aims to directly compare the two.

[8]http://pewresearch.org/pubs/1904/poll-illegal-immigration-border-security-path-to-citizenship–birthright-citizenship-arizona-law; http://www.gallup.com/poll/115240/Americans-Negative-Positive-Foreign-Trade.aspx

offshoring was depressing American jobs and diminishing American wages, workers in the service sector are increasingly adopting this aversion to offshoring. In a 2004 Gallup poll, two-thirds of investors reported that they believed offshoring was harmful to the US economy's overall strength.[9] There is some recent research supporting the point of view that American workers are harmed by trade and offshoring. Autor, Dorn and Hanson (2012) [3] show that exposure to Chinese imports has negative effects on local labor market employment and wages. However, most academic studies on offshoring highlight the labor market benefits. Ottaviano, Peri and Wright (2010) [19] conclude that offshoring has no negative effects on Employment. Using a different measurement technique, Wright (2011) finds that offshoring (in the US manufacturing sector 1997-2007) did displace domestic production workers, but because offshoring industries have greater output, overall employment in these industries increases. Like Wright, Olney (2011) [18] considers offshoring in the framework of traded tasks (from Grossman and Rossi-Hansberg (2008) [13]). Comparing the wage effects of immigration and offshoring, he finds stronger (positive) effects for wages from offshoring, which he cites as evidence of a productivity effect. Amiti and Wei (2009) [2] also stress the productivity effect: they credit service offshoring with 10 percent of the increase in labor productivity between 1992 and 2000.

Although these studies provide valuable insights to the aggregate effects of offshoring, these effects may not be felt equally throughout the wage distribution. It is essential to also investigate whether offshoring changes the shape of the wage distribution. Crinó (2010) [9], shows that medium and low-skilled occupations see a negative employment response to service offshoring. Although Crino looks exclusively at service industries, my analysis of both services and manufacturing confirms his results. Feenstra and Hanson (1996, 1999) conduct the most rigorous studies on the effects of offshoring for the wage distribution in the US [10], and show that offshoring is an important channel through which trade affects the demand for labor of different skill types. They find that that the increase in imported intermediates explains 11% to 51% of high-skilled labor's increased share of the total wage bill (the estimate varies based on the definition of offshoring that is used). However, other studies (e.g. Slaughter

[9] http://www.gallup.com/poll/11506/Investors-Support-Outsourcing.aspx

[10] their definition of inequality is the production workers' share of the total wage bill

(2001)[20]) find that the impact of offshoring on wage bill share is insignificant when time fixed effects are included.[11]

3.1 What is Offshoring?

Offshoring, also referred to as "trade in tasks," is defined as conducting some portion of final good production outside the domestic border. Offshoring is commonly but incorrectly called "outsourcing," which refers to arms length production that takes place either domestically or internationally. It includes both foreign outsourcing from unrelated suppliers of intermediate goods (international arms length production) and tasks performed abroad by subsidiaries or related entities of a multinational firm (foreign direct investment). Tempest (2006) describes Mattel's production process for the many components of a Barbie doll, which takes place in the United States, Saudi Arabia, Japan, Taiwan, China, Indonesia and Malaysia, and finally is marketed and distributed back in the U.S.. Automobiles and electronics are other examples of goods in which most of the manufacturing process occurs globally.

When offshoring takes the form of intermediate good production, physical goods are shipped from one country to another and counted as part of total trade volume. However, a growing portion of trade in tasks is actually in services. Accounting and tax services, radiology and other medical laboratory processes, customer service call centers, document processing, and data processing are all services that are now traded internationally. Given that much of these service products can be delivered between parties electronically, the transportation costs are close to zero.

The primary obstacle to measuring and studying offshoring in U.S. firms is that there is no official dataset or reporting process for trade in tasks. When trade in physical goods occurs between two unaffiliated firms, it is not always clear whether goods are intermediate inputs or final use commodities. The value of international transactions within a firm may be manipulated by the firm in order to avoid certain import taxes. Even without firm manipulation, the cost of importing both goods and services within the firm is much lower than importing them from an unaffiliated supplier. Finally, the fact that offshoring is widely prevalent speaks to another source of distortion: prices of international com-

[11] I use both time and industry fixed effects throughout my empirical analysis.

modities are not fully arbitraged, and imported inputs are generally cheaper than domestic substitutes. Much of the trade in services is not reported officially at all, although the BEA does now collect survey data from American firms on trade in services with affiliated parties. For these reasons, it is neccessary to construct an approximate measure of offshoring.

3.2 Offshoring measurement

Offshoring measurement for U.S. industries is not straightforward because the U.S. does not currently compile data on offshoring by American firms. Feenstra and Hansen (1996) introduced a method for measuring offshoring in the manufacturing sector, and Amiti and Wei (2009) follow a similar technique to measure offshoring in five broad service categories. I build on these previous measures of offshoring by including both manufacturing and service industries in the analysis, using industry level input-output tables and trade data for both sectors. I define offshoring as the share of an industry's non-energy inputs that are imported. Measurement according to this definition requires both information about the use of intermediate inputs and information about import intensities of all relevant inputs. I use a combination of international trade data from the Bureau of Economic Analysis (BEA) and industry level production data obtained from BLS input-output tables. The measure of each industry's offshoring (denoted as OSM_{it} for material inputs and OSS_{it} for service inputs) follows an index first introduced by Feenstra and Hanson (1996) [10] for goods offshoring, and also used by Amiti (2009) [2] for offshoring of services. The intermediate goods usage data is taken from the Bureau of Economic Analysis (BEA) input output accounts, based on the 2002 benchmark tables and downloaded from the Bureau of Labor Statistics (BLS) [12]. These tables give the breakdown of all input materials and services, by industry. The offshoring measure is defined as:

$$OS_{it} = \sum_j \left[\frac{\text{inputs}_{jit}}{\text{total non-energy inputs}_{it}} \right] * \left[\frac{\text{imports}_{jt}}{\text{production}_j + \text{imports}_j - \text{exports}_{jt}} \right]$$

[12]The data are available starting in 1993, .

For each input good or service *j*, the first term represents input purchases of that good (service) by the industry *i* during period *t*, as a fraction of all non-energy inputs (both material and service) for industry *i* at time *t*. The second term represents the share of good or service *j* that was imported nationally: total imports of good or service *j*, divided by total supply of *j* (total supply is equal to domestic production plus net imports of service. This second term is calculated at the country level for each year, since imports and exports of each input are not available by industry. It is neccessary to assume a constant share of imports in j for all industries that use j as an input. The metric can equivalently be expressed as:

$$OS_{it} = \frac{1}{Inputs_{it}} \left[\sum_j \frac{\text{inputs}_{jit} * \text{imports}_{jt}}{\text{total domestic supply}_{jt}} \right]$$

Throughout this paper I will use OSM to refer to manufacturing offshoring, and OSS to refer to service offshoring. The services that I included were (1) finance, (2) insurance, (3) telecommunications, (4) business support services,[13] and (5) computer and information services. Other major service categories (for example: educational services, transportation services) are not included because trade volumes are either equal to zero or simply unreported. The measure for OSM is a sum over 38 manufacturing industry inputs. Out of the 170 final use commodities in the BEA input-output tables, I am able to construct measures of OSM and OSS for 129 industries present in the Census in 1990, 2000 and 2010. Figure 5 and Figure 6 display the box plots of these measures over the period 1993 to 2000.[14]

From the figures, one can see that both measures are increasing over time, and increasing in variance. This is particularly true of the OSS measure. The data for trade in services is limited during the 1990s, and it was neccessary to aggregate many service inputs into the five categories described above. This and the fact that service imports were very low in the 1990s produce an OSS measure that is quite

[13]This includes business, professional, scientific and technical services. For example: legal, administrative, medical support services.

[14]I matched 1993 OSS and OSM measures with wage data from the 1990 Census, since the BEA data is unavailable for the year 1990.
The measure was adapted to the state level for a robustness check. In order to measure offshoring variables for a state, I calculated the weighted average of all industry level offshoring measurements, using each industry's share of gross state product for the weights.

small in magnitude and variance during the 1990s. In the 2010 data, the top three industries in material offshoring were metals processing, computer equipment manufacturing, and seafood production and packaging. Other industries with a high OSM measures tended to be manufacturing industries. The top three service offshoring industries included a service industry: insurance, as well as two manufacturing industries: computer equipment and pharmaceuticals.

4 Theoretical Framework

In order to inform the empirical analysis, I describe a simple task based model and characterize the effect of offshoring on wages within this framework.

4.1 Production

The factors of production are labor in the form of three types of tasks: manual (M), routine (R), or abstract (A). Total economic output is a Cobb-Douglas aggregation of the three task inputs: $Y = L_M^{\alpha} L_R^{\beta} L_A^{\gamma}$, with $\alpha + \beta + \gamma = 1$. One can think of the task-specific production $L_M, L_R,$ and L_A as intermediate good production, where overall economic output is an aggregate of these intermediate goods. Normalizing the price of the final good to 1 and assuming zero fixed costs, profit is equal to

$$L_M^{\alpha} L_R^{\beta} L_A^{\gamma} - p_M L_M - p_R L_R - p_A L_A$$

where p_k is the price of intermediate good $k \in \{M, R, A\}$. Profit maximization yields the following first order conditions:

$$FOC(L_M) : \alpha \frac{Y}{L_M} = p_M \tag{1}$$

$$FOC(L_R) : \beta \frac{Y}{L_R} = p_R \tag{2}$$

$$FOC(L_A) : \gamma \frac{Y}{L_A} = p_A \tag{3}$$

Dividing (3) by (2) and rearranging, we can write the relative demand for abstract tasks with respect to the demand for routine tasks, which is always increasing in $\frac{p_R}{p_A}$.

$$\frac{L_A}{L_R} = \frac{\gamma p_R}{\beta p_A} \tag{4}$$

Similarly, the relative demand for routine tasks versus manual tasks is increasing in $\frac{p_M}{p_R}$ and can be written as:

$$\frac{L_R}{L_M} = \frac{\beta p_M}{\alpha p_R} \tag{5}$$

4.2 Workers

Labor is supplied inelastically by workers in one of the three types of task (M, R, or A). Each worker has exogeneously determined skill level z, where $z \sim G(.)$ over the interval $[0,1]$. An individual with skill level z can produce $\phi_k(z)$ units of output, where $k \in \{M,R,A\}$. In this case, worker productivity is constant for task M, but linear and increasing in skill for tasks R and A.

$$\phi_k(z) = \begin{cases} a_M, & \text{for } k = M \\ a_R + b_R z, & \text{for } k = R \\ a_A + b_A z, & \text{for } k = A \end{cases}$$

Let $a_M > a_R > a_A$. This means that an individual with the lowest amount of skill, $z = 0$, would be the most productive in the M task, and very poor at producing the A task. Setting $0 < b_R < b_A$ means that productivity increases with skill in both the routine and the manual tasks, but the marginal return to skill is greater in the abstract task. These assumptions on the parameters of $\phi_k(.)$ imply that for three workers with skill levels $z' < z'' < z'''$, z' will have a comparative advantage in the manual task, z'' will have a comparative advantage in the routine task, and z''' will have a comparative advantage in the abstract task.[15] Hence, in an efficient allocation of labor, the least skilled workers will perform

[15] In general, the assumption that $\frac{\phi_A(z)}{\phi_R(z)}$ and $\frac{\phi_M(z)}{\phi_R(z)}$ are both increasing in z is sufficient to generate this pattern of comparative advantage.

manual tasks, the most skilled workers will perform abstract, and those workers in the middle of the skill distribution will perform the routine tasks.

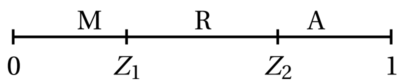


Figure 7 illustrates that this is the equilibrium allocation of skill to tasks: for every skill level z, the worker selects the task in which she earns the highest wage. Each worker will be paid the value of her marginal product: the unit price for task k multiplied by her productivity $\phi_k(z)$.

$$w_k(z) = p_k \phi_k(z)$$

We can solve for the threshold points Z_1 and Z_2 in terms of the productivity parameters and intermediate good prices. In equilibrium, the worker with skill level $z = Z_1$ will be indifferent to working in either manual or routine tasks:

$$p_M a_M = p_R (a_R + b_R Z_1) \tag{6}$$

$$\implies Z_1 = \frac{p_M a_M - p_R a_R}{p_R b_R} \tag{7}$$

Taking the partial derivative of Z_1 with respect to p_r, we can see that $\frac{\partial Z_1}{\partial p_R} < 0$.

$$\begin{aligned} \frac{\partial Z_1}{\partial p_R} &= \frac{\partial}{\partial p_R}\left(\frac{p_M a_M - p_R a_R}{p_R b_R}\right) \\ &= \frac{-a_R(p_R b_R) - b_R(p_M a_M - p_R a_R)}{(p_R b_R)^2} \\ &= -\frac{p_M b_R a_M}{(p_R b_R)^2} < 0 \end{aligned}$$

As the price for the routine task falls, the threshold skill level between the manual and routine tasks rises. As a result, some workers will switch from the routine to the manual task. Similarly, the worker with skill level $z = Z_2$ will be indifferent to working in either routine or abstract tasks:

$$p_R(a_R + b_R Z_2) = p_A(a_A + b_A Z_2) \tag{8}$$

$$\implies Z_2 = \frac{p_R a_R - p_A a_A}{p_A b_A - p_R b_R} \tag{9}$$

The threshold level Z_2 is increasing in p_R:

$$\begin{aligned}
\frac{\partial Z_2}{\partial p_r} &= \frac{\partial}{\partial p_r}\left(\frac{p_R a_R - p_A a_A}{p_A b_A - p_R b_R}\right) \\
&= \frac{a_R(p_A b_A - p_R b_R) - (p_R a_R - p_A a_A)(-b_R)}{(p_A b_A - p_R b_R)^2} \\
&= \frac{a_R p_A b_A - b_R p_A a_A}{(p_A b_A - p_R b_R)^2}
\end{aligned}$$

which is > 0 if and only if

$$a_R p_A b_A > b_R p_A a_A$$

$$\frac{a_R}{b_R} > \frac{a_A}{b_A}$$

The above inequality holds by assumption ($a_R > a_A$ and $b_R < b_A$). As the global price for the routine task increases, the threshold skill level between the routine and abstract tasks rises: some workers previously performing the routine task will switch to the abstract task. Substituting the parameters for Z_1 and Z_2, we can express the length of the skill interval in which routine tasks are performed as

$$Z_2 - Z_1 = \frac{\left(p_M a_M - p_A a_A\right) p_R b_R + \left(p_R a_R - p_M a_M\right) p_A b_A}{\left(p_A b_A - p_R b_R\right) p_R b_R} \tag{10}$$

This expression is increasing in P_R: the skill interval that represents the workers engaged in the routine task will narrow as the price for routine labor falls.

4.3 Labor Market Clearing

Market clearing in each type of task requires that the sum of the workers' productivity in each type of task must be equal to the total factor demand. The market clearing condition for manual tasks L_M is:

$$L_M = a_R G(Z_1) \tag{11}$$

Since $G'(.)$ is non-negative, the share of domestic labor in the manual task will increase as Z_1 increases (equivalently, as p_R decreases).

Market clearing for routine and abstract tasks are given by:

$$L_R = a_R\,(G(Z_2) - G(Z_1)) + b_R \int_{Z_1}^{Z_2} z.g(z)\,\mathrm{d}z \tag{12}$$

and

$$L_A = a_A\,(G(1) - G(Z_2)) + b_A \int_{Z_2}^{1} z.g(z)\,\mathrm{d}z \tag{13}$$

We can show that L_R, the mass of domestic labor production in the routine task, is generally increasing in p_R.

$$\frac{\partial L_R}{\partial p_R} = a_R \left[G'(Z_2)\frac{\partial Z_2}{\partial p_R} - G'(Z_1)\frac{\partial Z_1}{\partial p_R} \right] + b_R \left[\frac{\partial}{\partial p_R} \int_{Z_1(p_R)}^{Z_2(p_R)} z g(z)\mathrm{d}z \right] \tag{14}$$

The first term in (14) is positive:

$$a_R \left[G'(Z_2)\frac{\partial Z_2}{\partial p_R} - G'(Z_1)\frac{\partial Z_1}{\partial p_R} \right] > 0$$

because

$$G'(z) > 0$$
$$\frac{\partial Z_2}{\partial p_R} > 0$$
$$\frac{\partial Z_1}{\partial p_R} < 0.$$

The second term is also positive. We can write this term as:

$$b_R \left[\frac{\partial}{\partial p_R} \int_{Z_1(p_R)}^{Z_2(p_R)} zg(z)\mathrm{d}z \right] = b_R \left[\frac{\partial Z_2}{\partial p_R} Z_2 g(Z_2) - \frac{\partial Z_1}{\partial p_R} Z_1 g(Z_1) + \int_{Z_1}^{Z_2} \frac{\partial}{\partial p_R} \big(zg(z)\big)\,\mathrm{d}z \right].$$

Since

$$\frac{\partial Z_2}{\partial p_R} > 0$$
$$\frac{\partial Z_1}{\partial p_R} < 0$$
$$Z_2 g(Z_2) > 0$$
$$Z_1 g(Z_1) > 0$$
$$\frac{\partial}{\partial p_R} \big(zg(z)\big) = 0,$$

it follows that

$$b_R \left[\frac{\partial}{\partial p_R} \int_{Z_1(p_R)}^{Z_2(p_R)} zg(z)\mathrm{d}z \right] > 0$$
$$\implies \frac{\partial L_R}{\partial p_R} > 0.$$

Similarly, we can show that

$$\frac{\partial L_A}{\partial p_R} = \frac{\partial}{\partial p_R} \left[a_A \left(G(1) - G(Z_2)\right) + b_A \int_{Z_2}^{1} z.g(z)\,\mathrm{d}z \right] < 0. \tag{15}$$

4.4 Offshoring in the task based framework

Offshoring occurs when firms can use foreign workers to replace more costly domestic workers. As Autor (2008)[6] points out, certain characteristics make a specific class of occupations easier for a firm to offshore. For example, occupations requiring face to face contact (such as childcare providers, bartenders, public transportation attendants) may not require a high level of skill, but are difficult or impossible to offshore. Abstract tasks are also prohibitively difficult or costly to offshore, because these occupations require the worker to engage in a constantly changing enviroment and respond using human judgement. Assuming that routine (R) tasks are the potentially offshorable task input, access to cheap foreign labor for this task is equivalent to a decrease in the global price for R tasks: $p_R \downarrow$. As a result, some of the domestic middle task workers will be displaced by foreign workers, and switch to either the manual or the abstract task. From Equation (10) one can show that with a decline in p_R, $(Z_2 - Z_1)$ will decrease. Using Equation(12), this also means that the quantity of domestic labor employed in the routine task will fall. Furthermore, congruent with the Stolper Samuelson theorem, the relative payments to abstract task workers relative to routine workers will increase, since routine tasks are now being imported. Figure 8 shows the effect of this type of price shock on wages and on the allocation of workers between tasks.

In this framework, introduction of offshoring as a decline in the global price of mid-level labor implies that increased offshoring will be associated with decreased real wages for middle skilled workers, an increased 90/50 spread, as well as a decreased 50/10 spread. One could also consider the case in which routine and abstract tasks are price complements [16]: in this case a decline in the global price for routine tasks will increase the demand for abstract tasks, and we will see an increased wage level for high skill workers as in Figure 9.

[16] for example, a CES production function with elasticity of substitution<1

5 Empirical Strategy

5.1 Measuring Inequality

The empirical analysis uses data from several sources. For individual level wages, I use data from the 1990 and 2000 Census, and the 2011 American Community Survey (ACS).[17] I restrict the sample to civilian individuals aged 16 to 65 who worked for wages for at least one week in the year prior to the survey. Using annual earnings, weeks worked during the year, and average hours per week, I construct hourly wages for each individual. For each industry in 1990, 2000, and 2011, I use the difference in log wages between the 10 percentile and the median, as well as the log gap between the median and 90th percentile wage, as measures of lower and upper tail inequality, respectively. Table 1 describes the data aggregated at the industry-year level.[18] The mean industry employs a little under 1 million people. It pays an annual income to its 10th percentile, median, and 90th percentile workers of roughly $7,000, $28,000, and $63,000.[19] Employees of the average industry are 15 percent foreign born, 11 percent black, 37 percent female, 22 percent college educated, and 17 percent are union members. The final dataset used in the empirical analysis has 367 observations: 121 industries in 1990, and 123 in 2000 and 2011.

5.2 Econometric specification

I used a fixed effects model for the baseline analysis. The empirical framework for examining the effect of offshoring on inequality is the following:

$$Y_{it} = \alpha + \beta_1 \text{oss}_{it} + \beta_2 \text{osm}_{it} + \gamma \text{X}_{it} + \delta_i + \tau_t + e_{it}$$

where Y_{it} is the relevant outcome variable for industry i during year t, osm_{it} is offshoring of material inputs, oss_{it} is service offshoring, X_{it} includes industry characteristics: controls for female, black, and immigrant employment, college-educated share of employmnet, and unionization. (Observations are

[17] Earnings from the 2011 ACS are further removed from the 2008 recession shock than earnings in the 2010 ACS.

[18] Industries are defined at the 3-digit NAICS level, although it is neccesary to further combine some of the 3-digit industries in order to harmonize data from the Census and the BEA.

[19] All dollar amounts are given in 1999 dollars.

weighted by total industry employment, measured in persons employed.)[20]

The dependent variables that I use include: log hourly wage at the 10th, 50th, and 90th percentiles, and the spreads between the median log wage and the 10th and 90th percentile log wages, respectively.

$$\text{spread}_{50-10,i,t} = \ln \omega_{it}^{50} - \ln \omega_{it}^{10}$$

$$\text{spread}_{90-50,i,t} = \ln \omega_{it}^{90} - \ln \omega_{it}^{50}$$

These measures represent the mid-skill premium relative to low-skill wages, and the high-skill premium relative to mid-level wages.

6 Results

The results for the baseline fixed effects model are displayed in Table 2. Columns 1, 2, and 3 use the log wage at the 10th, 50th, and 90th percentiles as the dependent variable. The outcome variable in Column 4 is the lower tail inequality: the difference between the 10th percentile and 50th percentile log wage. Column 5 uses the upper tail inequality: the difference between the median and the 90th percentile. I also include log industry employment as a dependent variable; these results are in Column 6. All specifications include a full set of year and industry fixed effects. With the exception of Column 6, observations are weighted by industry employment.

Both OSS and OSM have a significant and positive effect on wages throughout the wage distribution. Because the magnitude of these effects is substantially larger for the industries' 90th percentile wage than for the median wage, OSM and OSS also each have a significant and positive effect on the upper tail wage spread, with estimated coefficients of $\hat{\beta}_{OSS} = 1.376^{**}$ and $\hat{\beta}_{OSM} = 0.215^{**}$ (see Column 5 of Table 2).[21]

[20] In a perfectly competitive model of the labor market, workers of equal skill levels should have identical wages across industries. However, there is plenty of empirical evidence of inter-industry frictions and resulting wage differentials; see Gibbons and Katz (1992) [11], Abowd, Kramarz and Margolis (1999)[16].

[21] Robustness checks: these results are robust to various alternative specifications. I separate the sample by gender, and also into services and manufacturing. I use weekly log wages to construct the wage levels and spreads, and I remove various industry level controls (not the fixed effects). I use different definitions for the wage spreads (for example: 30th-10th percentile spread, or 90th-70th percentile spread), and do not find any discontinuities. I also use the CPS wage data as an alternative to

Table 3 interprets the results of the fixed effect regression in the context of the sample data set. During the sample period 1990-2011, industry upper tail inequality ($ln(\frac{w_{90}}{w_{50}})$ has a standard deviation of 0.1735 log points. An estimated OSS coefficient of 1.376 for the upper tail regression means that an increase in the OSS measure of 1 standard deviation is associated with an increase in upper tail wage inequality of approximately 0.011 log points, or roughly 6% of the between industry standard deviation found in the data. An OSM coefficient of 0.215 implies that a 1 standard deviation increase in material offshoring results in an increased upper tail spread of 0.02 log points, which is 12.6% of the observed industry variance.

The time series interpretation is summarized in Table 4. Between 1990 to 2011, the mean industry in the sample experienced an increase in services offshoring from 0.0143 to 0.0287, a difference of 0.0144. This implies an increase in upper tail wage inequality of (1.376)(0.0144) = 0.02 log points, which is 32% of the observed increase in the 90/50 spread for this period.[22] Similarly, the increase in material offshoring of 0.114 [23] implies an increase in the 90/50 spread of 0.025 log points: 40% of the observed rise in upper tail inequality.

In contrast to the positive wage effects, material offshoring has a negative effect on employment: Column 6 shows that the estimated coefficent for OSM is -1.236**, indicating that a 10% increase in material offshoring leads to a 12% decline in industry employment. (Due to the limited variation of the trade services data, these results are not precise enough to give any information about the effect of service offshoring on employment.) Given the sample standard deviation in OSM of 0.102, this result attributes 9.5% of the standard deviation in employment to material offshoring. These data clearly indicate a tradeoff between employment and real wage levels for workers in offshoring industries.

the Census. In general these regressions have less precision, but do not contradict the results in the baseline equation.

[22] from Table 1: mean increase in 90/50 spread from 1990 to 2011 was 0.062 log points

[23] The mean industry OSM measure was 0.112 in 1990, and 0.226 in 2011.

6.1 Potential Mechanisms

There are three primary reasons that offshoring might have a positive effect on wages and the upper tail spread. The first standard explanation of many trade models is that offshoring is associated with more productive industries, and workers in such industries are rewarded for their relatively high marginal product with higher wages. If these wage effects are increasing in the wage rank, they would act to exacerbate the upper tail spread as well. It is important to note that this mechanism is not consistent with a competive labor market model: in a competitive model, wages are determined on a macro level by labor supply and demand and firms choose a level of production at which the marginal product of labor is equal to the market wage. [24]

However, several other authors including Grossman and Rossi-Hansberg [13], Ottaviano et al. [19], and Wright [21] assume a model in which offshoring decreases production costs and increases productivity in all workers. In order to address this viewpoint, I include industry level productivity as a control in the fixed effects regression. (Productivity is defined as output per labor hour.) In Table 5, I include industry productivity, and find that the coefficients for wage levels and spreads are very similar to those in the baseline fixed effects model. In addition, the productivity coefficients in the wage level and wage spread regresions are insignificant. From these results there is no evidence that the wage effects in Table 2 are driven by increased productivity. Regressing productivity on industry controls and the offshoring measures also fails to indicate that either form of offshoring has any significant effect on productivity.

Secondly, the positive wage effects could be driven by the fact that industries that offshore heavily are disproportionately replacing their low and middle skilled domestic workers with foreign workers. This explanation is supported by the large negative effect of OSM on employment, shown in Column 6 of Table 2.[25] In the extreme case, if the total unemployment implied by the additional offshoring came

[24]Example: CD Production ($Y = L^{\alpha} K^{1-\alpha}$)

Profit maximization $\rightarrow$

$$\alpha L^{\alpha-1} K^{1-\alpha} = \omega$$

$$\text{productivity} = \frac{L^{\alpha} K^{1-\alpha}}{L} = \alpha^{-1}\omega$$

Productivity $\uparrow$ because $\omega \uparrow$

[25]This negative effect of offshoring on employment contradicts the findings of Olney (2011)

from the bottom half of the distribution, this would result in higher average wages for the new distribution of surviving workers. By construction, 10th percentile wages in an industry that has previously laid off the low skilled workers will be higher than the 10th percentile wage in an identical industry that did not undergo such layoffs.

I carry out the following bounding exercise in order to assess the extent to which the employment effects could create the illusion of higher wages throughout the wage distribution. First, for each industry in the 1990 sample, I multiply the observed change in OSM between 1990 and 2000 by the value of the OSM coefficient in the fixed effects model of log employment (approximately 1.2, Table 2, column 6).

$$\beta_{OSM} * \triangle \text{OSM}_{i,1990-2000} * 100\%$$

This gives the predicted percentage decrease in employment implied by the regression results in column (6) of Table 2. Then, I look at the case in which the full change in employment comes from the lower end of the wage distribution. For example, suppose an industry increased OSM by 0.08 ($dOSM_{i,1990-2000} * 100 = 8\%$). The implied percentage decrease in industry i as a result of material offshoring is equal to

$$\begin{aligned} 1.2 * dOSM_{i,1990-2000} * 100\% = \\ 1.2 * 8\% = 10\% \end{aligned}$$

where $dOSM_{i,1990-2000}$ is the change in the OSM measure between 1990 and 2000. All workers in the 1990 sample are ranked according to their hourly wages, and the lowest 10 percent of workers are eliminated. I use a similar method to truncate all industries in the 2000 sample, using the change in OSM between 2000 and 2010. The 2010 sample is unchanged for this exercise.

Table 6 shows the results from the bounded dataset. The coefficient for OSS is not much changed for any of the outcomes. This is in line with reasonable expectations since the datsets were not truncated on the basis of changes in the OSS. It also supports the weak correlation between OSS and OSM. However, the effects of OSM on the low level and median wage are now significantly negative, and the effect on the high level wage is statistically zero. Both the lower tail spread (column 4) and upper tail spread (column 5) regressions show a postive coefficient for OSM. The coefficient in column 5, for the upper tail spread, has increased from 0.215*** to 0.473***. So, it is possible that the negative employment effects are not only giving the offshoring industries the appearance of higher wages, but also masking the full impact on upper tail inequality. It is important to emphasize that since I cannot track which individuals are laid off between Censuses, this bounding exercise shows only what the employment effect may be doing, and it cannot provide any definitive empirical support for this mechanism. It shows only that this mechanism cannot be ruled out.

Thirdly, in keeping with the task based framework, it could be that offshoring acts as a substitute for the routine task inputs originally performed by workers in the middle of the wage distribution. When industries experience increased access to offshoring, the global price of routine task inputs drop. As a result, domestic workers see their market wage fall relative to workers in manual and abstract tasks, as depicted in Figure 8. This mechanism alone would explain a positive effect of offshoring on the upper tail spread, but it would not directly implicate higher real wages throughout the skill distribution. Furthermore, if only routine tasks and not low skill manual tasks are offshored, we would see a negative effect of offshoring on the 50/10 spread.

Some authors (Acemoglu et al. [1]) have proposed that offshoring operates like an abstract task enhancing technological shock (see Figure 9). For example, if offshoring is complementary to the highly complex task, and substitutble with routine occupations, increased offshoring would produce an increased wage gap between these two categories and explain the positive wage effects seen at the 90th percentile level. The observable implications are similar if routine and abstract tasks are p-complements. Nontheless, without an overall increase in worker productivity, this still does not explain the positive wage effects at the 10th and 50th percentiles.

In order to investigate this task based model as a potential explanation, I use data on task characteristics from the O*NET database.[26] The O*NET dataset contains various measures of task characteristics associated with several hundred different occupations. I start with a rough partition that classifies all of occupations as being either routine, manual or abstract, then refine these classifications into six different measurements. Following the practice of Autor Levy Murnane (2003) [7], Autor and Dorn (2012) [4] and Autor Katz and Kearney (2006) [5], the refined measures are organized along two broad dimensions: (i) routine versus non-routine, and (ii) cognitive versus manual. Non-routine tasks are further described as either analytic or interpersonal. Additionally, non-routine occupations could be either physical (truck drivers, fire fighters) or cognitive (lawyers, teachers) in nature. Table 7 gives descriptions and examples for each of the six measures: non-routine cognitive analytic, non-routine cognitive personal, routine cognitive, routine manual, non-routine manual physical, non-routine manual personal. Examples of non-routine cognitive analytic occupations are physicians, mathematicians, and economists. Examples of Routine Cognitive occupations include switchboard operators and call center workers.

These measures are normalized across the occupations that appear in the 1990 Census, which serves as my base year. I assigned each occupation in my dataset a binary score for each of these nine measures, equal to 1 if the occupation's score was above the mean occupation score in the 1990 sample. For example, in 1990, the (weighted[27]) mean routine cognitive score for all ocupations was equal to -.0771. So, an occupation in any year is classified as Routine Cognitive (RCog=1) if it has a routine cognitive score greater than -.0771. Then, industries are described by the fraction of occupations in each of the six main categories. These means that an occupation has a binary variable in each of the three course categories, and each of the six finer categories, and each industry has nine corresponding continuous variables that vary between zero and one.

To summarize the relationships between these task measures and offshoring, I regressed service and material offshoring on the lagged industry level measures. Lagging the occupational composition reduces the potential for endogeneity, assuming that current offshoring does not affect past industry

[26] The Occupational Informational Network, or O*NET, is a database produced jointly by the US Deparment of Labor and the Employment and Traning Administration. It is available online at http://www.onetcenter.org/.

[27] weighted by the occupation's 1990 population

composition. Table 8 shows the results from regressing OSS on the three coarse categories in Column (1), and the results from regressing OSM on the three coarse categories in Column (2). It is clear that there are fundamental differences between the two different forms of offshoring. OSS increases with the share of routine jobs and decreases with the share of manual jobs. This is consistent with the notion that the routine tasks are highly offshorable, while manual tasks require a proximate worker and are harder to move overseas. However, Column (2) shows that material offshoring decreases with routine jobs and increases with the share of abstract tasks.

Since the latter result appears to contradict the assumptions of the task based model, I re-estimate the two equations using the finer task descriptions. The estimated coefficients for the finer measures are given in Columns (3) and (4) of Table 8. With respect to service offshoring, the positive effect of routine tasks in Column (1) is supported by the positive effect of Routine Cognitive tasks in Column (3). The negative effect of manual tasks on OSS is also confirmed, since the variables nonroutine manual physical and nonroutine manual personal also have negative signs. The material offshoring measure is less straightforward. Both types of routine task measures–cognitive and manual–have negative signs, although only the former effect is statistically significant. But the coarse abstract measure is divided into Nonroutine Cognitive Analytical and Personal. While both these measures have a positive effect on OSM, neither is significant.

Finally, I run the baseline fixed effects regression including all original control variables in addition to the 10 year lagged fraction of occupations in the industry that are in each of the three coarse categories, followed by the six finer measures.[28] Tables 9 and 10 show that including these lagged occupation shares does change the estimated effect of the OSM measure and OSS meausures. For a given occupational composition, an industry will see larger effect on upper tail inequality from OSS and a slightly smaller but still positive effect from OSM.

[28]Using current occupation shares does not change the offshoring coefficients from those seen in the baseline regression; moreover current offshoring measures appear uncorrelated with current industry composition

7 Conclusion

In this paper, I examine the impact of offshoring on wage convexification through the framework of a task based model. In particular, I look for evidence to support the hypothesis that offshoring decreases relative wages of middle skilled workers because these workers perform highly routine tasks. I use industry level measures of offshoring and aggregate individual wage data to construct industry measures of upper and lower tail inequality. I find that offshoring significantly increases wage levels at each point in the earnings distribution and also increases the 90/50 spread.

Of the three mechanisms that I consider, both a productivity effect and selection are consistent with the positive wage effects. I show that the positive wage effects could be fully explained by selection, and this explanation is plausible because the increased wages in offshoring industries are accompanied by a large decrease in employment. However there is no empirical evidence of productivity enhancement. In other words, elevated wages in highly offshored industries are most likely due solely to the fact that domestic positions for low paid, low skilled workers are being eliminated. The positive effect of service offshoring on the 90/50 spread is magnified when lagged occupational composition is controlled for, while the positive effect of material offshoring is dampened. This study provides support for the hypothesis that offshoring is directly increasing inequality in the upper half of the wage distribution, but also shows that positive wage effects of offshoring are due to selection in layoffs. The results shown in this paper indicate that offshoring acts as a substitute for domestic workers in routine service occupations.

References

[1] Daron Acemoglu and David Autor. Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labor Economics*, 4b:1043–1171, 2011.

[2] Mary Amiti and Shang-Jin Wei. Service Offshoring and Productivity: Evidence from the US. *The World Economy*, 32(2):203–220, February 2009.

[3] David Autor, David Dorn, and Gordon H. Hanson. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *SSRN Electronic Journal*, 2012.

[4] David H Autor and David Dorn. The Growth of Low Skill Service Jobs and the Polarization of the U . S . Labor Market. 2009.

[5] David H Autor, Lawrence F Katz, and Melissa S Kearney. The Polarization of the U.S. Labor Market. *American Economic Review*, 96(2):189–194, 2006.

[6] David H. Autor, Lawrence F. Katz, and Melissa S. Kearney. Trends in U.S. Wage Inequality: Revising the Revisionists. *The Review of Economics and Statistics*, 90(2):300–323, May 2008.

[7] David H. Autor, Frank Levy, and Richard J. Murnane. The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4):1279–1333, 2003.

[8] David Card and John E Dinardo. Skill-Biased Technological Change and Rising Wage Inequality : Some Problems and Puzzles. *Journal of Labor Economics*, 20(4):733–783, 2002.

[9] Rosario Crinò. Service Offshoring and White-Collar Employment. *The Review of Economic Studies*, 77(2):595–632, April 2010.

[10] Robert C Feenstra and Gordon H Hanson. Globalization , Outsourcing , and Wage Inequality. *The American Economic Review*, 86(2):240–245, 1996.

[11] Robert Gibbons and Lawrence F. Katz. Does Wage Unmeasured Ability Inter-Industry Differentials ? *The Review of Economic Studies*, 59(3):515–535, 1992.

[12] Maarten Goos and Alan Manning. Lousy and Lovely Jobs: the Rising Polarization of Work in Britain. *Review of Economics and Statistics*, 89(February):118–133, 2007.

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

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

[15] Thomas Lemieux. Increasing Residual Wage Inequality : Composition Effects , Noisy Data , or Rising Demand for Skill ? *American Economic Review*, 96(3):461–498, 2006.

[16] David N Margolis, John M Abowd, and Francis Kramarz. High Wage Workers and High Wage Firms. *Econometrica*, 67(2):251–333, 1999.

[17] Lindsay Oldenski. Offshoring and the Polarization of the U . S . Labor Market.

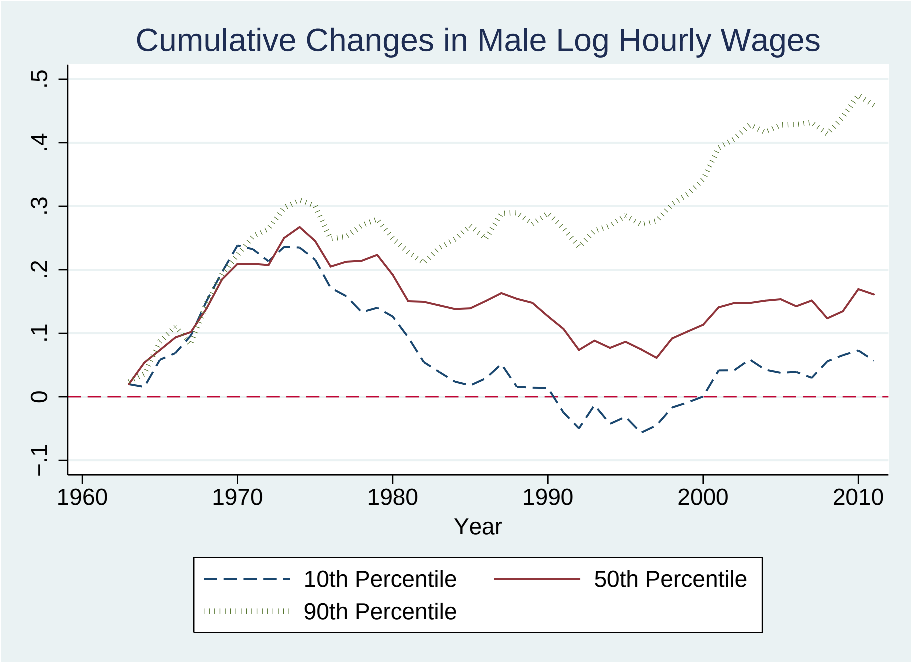
[18] William W Olney. Offshoring , Immigration , and the Native Wage Distribution. 2011.

[19] Gianmarco I.P. Ottaviano, Giovanni Peri, and Greg C Wright. Immigration, Offshoring and American Jobs. 2010.

[20] Matthew J Slaughter. International trade and labor demand elasticities. *Journal of International Economics*, 54:27–56, 2001.

[21] Greg C Wright. Revisiting the Employment Impact of offshoring. 2011.

Figure 1: Evolution of Hourly Wages (Men)



Data for Tables 1 & 2 from Current Population Survey, available at www.nber.org

Figure 2: Evolution of Hourly Wages (Women)

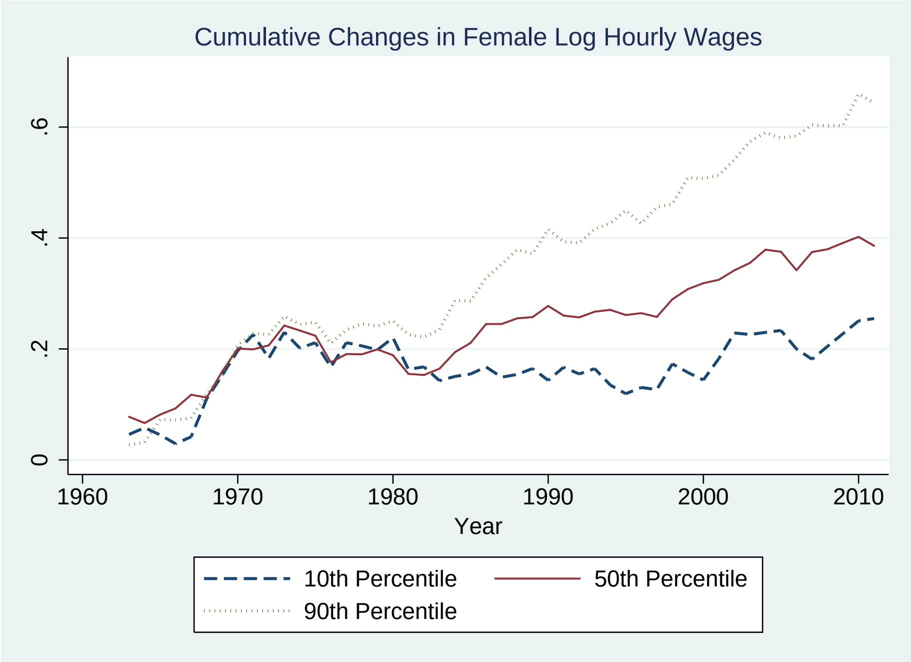
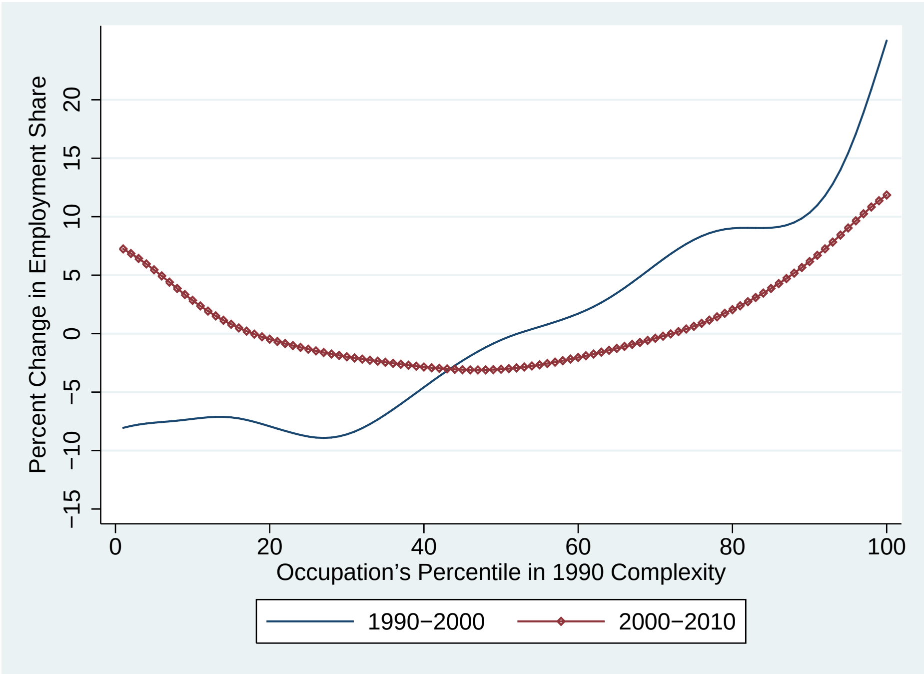
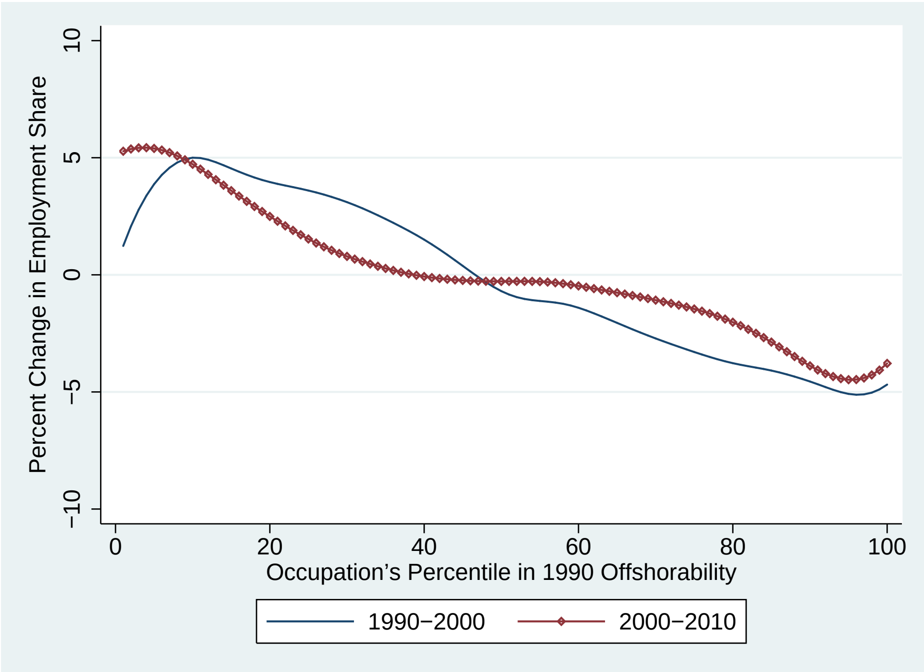


Figure 3: Changes in Employment Shares by Complexity



Data from US Census, available at usa.ipums.org

Figure 4: Changes in Employment Shares by Offshorability



Data from US Census, available at usa.ipums.org

Figure 5: Offshoring of Material Inputs

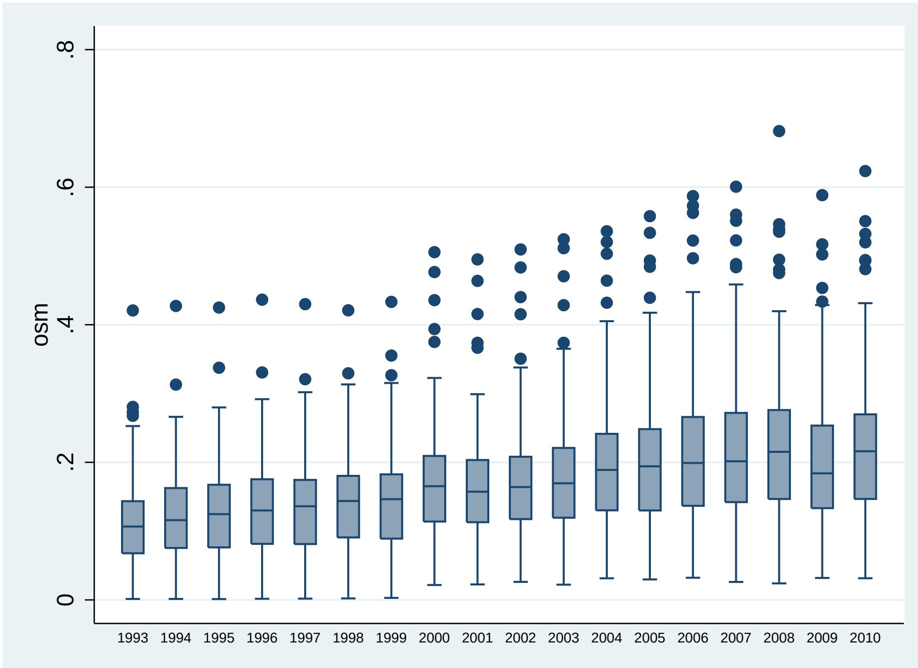


Figure 6: Offshoring of Service Inputs

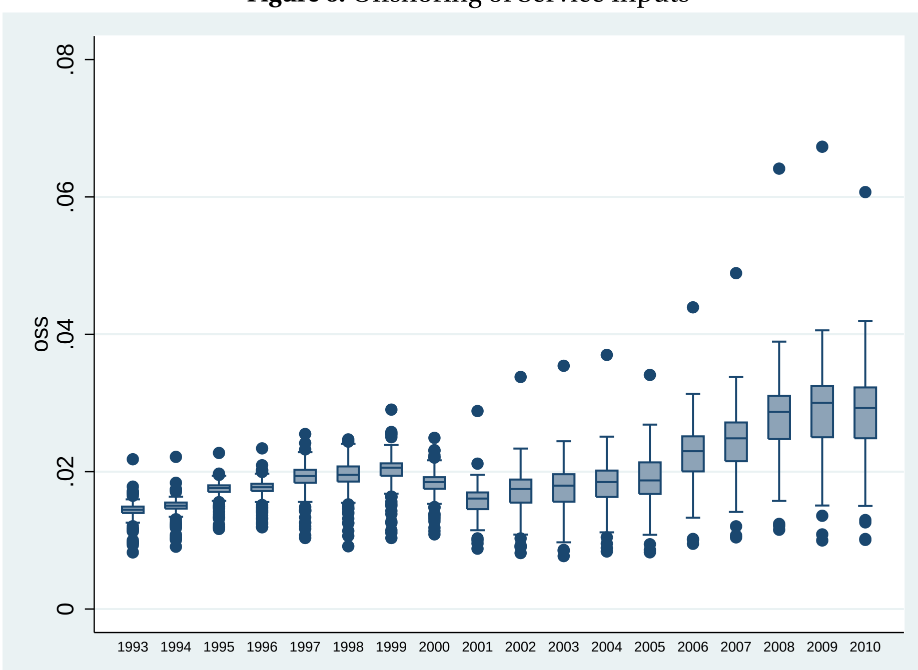


Figure 7: Wage Schedule for Efficient Task Allocation

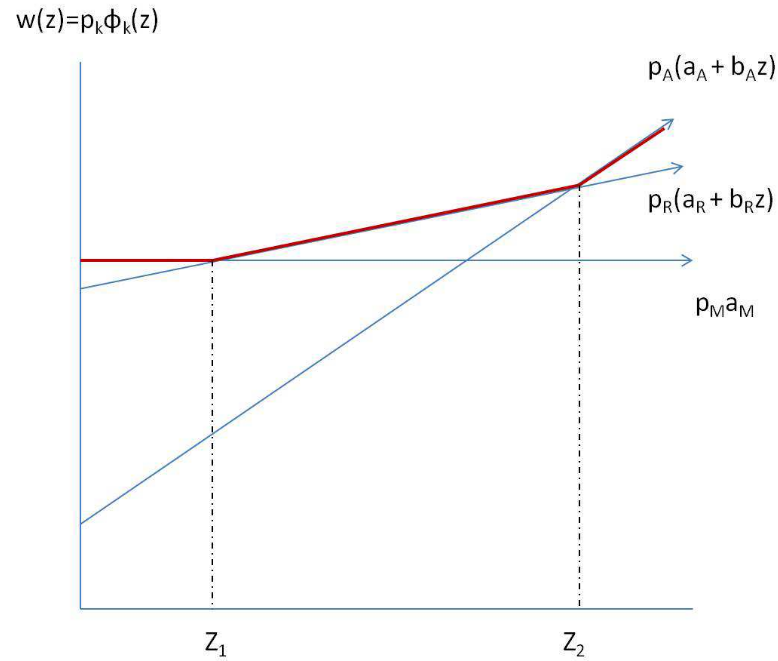


Figure 8: Decline in the Global Price for Routine Tasks

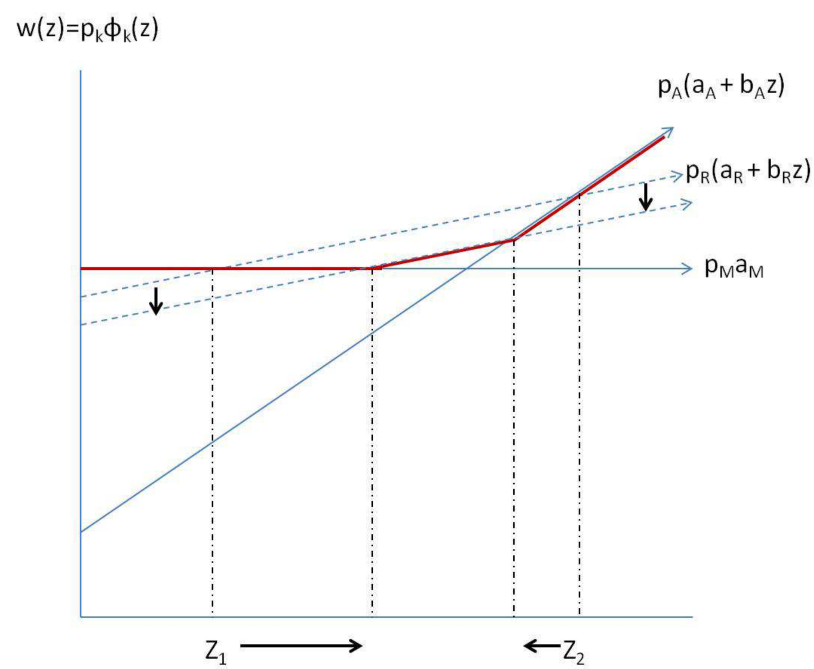


Figure 9: Abstract Task Enhancing Technology

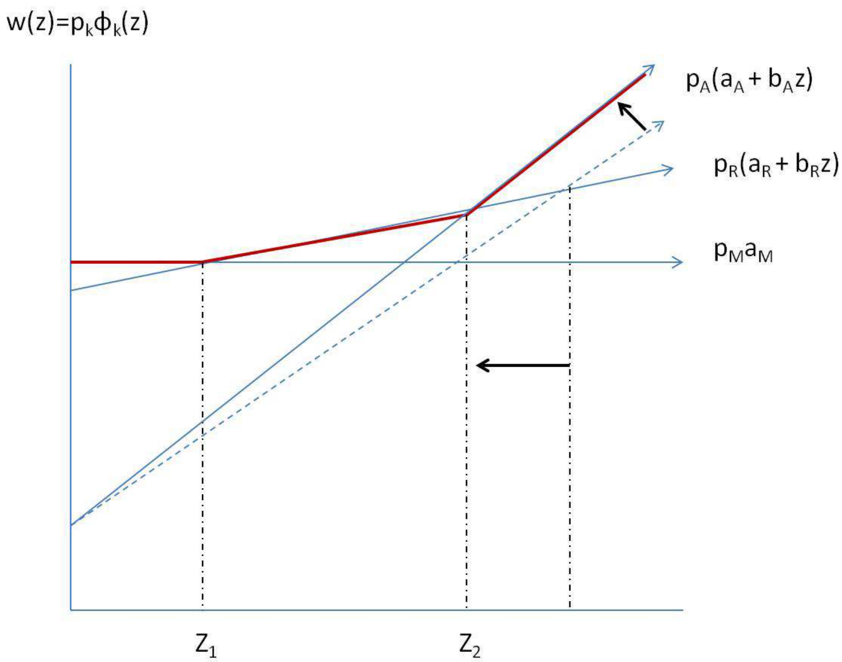


Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Industry Size					
Industry Employment (millions)	0.987	1.987	0.0097	16.9	367
Industry Log Employment	12.868	1.322	9.178	16.645	367
Income (2000 dollars)					
10th Percentile Annual	7,469.88	4,707.80	776.56	31,000	367
Median Annual	27,615.18	10,118.53	6,986.45	58,241.70	367
90th Percentile Annual	63,085.57	22,375.95	21,496.77	226,754.4	367
10th Percentile (Hourly) LWage	1.789	0.303	1.055	2.680	367
Median Hourly LWage	2.605	0.290	1.896	3.288	367
90th Percentile LWage	3.380	0.283	2.741	4.582	367
Lower Tail Spread	0.8157	0.1250	0.4853	1.2646	367
Upper Tail Spread	0.7749	0.1719	0.2877	1.5307	367
d90/50 1990-2000	0.05472	0.1218	-0.2559	0.5051	127
d90/50 2000-2011	0.0072	0.1109	-0.4910	0.3288	129
Other Industry Characteristics					
Foreign Born	0.1350	0.0848	0.0000	0.5212	367
Black	0.1046	0.0507	0.0000	0.2870	367
Female	0.3697	0.2007	0.0584	0.9490	367
College Degree	0.2213	0.1529	0.00	0.7269	367
Union	0.1218	0.1159	0.00	0.6712	367
Offshoring Measures					
Material Offshoring	0.1706	0.1017	0.0014	0.6235	367
ΔOSM 1990-2000	0.0590	0.0609	0.0021	0.4914	126
ΔOSM 2000-2011	0.0558	0.0433	-0.0124	0.2484	128
Service Offshoring	0.0206	0.0076	0.0082	0.0607	367
ΔOSS 1990-2000	0.0039	0.0018	-0.0056	0.0103	126
ΔOSS 2000-2011	0.0105	0.0059	-.0017	0.0376	128

Table 2: Labor Market Outcomes
Industry Wages, Inequality and Employment

VARIABLES	(1) 10th Pctle Wage	(2) Med. Wage	(3) 90th Pctle Wage	(4) 50/10 Sprd	(5) 90/50 Sprd	(6) Log Emp
Service Offshoring	1.976**	2.127***	3.503***	0.151	1.376**	4.239
	(0.914)	(0.706)	(0.992)	(0.684)	(0.676)	(7.218)
Material Offshoring	0.496***	0.340***	0.555***	-0.156	0.215**	-1.236**
	(0.128)	(0.0989)	(0.139)	(0.0958)	(0.0947)	(0.592)
Black	-0.131	-0.00512	-0.0759	0.126	-0.0708	1.529
	(0.271)	(0.210)	(0.294)	(0.203)	(0.201)	(1.167)
Female Share	-0.0302	-0.423***	-0.718***	-0.393***	-0.295***	-0.179
	(0.142)	(0.109)	(0.154)	(0.106)	(0.105)	(0.670)
Foreign Born	0.0141	0.0586	0.0709	0.0444	0.0123	-1.022
	(0.199)	(0.154)	(0.216)	(0.149)	(0.147)	(0.815)
Share Union	0.262*	0.369***	0.0493	0.107	-0.319***	1.579**
	(0.135)	(0.104)	(0.147)	(0.101)	(0.0999)	(0.680)
Share with BA	0.338***	0.497***	0.614***	0.159*	0.116	0.620
	(0.112)	(0.0867)	(0.122)	(0.0841)	(0.0831)	(0.516)
Observations	367	367	367	367	367	367
Adjusted R^2	0.963	0.978	0.957	0.828	0.917	0.901

All regressions include year and industry fixed effects
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Industry Wages, Inequality and Employment
Contextual Interpretation of OSS and OSM Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	10th Pct. Wage	Med. Wage	90th Pct. Wage	50/10	90/50	Ln Emp
Variable SD	0.3116	0.2959	0.290	0.128	0.1735	1.319
β_{OSS}	1.976	2.127	3.503	insig.	1.376	insig.
% exp. by ↑ OSS	4.83%	5.48%	9.20%	–	6.04%	–
β_{OSM}	0.496	0.34	0.555	insig.	0.215	-1.236
% exp. by ↑ OSM	16.18%	11.68%	19.46%	–	12.60%	-9.53%

OSS SD=0.008, OSS SD=0.102

Table 4: Effect on Upper Tail Inequality

Share of 90/50 Increase Explained by Offshoring (Mean Industry 1990-2011)

	Δ 1990-2011	β	Pred. Change in 90/50	$\frac{\text{Predicted}}{\text{Mean Observed Change}}$
OSS	0.0144	1.376	0.0199	0.32
OSM	0.1151	0.215	0.0247	0.40

Table 5: Industry Wages and Inequality
Controlling for Productivity

VARIABLES	(1) 10th Pct. Wage	(2) Med. Wage	(3) 90th Pct. Wage	(4) 50/10 Spread	(5) 90/50 Spread	(6) Log Emp
Service Offshoring	1.974**	2.023***	3.512***	0.0493	1.489**	4.162
	(0.790)	(0.683)	(0.970)	(0.622)	(0.673)	(5.451)
Material Offshoring	0.332***	0.280***	0.505***	-0.0521	0.225**	-0.904**
	(0.111)	(0.0961)	(0.136)	(0.0876)	(0.0947)	(0.449)
Black	-0.214	-0.00810	-0.0818	0.206	-0.0737	1.567*
	(0.231)	(0.200)	(0.283)	(0.182)	(0.197)	(0.875)
Female Share	-0.0596	-0.448***	-0.713***	-0.388***	-0.265**	0.417
	(0.126)	(0.109)	(0.154)	(0.0989)	(0.107)	(0.518)
Foreign Born	-0.123	-0.00685	0.0286	0.117	0.0354	0.322
	(0.167)	(0.145)	(0.206)	(0.132)	(0.143)	(0.616)
Share Union	0.281**	0.382***	0.00863	0.101	-0.374***	1.677***
	(0.117)	(0.101)	(0.143)	(0.0920)	(0.0995)	(0.512)
Share with BA	0.411***	0.501***	0.562***	0.0908	0.0604	0.795**
	(0.0970)	(0.0838)	(0.119)	(0.0764)	(0.0826)	(0.387)
Productivity	11.80	25.50	55.95	13.70	30.45	-1,697***
	(44.50)	(38.47)	(54.61)	(35.05)	(37.90)	(129.2)
Observations	367	367	367	367	367	367
Adjusted R^2	0.971	0.980	0.958	0.837	0.917	0.943

All regressions include year and industry fixed effects
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Industry Wages and Inequality: Bounding Experiment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	10th Percentile Wage	Median Wage	90th Percentile Wage	50/10 Spread	90/50 Spread
Service Offshoring	2.643**	2.179***	3.597***	-0.464	1.418**
	(1.039)	(0.729)	(1.010)	(0.749)	(0.654)
Material Offshoring	-1.459***	-0.379***	0.0934	1.080***	0.473***
	(0.146)	(0.103)	(0.142)	(0.105)	(0.0920)
Black	0.126	-0.000518	-0.0558	-0.127	-0.0553
	(0.304)	(0.213)	(0.295)	(0.219)	(0.191)
Female Share	-0.217	-0.511***	-0.741***	-0.294**	-0.231**
	(0.165)	(0.116)	(0.160)	(0.119)	(0.104)
Foreign Born	-0.245	-0.0107	0.0293	0.234	0.0400
	(0.219)	(0.154)	(0.213)	(0.158)	(0.138)
Share union members	0.401***	0.390***	-0.0388	-0.0110	-0.429***
	(0.154)	(0.108)	(0.149)	(0.111)	(0.0968)
Share with BA	0.670***	0.621***	0.615***	-0.0497	-0.00536
	(0.127)	(0.0894)	(0.124)	(0.0918)	(0.0803)
Observations	367	367	367	367	367
Adjusted R^2	0.960	0.977	0.956	0.875	0.926

All regressions include year and industry fixed effects

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The data for these regressions were truncated by eliminating individual workers according to the predicted change in employment from the results in Table 2, Column (7), and the observed change in the industry's measure of material offshoring. For the purposes of this exercise,the least paid workers in the sample are assumed to the be first laid off. The 1990 observations were adjusted based on the change in offshoring between 1990 and 2011, and the 2000 observations were adjusted based on the change between 2000 and 2011. See Section 6.1 for details.

Table 7: Description and Examples of Task Measures

Task Measure	Description	Examples of Tasks or Occupations with a high score
1. Non-routine cognitive analytic	Mathematical or complex problem solving ability	Engineer, Physician, Economist, Mathematician
2. Non-routine cognitive personal	Ability to direct, control and plan projects or activities	Managers, Teachers, Attorneys
3. Routine cognitive	Requires ability to precisely attain limits or standards	Navigation, maintain records or measurements, switchboard operater, call center worker
4. Routine manual	Ability for small object manipulation	Cooking and baking by recipes, assembly line worker, packing objects for storage or shipping
5. Non-routine manual physical	Hand-eye-foot coordination	Bus driver, Gardener, Janitor, Pilot, Cattle rancher, Farmer
6. Non-routine manual personal	Adaptability and interactive ability in physical tasks	Hairdresser, Aesthetician, Daycare provider, Massage Therapist

Task measures and descriptions are from Autor et al.

Table 8: The Determinants of Industry Offshoring

VARIABLES	(1) Service Offshoring	(2) Material Offshoring	(3) Service Offshoring	(4) Material Offshoring
Routine Cognitive L10			0.0215**	-0.204***
			(0.0108)	(0.0769)
Routine Manual L10			0.00682	-0.0186
			(0.00942)	(0.0668)
Nonrout. Cognitive Analytical L10			0.0125*	0.0298
			(0.00701)	(0.0497)
Nonrout. Cognitive Personal L10			-0.0166*	0.0734
			(0.00893)	(0.0634)
Nonrout. Manual Physical L10			-0.0287***	-0.0173
			(0.0105)	(0.0747)
Nonrout. Manual Personal L10			-0.0342***	0.0469
			(0.0103)	(0.0729)
Routine L10	0.0344***	-0.166**		
	(0.00987)	(0.0720)		
Manual L10	-0.0616***	-0.0534		
	(0.0141)	(0.103)		
Abstract L10	0.00396	0.0791**		
	(0.00440)	(0.0321)		
Observations	367	367	367	367
Adjusted R^2	0.713	0.869	0.701	0.871

All regressions include year and industry fixed effects

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Controlling for Coarse Composition L10

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	10th Percentile Wage	Median Wage	90th Percentile Wage	50/10 Spread	90/50 Spread	Log Emp
Service Offshoring	1.546	2.070***	4.332***	0.524	2.262***	4.235
	(0.981)	(0.757)	(1.059)	(0.736)	(0.712)	(7.358)
Material Offshoring	0.531***	0.370***	0.557***	-0.160	0.186*	-1.206**
	(0.131)	(0.101)	(0.141)	(0.0981)	(0.0949)	(0.597)
Routine share L10	0.112	0.00873	-0.276	-0.104	-0.285**	1.071
	(0.164)	(0.126)	(0.176)	(0.123)	(0.119)	(0.804)
Abstract share L10	-0.0913	-0.105*	-0.0863	-0.0140	0.0190	0.252
	(0.0700)	(0.0540)	(0.0756)	(0.0525)	(0.0508)	(0.501)
Manual share L10	-0.202	-0.0246	0.353	0.178	0.377**	0.516
	(0.222)	(0.171)	(0.239)	(0.166)	(0.161)	(1.130)
Observations	367	367	367	367	367	367
Adjusted R^2	0.963	0.978	0.957	0.827	0.920	0.900

All regressions include year and industry fixed effects

Other controls: foreign born/female/black/college educated/unionized shares of industry

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Controlling for Fine Composition L10

VARIABLES	(1) 10th Percentile Wage	(2) Median Wage	(3) 90th Percentile Wage	(4) 50/10 Spread	(5) 90/50 Spread	(6) Log Emp
Service Offshoring	1.661*	2.173***	4.219***	0.512	2.046***	3.191
	(0.937)	(0.733)	(1.029)	(0.717)	(0.709)	(7.335)
Material Offshoring	0.587***	0.398***	0.573***	-0.189*	0.175*	-1.092*
	(0.128)	(0.100)	(0.141)	(0.0981)	(0.0971)	(0.598)
Routine Cognitive share L10	0.593***	0.281**	0.184	-0.312**	-0.0964	1.235*
	(0.157)	(0.123)	(0.172)	(0.120)	(0.119)	(0.679)
Routine Manual share L10	-0.300**	-0.287**	-0.428***	0.0129	-0.141	1.124
	(0.142)	(0.111)	(0.156)	(0.109)	(0.108)	(0.831)
Nonrout. Cognitive Analytic share L10	-0.0348	-0.0830	-0.0467	-0.0482	0.0363	-0.00521
	(0.101)	(0.0787)	(0.111)	(0.0770)	(0.0762)	(0.569)
Nonrout. Cognitive Personal share L10	-0.143	-0.0435	-0.0554	0.0993	-0.0120	0.594
	(0.125)	(0.0980)	(0.138)	(0.0959)	(0.0948)	(0.840)
Nonrout. Manual Physical share L10	-0.219	0.0418	0.196	0.261**	0.155	0.392
	(0.154)	(0.120)	(0.169)	(0.118)	(0.116)	(0.860)
Nonrout. Manual Personal share L10	-0.0980	-0.0419	0.196	0.0560	0.238**	0.195
	(0.148)	(0.116)	(0.163)	(0.114)	(0.112)	(0.932)
Observations	367	367	367	367	367	367
Adjusted R^2	0.965	0.979	0.958	0.831	0.918	0.902

All regressions include year and industry fixed effects

Other controls: foreign born/female/black/college educated/unionized shares of industry

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1